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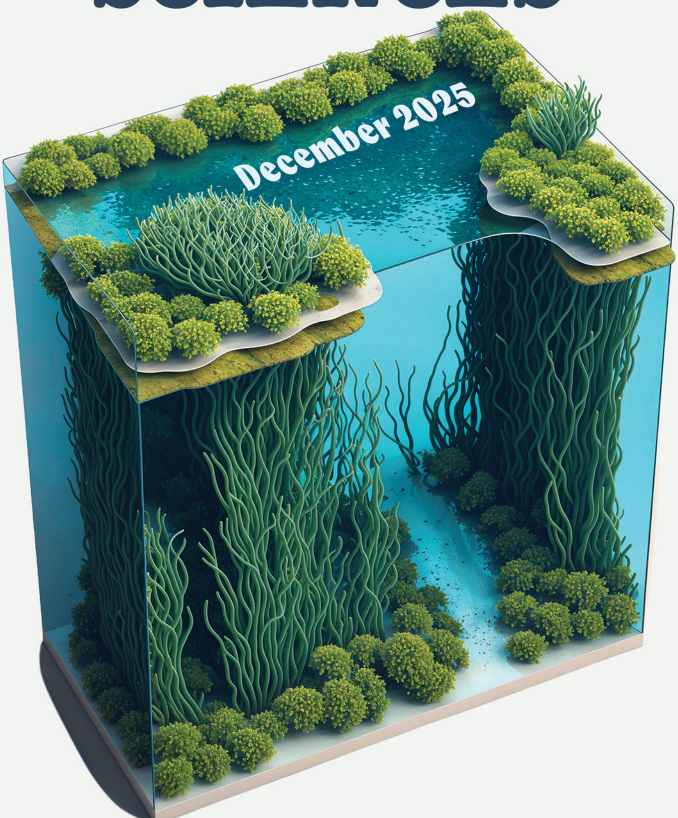

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INTERNATIONAL COMPILATION OF RESEARCH AND STUDIES IN THE FIELD OF AGRICULTURE, FORESTRY AND AQUACULTURE SCIENCES

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SERÜVEN YAYINEVİ

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Chapter 1

THE ROLE OF IRRIGATION COOPERATIVES IN ADAPTING AGRICULTURE TO CLIMATE CHANGE: AN ASSESSMENT OF IZMIR PROVINCE

Dilek YÜCEL ENGİNDENİZ[1]

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1. Introduction

Climate change has emerged in recent years as one of the most significant environmental challenges directly impacting agricultural production. The global rise in greenhouse gas emissions leads to increasing average temperatures and substantial shifts in precipitation regimes (Hatfield et al., 2014). This situation results in consequences such as yield losses -particularly in water-dependent agricultural systems- increased production costs, changes in crop patterns, and risks to food security.

Due to its geographical location, Türkiye is under the influence of various climatic zones and exhibits a high sensitivity to climate change. Recent research reveals that average temperatures in Türkiye are rising, precipitation amounts are decreasing, and the frequency of droughts is increasing (MGM, 2023). This leads to serious outcomes, such as the depletion of water resources and an increased need for irrigation, especially in the Aegean, Central Anatolia, and Southeastern Anatolia regions where agricultural production is intensive.

The efficient, equitable, and sustainable management of water in agricultural production is a fundamental component of the climate change adaptation process. Approximately 70% of agricultural water use in Türkiye is for irrigation purposes, and a significant portion of this usage is managed through local organizations. Irrigation cooperatives stand out as local institutional structures that enable producers to act collectively, performing critical functions such as water distribution, operation of irrigation infrastructure, maintenance and repair activities, and energy management. In these respects, irrigation cooperatives are not merely technical service providers; they are also social structures that strengthen participatory governance, solidarity, and the sense of collective responsibility in rural areas.

In the literature, it is emphasized that climate change increases the pressure on agricultural production and water resources, particularly in the Mediterranean Basin; furthermore, temperature increases, irregular precipitation regimes, and the rising frequency of droughts have turned water management into a critical policy area (Türkeş et al., 2000; Lal, 2009; Kendirli et al., 2010; Bozkurt & Şen, 2011; Dellal et al. 2012; Demircan et al., 2013; Türkeş, 2019; MGM, 2023; 2024; Karahan & Pınar, 2023; Zobar et al., 2025). In this context, irrigation cooperatives are considered institutional structures that ensure the collective management of water resources at the local scale and gain increasing importance in the climate change adaptation process (Aküzüm et al., 2010; Taş et al., 2011; Ünver, 2016; Aküzüm et al., 2019; Altın & Barak, 2020; Islam, 2023). Various studies demonstrate that cooperative-based water management approaches increase water use efficiency, strengthen coordination among producers, and contribute to the management of climate-related risks (Everest et al., 2019; Vu et al., 2023; Uysal & Yıldız, 2025). Moreover, modern irrigation techniques, digital monitoring systems, and energy-efficiency-based applications emerge as fundamental tools supporting both environmental and economic sustainability in agricultural production (Çakmak & Gökalp, 2011; 2013; 2015a; 2015b; Çaltı & Somuncu, 2019; Bildirici, 2024; Wang & Xu, 2025). National and international reports also highlight the strengthening of local institutional structures as a priority area in water governance and agricultural adaptation policies (TGDF, 2017; CIHEAM, 2020; OECD, 2021; FAO, 2022; World Bank, 2023; TÜİK, 2024).

As one of the major agricultural centers of the Aegean Region, the province of Izmir is among the regions that feel the effects of climate change intensely. Its multi-basin structure, encompassing the Gediz, Küçük Menderes, and Bakırçay basins, faces increasing pressure on water resources due to rising temperatures and irregular precipitation patterns; this situation renders the strategic importance of irrigation in agricultural production even more prominent (Bozkurt & Şen, 2011; Demircan et al., 2013; Türkeş, 2019; MGM, 2023; 2024, Zobar et al., 2025). The crop pattern in Izmir, which is widely cultivated in plant production and has high water demand, necessitates the sustainable management of groundwater and surface water resources. In this regard, irrigation cooperatives stand out as critical local actors in ensuring the efficient and equitable use of water. Regional plans and reports indicate that irrigation cooperatives operating in Izmir hold significant potential for maintaining the continuity of agricultural production, increasing water use efficiency, and strengthening the resilience of producers against climate risks (Atış et al., 2023; IZKA, 2023; TAGEM, 2023; Izmir Provincial Directorate of Environment, Urbanization and Climate Change, 2025).

By addressing the impacts of climate change on Turkish agriculture within a general framework, this study aims to evaluate the role of irrigation cooperatives in climate change adaptation through the case of Izmir province. The study examines the structure, spatial distribution, and functions of irrigation cooperatives in Izmir, discussing their current and potential contributions to water management, agricultural productivity, and rural development. Furthermore, by developing recommendations at the policy, management, and implementation levels to enhance the climate change adaptation capacity of irrigation cooperatives, it aims to provide a guiding framework for water management and agricultural policies. This study is a descriptive evaluation based on secondary data analysis and a literature review.

2. Impacts of Climate Change on Agriculture

Climate change creates direct and indirect effects on agricultural production in Türkiye, as it does on a global scale (Bozoğlu et al., 2019;

Karahan & Pinar, 2023; Candan Demirkol & Gündüzoğlu, 2025). Temperature increases, irregularities in precipitation regimes, the depletion of water resources, the rise in extreme weather events, and seasonal shifts threaten all agricultural systems, from crop production to livestock (Demircan et al., 2013; Demircan, 2022; Demirtaş et al., 2023). Türkiye's semi-arid climatic characteristics increase its vulnerability to climate change; this situation raises production costs, lowers farmers' income levels, and amplifies food security risks, particularly in regions where water-dependent production systems are prevalent (TGDF, 2017; OECD, 2021). In this context, it is possible to examine the impacts of climate change on agricultural production under four main headings.

2.1. Temperature Increase and Precipitation Patterns

The temperature increases observed in Türkiye in recent years are leading to significant changes in crop production patterns. According to long-term data from the General Directorate of Meteorology (MGM), Türkiye's average annual temperature rose from 13.2°C in the 1971–2000 period to 14.1°C in the 2000–2020 period (MGM, 2023). This increase causes plants to undergo water stress by raising the risk of drought, especially during the summer months (Demircan et al., 2013). Along with the temperature rise, significant changes have occurred in precipitation patterns. While a decrease in total precipitation has been experienced in the western and southern regions of Türkiye, the frequency of short-term but intense rainfall has increased in the Black Sea Region (World Bank, 2023). This situation has increased the risk of drought on one hand, and the likelihood of floods and overflows on the other. Water scarcity creates serious problems in the production of water-dependent crops (cotton, maize, vegetable species, etc.) in Southeastern Anatolia, Central Anatolia, and the inner parts of the Aegean (CIHEAM, 2020).

2.2. Depletion of Water Resources

One of the most critical impacts of climate change on Türkiye is the depletion of freshwater resources. With the annual amount of available water per capita falling below 1,300 m³, Türkiye is categorized among "water-stressed countries" (OECD, 2021). Increasing temperatures and evaporation reduce water levels in lakes and dams, while the early melting of snow cover disrupts river regimes, creating imbalances in irrigation cycles (Aktaş, 2014). This process is becoming particularly evident in the Konya Basin, and the Büyük Menderes and Gediz basins. Excessive extraction of groundwater leads to a drop in the water table and an increase in salinity (Bozoğlu et al., 2019). This situation is one of the most significant environmental problems threatening the sustainability of agricultural production.

2.3. Decline in Agricultural Productivity

Climate change has direct negative effects on agricultural productivity in Türkiye. Rising temperatures, water scarcity, and drought conditions cause yield declines by creating stress during the growth periods of plants. The drought experienced in the Central Anatolia Region in 2021 reduced wheat yields by 30% in some provinces (TGDF, 2017; Plevneli et al., 2023). It has also been reported that temperature increases facilitate the spread of harmful organisms and plant diseases, creating additional pressure on production quality (Uysal & Yıldız, 2025). Shifts in early flowering or ripening periods seen in fruit and vegetable production lead to quality losses and difficulties in market planning.

2.4. Extreme Weather Events

Another consequence of climate change is the increase in the frequency and intensity of extreme weather events. The prolonged droughts experienced in Türkiye between 2020 and 2023 reduced dam occupancy rates and led to shorter irrigation seasons (World Bank, 2023). Furthermore, sudden rainfall, hail, storms, and heatwaves have caused serious yield losses in agricultural production (Yılmaz et al., 2025). Such events affect not only crop production but also agricultural infrastructure. The clogging of irrigation canals, the disruption of drainage systems, and rising energy costs create uncertainty in production planning. In particular, the increase in flood and hail events has raised the economic vulnerability of producers by increasing the burden on agricultural insurance systems (OECD, 2021).

In conclusion, climate change in Türkiye appears as a multi-dimensional environmental and socio-economic problem that threatens the sustainability of agricultural production. Therefore, the development of adaptation and resilience strategies in agricultural production is a priority requirement at the policy level.

3. The Role of Irrigation Cooperatives in Agriculture and Water Management

3.1. Efficiency in Operation of Irrigation Infrastructure and Water Distribution

One of the most fundamental functions of irrigation cooperatives is the operation and maintenance of irrigation infrastructure and ensuring the equitable distribution of water. In many regions of Türkiye, the operation of irrigation canals, pumping stations, and pressurized pipe networks is largely carried out by cooperatives. Reducing water losses, increasing on-farm water efficiency, and maintaining operating costs at a sustainable level are directly related to the institutional capacity of these cooperatives. Indeed, research indicates that yield per unit of irrigation water in networks operated by cooperatives increases by 15–40%, while water loss rates decrease by 10–30%. This efficiency ensures lower energy costs -especially in areas where groundwater is pumped- and makes irrigation periods more predictable. Furthermore, equitable water distribution reduces the risk of conflict among producers and prevents delays during the irrigation season.

3.2. Management Structure, Participation, and Decision-Making Processes

The success of irrigation cooperatives is closely linked not only to physical infrastructure but also to their organizational structure and the inclusiveness of their decision-making processes. The structure of cooperatives, based on democratic management principles, allows producers to participate actively in decision processes. When members collectively decide on issues ranging from water distribution schedules and infrastructure investments to water pricing policies and maintenance priorities, both legitimacy and institutional commitment are strengthened. Thanks to these participatory mechanisms:

- Disputes regarding water use are reduced,
- Trust and cooperation among producers are strengthened,
- The implementation rate of decisions increases,
- Problem-solving processes are accelerated.

In international literature, the participatory management model of cooperatives is considered one of the successful examples of "localization" and "multi-stakeholder governance" principles in water management.

3.3. Agricultural Productivity, Costs, and Economic Efficiency

Irrigation cooperatives play both direct and indirect roles in increasing agricultural income. Collectively operated irrigation infrastructures lower the energy, maintenance, and investment costs that producers would struggle to meet individually. This facilitates access to irrigation services, particularly for small-scale producers, and contributes to the continuity of production activities. From the perspective of economic efficiency, cooperativization provides the following advantages:

- Sharing of energy costs: In regions with pumping systems, distributing energy expenses according to the number of members significantly reduces the individual burden on producers (Bildirici, 2024).
- Reduction in maintenance and repair costs: Collective organization facilitates planned maintenance and allows for rapid intervention in case of malfunctions.

- Yield increase: Regular and timely irrigation minimizes yield losses by supporting plant development.
- Increased bargaining power: Cooperatives empower producers in terms of energy tariffs, equipment procurement, and access to public subsidies (Everest et al., 2019; Uysal & Yıldız, 2025).

Studies in the literature reveal that in regions where irrigation cooperatives operate effectively, agricultural productivity per decare increases by 12–35%, while operating costs are reduced by 8–20% (Çakmak & Gökalp, 2011; 2013; 2015a; 2015b; Caltı & Somuncu, 2019; Wang & Xu, 2025). These findings demonstrate that irrigation cooperatives are an important institutional tool not only for water supply but also for enhancing economic efficiency in agricultural production.

3.4. Technological Modernization and Digitalization in Water Management

In recent years, the use of digital technologies in agricultural water management has been steadily increasing. Pressurized irrigation systems, automatic control units, soil moisture sensors, meteorological stations, and remote monitoring software enable the precise management of water. Irrigation cooperatives act as a vital catalyst in the dissemination of these technologies. By sharing the cost of technology investments among members, cooperatives accelerate the transition to modern systems; they also facilitate the adaptation process by providing training and technical consultancy to producers. Through digitalization, water consumption is measured more accurately, irrigation timing is optimized, and energy efficiency is enhanced. These developments both strengthen climate change adaptation and support the sustainable use of water resources.

3.5. Socioeconomic Contributions and Role in Rural Development

Beyond supporting agricultural production, irrigation cooperatives make significant contributions to strengthening the rural social structure. Increased access to water and the regularization of irrigation services support the economic stability of rural households by raising agricultural productivity and income levels; this contributes to maintaining living standards in rural areas and reduces the tendency of the younger population to leave agriculture and migrate to cities (Ünver, 2016; Aküzüm et al., 2019).

The institutional presence of cooperatives allows for the development of local governance capacity in rural regions and enables communities to manage their own natural resources in a more effective, fair, and participatory manner. Collective decision-making processes conducted through irrigation cooperatives contribute to the strengthening of social capital among producers, the development of trust, and an increased capacity to solve common problems together (Everest et al., 2019; Vu et al., 2023). Moreover, by reinforcing the culture of organization at the local level, cooperatives create a suitable institutional ground for the emergence of other rural development initiatives such as marketing cooperatives, producer unions, and rural tourism. In this regard, irrigation cooperatives are regarded as integrated structures that bring together the economic, social, and institutional dimensions of rural development (Izmir Development Agency, 2023; Atış et al., 2023).

4. Structure and Distribution of Irrigation Cooperatives in Izmir Province

In Türkiye, cooperatives under the Ministry of Agriculture and Forestry are examined under two main groups according to their functions and purposes: (i) agricultural cooperatives and (ii) agricultural credit cooperatives. Agricultural cooperatives include agricultural development cooperatives, irrigation cooperatives, fishery cooperatives, and beet growers' cooperatives.

According to data from the Ministry of Agriculture and Forestry, the highest proportion in terms of the number of cooperatives nationwide is observed in agricultural development cooperatives, followed by irrigation cooperatives and agricultural credit cooperatives, respectively. Total agricultural cooperatives constitute approximately 69% of all cooperatives in Türkiye. In terms of the number of members, beet growers' cooperatives stand out. There are only 31 beet growers' cooperatives across Türkiye, yet they have approximately 1.4 million members; this figure represents about 56% of the total number of members of agricultural cooperatives. The primary reason for such a high number of members is that producers are mandatorily required to be cooperative members due to the quota system applied in beet production. In the ranking of member numbers, beet growers' cooperatives are followed by agricultural credit cooperatives and agricultural development cooperatives. When agricultural organizations in Türkiye are examined, apart from the five main types of cooperatives under the Ministry (agricultural development, irrigation, fishery, beet growers, and agricultural credit), there are also different types such as agricultural sales cooperatives, tobacco production and marketing cooperatives, and fresh fruit and vegetable marketing cooperatives.

This general organizational structure and the distribution of cooperative types necessitate a more concrete evaluation of the position and importance of irrigation cooperatives within the Turkish agricultural system. Especially in a period when water-dependent production is increasing and the pressure of climate change on agricultural activities is intensifying, a temporal examination of the numerical development and changes in the partnership structure of irrigation cooperatives is critically important for understanding the dynamics of this form of organization. In this context, the development trends shown by irrigation cooperatives over the years should be handled together with agricultural policies, rural development approaches, and structural transformations regarding water management.

Table 1, prepared based on data from the Ministry of Agriculture and Forestry, presents the numerical development of irrigation cooperatives in Türkiye during the 2000–2024 period, showing changes in the number of cooperatives and members from a holistic perspective. The table provides a quantitative basis for subsequent evaluations by allowing for the analysis of growth and contraction trends over time. When the data is examined, a steady increase in both the number of cooperatives and members is observed between 2000 and 2015. This increase was driven by the expansion of localization policies in water management, the rise in rural development investments, and the acceleration of the transition to pressurized irrigation systems. Conversely, after 2015, a downward trend in the number of irrigation cooperatives emerged due to the significant rise in energy costs, economic uncertainties created by the COVID-19 pandemic, the increasing frequency of droughts, and the impacts of the climate crisis. However, it is noteworthy that despite the decline in the number of cooperatives during this period, the number of members remained largely protected or even showed a limited increase. This indicates that irrigation cooperatives maintain their importance for agricultural production and water management, and the need for producers for this type of organization continues. The decline in the number of cooperatives observed particularly in the 2023–2024 period is associated with the acceleration of liquidation and merger processes rather than a loss of function.

Table 1. Number of Irrigation Cooperatives and Members in Türkiye

Year	Number of Cooperatives (Units)	Number of Members (Persons)	Notes / Key Developments
2000	2,378	258,420	Localization steps in water management.
2005	2,455	275,600	Increase in rural development investments.
2010	2,512	294,150	Transition process to pressurized irrigation systems.
2015	2,540	310,420	Period of rising energy costs.
2020	2,505	318,850	Stagnation due to pandemic and drought effects.
2023	2,446	321,196	Decrease due to climate crisis and operating costs.
2024	2,446	319,500	Current liquidation and merger processes.

Source: Ministry of Agriculture and Forestry Statistical Bulletin — "Agricultural Organizations, 2024" (Official annual compilation, KoopBİS data).

In Izmir, irrigation cooperatives continue their activities in districts where agricultural production is intensive and play a fundamental role in producers' access to irrigation services despite dwindling water resources. There are 69 active irrigation cooperatives operating across the city. These cooperatives serve a total of 12,657 members, and the average number of members per cooperative is calculated as 183.

According to data from the Ministry of Agriculture and Forestry and the Izmir Development Agency, irrigation cooperatives in Izmir operate in 18 districts, with the spatial distribution of cooperatives concentrating in certain regions. In particular, the districts of Kemalpaşa, Ödemiş, Menderes, and Tire stand out as areas with the highest number of cooperatives. When the distribution of irrigation cooperatives in Izmir by district is examined, it is seen that they are spatially concentrated in specific regions. The distribution of a total of 69 cooperatives reflects both the level of water resource utilization and the intensity of agricultural activities.

Table 2. Distribution and Featured Characteristics of Irrigation Cooperatives in Izmir Province

District	**Number of Cooperatives**	**Percentage (%)**	**Density / Featured Characteristics**
Kemalpaşa	9	13.0	Highest number of cooperatives; fruit-growing focus
Ödemiş	8	11.6	Large irrigable land and intensive livestock
Menderes	6	8.7	Greenhouse (protected) cultivation and vegetable production
Tire	6	8.7	Water management within the Greater Menderes Basin
Bergama	5	7.2	Large agricultural lands and modern infrastructure needs
Torbalı	5	7.2	Industry–agriculture balance and intensive field crop production
Bayındır	4	5.8	Irrigation for floriculture and sapling production
Menemen	4	5.8	Final station water management in the Gediz Basin
Others (10 districts)	22	31.9	Foça, Kınık, Selçuk, Urla, etc.; 1–3 cooperatives each
Total	**69**	**100.0**	**12,657 total members**

Source: Compiled from Izmir Development Agency (İZKA), 2023

The district with the highest number of irrigation cooperatives is Kemalpaşa, containing 13.0% (9 cooperatives) of the total. Kemalpaşa is followed by Ödemiş (11.6%), Menderes (8.7%), and Tire (8.7%), which are important agricultural production centers. The primary reasons for the high number of irrigation cooperatives in these districts are the extensive presence of irrigable land, the intensity of agricultural production, and the necessity of organizing water management through collective structures. On the other hand, the number of cooperatives is also relatively high in districts such as Bergama (7.2%) and Torbalı (7.2%). Shared characteristics of these districts include large agricultural lands, diverse crop patterns, and the need for modern irrigation infrastructure. Districts with a low number of cooperatives include Foça, Kınık, Narlıdere, Selçuk, and Urla, each having only one cooperative (1.4%). This situation may indicate that agricultural production in these districts is more limited, or that irrigable areas are smaller in scale or scattered. Similarly, the low number of cooperatives is evaluated to be related to the mode of access to water resources and the specific characteristics of the production structure.

In general, the distribution in Izmir shows that irrigation cooperatives are clustered in districts where agricultural production is concentrated and water dependency is high. This spatial pattern is closely related to urban and rural development trends, topography, and the accessibility of water resources.

Regarding member counts, a significant portion of irrigation cooperatives are concentrated in the 101–500 member range. Cooperatives with more than 500 members are found only among those established between 1961 and 1980. This indicates that older cooperatives have gathered more members over time, while member counts in newly established cooperatives remain relatively lower. Therefore, it can be said that as the year of establishment becomes more recent, the number of members tends to decrease. This trend can be associated with factors such as changes in the number of producers, the shrinking of irrigation areas, or new initiatives starting on a smaller scale.

Table 3. Distribution of Irrigation Cooperatives in Izmir Province by Member Count Range

Member Count Range	**Number of Irrigation Cooperatives**
7–10	2
11–50	12
51–100	13
101–500	39
501–1000	3
1001 and above	0
TOTAL	**69**

Source: Izmir Development Agency (İZKA), 2023.

5. Irrigation Cooperatives in Climate Change Adaptation in Izmir Province

Agricultural production in Türkiye is largely dependent on irrigation, and the effective management of water resources stands out as a decisive factor in the climate change adaptation process (Bozoğlu et al., 2019; FAO, 2022). Izmir, which encompasses the Gediz, Küçük Menderes, and Bakırçay basins, is one of the provinces experiencing this process most vividly due to both its agricultural production intensity and the pressure on water resources. In this context, irrigation cooperatives emerge not only as structures that organize water distribution but also as strategic actors that provide producers with access to technical knowledge, manage collective decision-making processes, and increase adaptation capacity against climate risks. This section discusses the role of irrigation cooperatives in Izmir regarding climate change adaptation through the dimensions of collective water management, modern irrigation practices, producer training, and risk management.

5.1. Collective Water Management

Agricultural irrigation in Izmir relies heavily on limited surface and groundwater resources. Particularly in the Gediz and Küçük Menderes basins, the decline in groundwater levels and the increasing frequency of droughts have necessitated the planned and balanced use of water. At this point, irrigation cooperatives develop collective management mechanisms that ensure the equitable sharing of water among producers. These mechanisms include preparing irrigation schedules based on seasonal precipitation and meteorological data, directing water to priority crops during drought periods, and limiting excessive water extraction. Irrigation cooperatives in Izmir implement water management plans that individual producers struggle to apply alone through joint decision-making processes. This situation both reduces potential conflicts among producers and contributes to the sustainable use of water resources. Collective water management also plays an important role in reducing the risks of salinity and soil degradation (Aktaş, 2014; Ciampittiello et al., 2024; Abdourhimou et al., 2025).

The most advanced example of this collective management is the Bayındır Hasköy Irrigation Cooperative. In cooperation with the local government, the cooperative distributes “Class A” reclaimed water from the IZSU treatment plant to its members, thereby offering a resilient circular agriculture model against climate change by reducing the pressure on groundwater.

5.2. Dissemination of Modern Irrigation Techniques

One of the primary strategies of irrigation cooperatives in Izmir during the climate change adaptation process is the dissemination of water-saving modern irrigation techniques. Drip and sprinkler irrigation systems significantly reduce water use compared to traditional flood irrigation methods and increase yield per unit area (FAO, 2022). Particularly in the Küçük Menderes Basin, producers who have transitioned to pressurized irrigation systems observe both a decrease in water consumption and a drop in production costs. However, many irrigation infrastructures in Izmir are old and based on open channels, which increases water losses. Infrastructure modernization works carried out by irrigation cooperatives include transitioning to closed pipe systems and using energy-efficient pumps. These applications not only reduce water losses but also strengthen the economic resilience of producers against rising energy costs.

Within the scope of modernization efforts, high-pressure underground pipe systems (Closed-Circuit) are being installed instead of old concrete canals in the Ödemiş and Kiraz basins. Furthermore, to combat rising energy costs, structures like the Dikili Yahşibey Irrigation Cooperative have reduced the cost of extracting water from deep wells by 40-60% by establishing Solar Power Plants (SPP). These practices directly strengthen the economic durability of the producers (Izmir Provincial Directorate of Environment, Urbanization and Climate Change, 2025).

As seen in the case of the Tire Karateke Irrigation Cooperative, practical training provided to producers within the scope of EU-supported projects promotes the use of sensor technologies and digital agricultural tools, ensuring the spread of precision farming practices. It is emphasized in the literature that such applications contribute to more effective water use and the prevention of yield losses through soil moisture monitoring (CIHEAM, 2020; Wang & Xu, 2025).

5.3. Producer Training and Awareness Raising

Irrigation cooperatives also play a major role in producer training and awareness activities, which constitute the social dimension of the climate change adaptation process in Izmir. Trainings organized through cooperatives cover topics such as choosing drought-resistant plant varieties, optimizing irrigation timing, preserving soil moisture, and maintaining the fertilizer-water balance. These trainings ensure that producers respond to climatic conditions in a more conscious and planned manner.

In this context, the "Training on Implementation Plans for the Project on Strengthening Climate Change Adaptation Action in Türkiye," organized by the Ministry of Environment, Urbanization and Climate Change on June 30, 2025, played a critical role in increasing the institutional capacity of local cooperatives and localizing climate action plans. The S.S. Tire Karateke

Neighborhood Irrigation Cooperative (through technology transfer and EU projects) and S.S. Ödemiş Bademli (with drought-resistant production models and sapling diversity) have been the most important field practitioners of these trainings. Practices carried out in the Aegean Region show that producers participating in irrigation and climate-related trainings can maintain similar yield levels while using less water (Bozoğlu et al., 2019). This demonstrates that the dissemination of information is as important as technical investments in climate change adaptation.

5.4. Risk Management and Disaster Preparedness

Rising temperatures, irregular precipitation, and extreme weather events in Izmir directly threaten agricultural production. Irrigation cooperatives take on a preventive and planning role against these risks. Key practices include increasing water storage capacity for dry periods, strengthening drainage infrastructure against sudden rainfall, and flexibly updating irrigation schedules. Cooperatives also contribute to the repair of irrigation infrastructure and the reorganization of production plans by providing coordination among producers in post-disaster processes. This approach increases the resilience of the agricultural system against climate shocks (FAO, 2022).

The "Prepaid Smart Card Meter System," implemented by cooperatives in the Tire and Bergama regions, digitally prevents excessive water consumption during drought periods and offers data-based preparedness for disasters by keeping a record of every drop.

5.5. Strategic Measures and Policy Recommendations

To strengthen the climate change adaptation capacity of irrigation cooperatives in Izmir, the following strategic measures stand out:

- Infrastructure: Preventing leakage losses by converting irrigation lines into closed systems.
- Technology: Disseminating smart and sensor-supported "precision irrigation" systems.
- Energy: Increasing SPP incentives so that irrigation cooperatives can produce their own energy.
- Education: Ensuring the continuity of climate-friendly agriculture and water management training for producers.
- Planning: Preparing "Drought Action Plans" on a cooperative basis for collective water management and crisis periods.

These measures support the sustainable use of water resources in Izmir's agriculture while further strengthening the strategic role of irrigation cooperatives in the climate change adaptation process (OECD, 2021; MDPI, 2021).

6. Conclusion and Discussion

This study has examined in depth the critical role assumed by irrigation cooperatives in the face of increasing pressure from climate change on agricultural production and water resources, specifically within the province of Izmir. The findings reveal that irrigation cooperatives are not merely technical structures providing water distribution services; on the contrary, they are strategic actors building local resilience against the climate crisis and merging social capital with technical innovation.

With its structure encompassing the Gediz, Küçük Menderes, and Bakırçay basins, Izmir constitutes an agricultural region that perceives the effects of climate change early and intensely. This multi-basin structure of Izmir and the water dependency of its crop patterns render the role of irrigation cooperatives more critical compared to many other Anatolian provinces. This situation necessitates the planned use of water resources and increases the importance of collective management mechanisms. The “Class A Reclaimed Water” project carried out by the S.S. Bayındır Hasköy Irrigation Cooperative in collaboration with IZSU, which was examined in this study, is one of the most successful field reflections of the “circular water management” theory in literature. This project offered farmers a “climate-independent” water supply guarantee during a period when groundwater levels dropped to critical stages. Similarly, the Solar Power Plant (SPP) investments aimed at reducing energy costs observed in the cases of S.S. Dikili Yahşibey and S.S. Bergama have proven that climate adaptation cannot be considered independently of economic sustainability.

The dissemination of modern irrigation techniques also stands out as one of the fundamental contributions of irrigation cooperatives to the climate change adaptation process in Izmir. While the transition to drip and sprinkler irrigation systems increases water use efficiency, it also strengthens the economic resilience of producers against rising energy costs. Infrastructure modernization and the use of energy-efficient systems demonstrate that irrigation cooperatives address both environmental and economic sustainability together. This situation reveals that cooperatives develop long-term strategies rather than merely short-term solutions for climate change adaptation. It has also been observed that modernization is not limited to physical infrastructure (closed-circuit pipe systems) but is evolving into a digital transformation. The leadership of the S.S. Tire Karateke Neighborhood Irrigation Cooperative regarding “precision agriculture” and sensor technologies has ensured that every drop of water becomes measurable and manageable. It is an indisputable fact that training activities create a more permanent impact than technical investments in transforming producers' water use habits from "wild irrigation" to "needs-based irrigation."

Producer training and awareness efforts constitute the social dimension of the adaptation process. Training activities conducted through irrigation cooperatives in Izmir support producers in using water more consciously and in making production decisions suitable for climatic conditions. This finding indicates that technical investments alone are not sufficient; information sharing and the strengthening of institutional capacity are decisive in adapting to climate change.

When evaluated in terms of risk management and disaster preparedness, it is observed that irrigation cooperatives perform a significant coordination function at the local scale against droughts, excessive precipitation, and other extreme weather events. Increasing water storage capacity, strengthening drainage infrastructure, and reorganizing irrigation schedules during crisis periods enhance the resilience of the agricultural system against climate shocks. In this respect, irrigation cooperatives function as a buffer mechanism against climate change in Izmir's agriculture.

Evaluated overall, irrigation cooperatives in the province of Izmir stand out as a critical institutional structure in the climate change adaptation process. However, to maintain the effectiveness of this structure in the face of increasing climate pressures, the technical, financial, and managerial capacities of cooperatives must be strengthened. Increasing public support, implementing climate adaptation policies at the local level through cooperatives, and further strengthening producer participation are of vital importance for the future of Izmir's agriculture.

In conclusion, this study demonstrates that irrigation cooperatives are not merely complementary but central actors in adapting to climate change, specifically in Izmir. Strengthening these cooperatives should be considered a fundamental policy area for both the sustainable management of water resources and the continuity of agricultural production under climate change conditions.

Within this framework, the findings indicate that irrigation cooperatives in the province of Izmir possess significant institutional potential in the climate change adaptation process; however, this potential cannot be fully utilized under current conditions. The increasing risk of drought, pressure on water resources, and uncertainties encountered in agricultural production necessitate that irrigation cooperatives be supported not only with existing practices but also with goal-oriented and applicable policies. Therefore, at this stage of the study, in light of the evaluations presented in the previous sections, practical solution recommendations aimed at strengthening the climate change adaptation capacity of irrigation cooperatives in Izmir are provided.

To increase the effectiveness of irrigation cooperatives in the climate change adaptation process in Izmir, the following practical recommendations have been developed based on the study's findings. These recommendations aim to strengthen existing institutional structures and disseminate solutions suitable for local conditions.

1. Infrastructure Renewal and Modernization: First and foremost, the renewal and modernization of irrigation infrastructure emerge as a priority need. The open channels and outdated pumping systems used by many irrigation cooperatives in Izmir lead to significant water and energy losses. Encouraging the transition to closed-conduit systems and the use of high-energy-efficiency pumps and motors will not only increase water conservation but also strengthen the resilience of producers against rising input costs.

2. Smart and Climate-Sensitive Irrigation: It is necessary to disseminate smart and climate-sensitive irrigation practices. Introducing soil moisture sensors, automation systems, and remote monitoring technologies to producers through cooperatives will ensure that irrigation timing is optimized according to climatic conditions. Such applications will contribute to more effective water use, particularly in basins with a high risk of drought.

3. Continuous Producer Training: Ensuring the continuity of producer training is of critical importance. Informing producers about climate change, water management, and drought-resistant production techniques through regular training programs within irrigation cooperatives will increase the effectiveness of technical investments. Planning training activities according to local needs and including practice-oriented content will support the success of this process.

4. Collective Planning and Governance: Collective planning and governance mechanisms must be strengthened. Preparing irrigation schedules with producer participation, operating joint decision-making processes during crisis periods, and increasing intra-cooperative communication will support the equitable and sustainable use of water resources. This approach will strengthen the capacity for collective action against climate risks by fostering solidarity among producers.

5. Risk and Disaster Management: The development of local-scale plans for risk and disaster management is recommended. Creating preparedness plans at the cooperative level against climate-induced risks such as drought, excessive precipitation, and flooding—along with increasing water storage capacity and developing coordination mechanisms for post-disaster production processes—will enhance the resilience of the agricultural system.

6. Strategic Support and Technology Integration: To maximize the climate change adaptation capacity of irrigation cooperatives in Izmir, gradual support mechanisms should be developed by considering the spatial distribution of districts such as Kemalpaşa (13%) and Ödemiş (11.6%) and the drought sensitivity of the basins. To alleviate the increasing energy burden on cooperatives, Solar Power Plant (SPP) investments should be accelerated through "public-cooperative partnership" models. Furthermore, the strategy of using treated wastewater in agriculture, successfully implemented in the Bayındır model, should be integrated into other advanced biological treatment plants in Izmir and established as a regional policy. Additionally, "Drought Early Warning Units" that process real-time meteorological data should be established within cooperatives, ensuring that this data is shared directly with the S.S. Izmir Region Union of Irrigation Cooperatives via a digital network.

These practical solution recommendations aim to strengthen the climate change adaptation capacity of irrigation cooperatives in Izmir and support the sustainability of agricultural production. The implementation of these proposals will contribute to irrigation cooperatives assuming a more effective role in the execution of climate adaptation policies at the local scale.

References

Abdourhimou, A. I., Salamatou, A. I., Boubacar, M. M., Bachirou, H. Y., Idrissa, S., & Ali, M. (2025). Integrated water resource management in changing climate and local development and social cohesion mechanisms. Discover Environment, 3(1), https://doi.org/10.1007/s44274-025-00375-8

Aktaş, Ö. (2014). Impacts of climate change on water resources in Türkiye. *Environmental Engineering and Management Journal, 13*(4), 881–889.

Aküzüm, T., Çakmak, B., & Gökalp, Z. (2010). Evaluation of water resources management in Türkiye. *Research Journal of Agricultural Sciences, 1*, 67–74.

Aküzüm, T., Çakmak, B., & Gökalp, Z. (2019). Türkiye'de su kaynakları yönetiminin değerlendirilmesi. *International Journal of Agricultural and Natural Sciences, 3*(1), 67–74.

Altın, M., & Barak, B. (2020). Tarımda kuraklık riskinin yönetimi: Türkiye uygulamaları. *Toprak Su Dergisi, 9*(2), 45–58.

Atış, E., Günden, C., Salalı, H. E., Akyüz, Y., & Çuhadar, M. (2023). İklim değişikliği koşullarında üreticilerin sulama yöntemi tercihi: Gediz Havzası örneği. *Tarım Ekonomisi Dergisi, 28*(2), 241–247.

Bildirici, M. E. (2024). *Determinants of water use in agriculture* (Doktora tezi). Orta Doğu Teknik Üniversitesi, Ankara.

Bozoğlu, M., Başer, U., Alhas Eroğlu, N., & Kılıç Topuz, B. (2019). Impacts of climate change on Turkish agriculture. *Journal of International Environmental Application & Science, 14*(3), 97–103.

Bozkurt, D., & Şen, O. L. (2011). Climate change impacts in the Mediterranean: Hydroclimate modeling. *Journal of Hydrology, 405*(1–2), 1–12.

Candan Demirkol, E., & Gündüzoğlu, H. A. (2025). *İklim değişirken Karaburun'da toprağı nasıl kullanmalı, karnımızı nasıl doyurmalı?* 24. Ulusal Bölge Bilimi ve Bölge Planlaması Kongresi, Mersin, Türkiye, 15–17 Mayıs, 32.

Caltı, N., & Somuncu, M. (2019). İklim değişikliğinin Türkiye'de tarım üzerindeki etkisi ve çiftçilerin iklim değişikliğine yönelik tutumları. In B. Gönençgil et al. (Eds.), *1st Istanbul International Geography Congress Proceedings Book* (pp. 890–912). İstanbul Üniversitesi Yayınları.

Ciampittiello, M., Marchetto, A., & Boggero, A. (2024). Water resources management under climate change: A review. *Sustainability, 16*(9), 3590.

CIHEAM. (2020). *Agriculture and climate change in Türkiye*. https://www.ciheam.org/uploads/attachments/261/018_Tekeli_WL_37.pdf

Çakmak, B., & Gökalp, Z. (2011). İklim değişikliği ve etkin su kullanımı. *Tarım Bilimleri Araştırma Dergisi, 4*(1), 87–95.

Çakmak, B., & Gökalp, Z. (2013). Tarımda su kullanımı ve su tasarruf teknikleri. In 3. Ulusal Toprak ve Su Kaynakları Kongresi Bildiriler Kitabı (pp. 733–741), 22-24 Ekim, Tokat, Türkiye:

Çakmak, B., & Gökalp, Z. (2015a). *Agricultural water management in Türkiye and concept of virtual water*. In 50th Croatian and 10th International Symposium on Agriculture (Conference proceedings). Opatija, Croatia.

Çakmak, B., & Gökalp, Z. (2015b). *Agricultural water use in Türkiye and water footprint*. In 2nd International Conference on Sustainable Agriculture and Environment (Conference proceedings).

Dellal, İ., Başçetinçelik, A., & Yılmaz, G. (2012). İklim değişikliğinin tarım sektörüne etkileri. *Tarım Ekonomisi Dergisi, 18*(2), 45–58.

Demircan, M., Gürkan, H., Eskioğlu, O., Arabacı, H., & Coşkun, M. (2013). *Climate change projections for Türkiye*. Turkish State Meteorological Service.

Demircan, V. (2022). İklim değişikliğinin Türkiye tarımı üzerindeki olası etkileri. *Tarım Ekonomisi Dergisi, 28*(1), 12–20.

Demirtaş, M., Yıldız, E., & Güner, S. (2023). Türkiye'de iklim değişikliğinin tarım sektörü üzerindeki etkileri. *Tarım Bilimleri Dergisi, 29*(2), 245–258.

Everest, B., Yercan, M., & Tan, S. (2019). Tarımsal kalkınma, sulama ve su ürünleri kooperatiflerinde kurumsal yapı ve yönetici profilinin tespiti: Çanakkale ili örneği. *Turkish Journal of Agricultural and Natural Sciences, 6*(2), 343–353.

FAO. (2022). *Climate-smart agriculture in Türkiye*. http://www.fao.org/Türkiye/news/detail-events/en/c/1472133/ Access date: December 2025.

Hatfield, J. L., Boote, K. J., & Kimball, B. A. (2014). Climate impacts on agriculture: Implications for crop production. *Agronomy Journal, 106*(1), 1–17.

Islam, M. (2023). Impacts of Climate Change on Water Resources, Agricultural Production and Food Security: Evidence from Turkiye. *Journal of Economy Culture and Society*(66), 163-179.

İzmir Çevre, Şehircilik ve İklim Değişikliği İl Müdürlüğü. (2025). *İzmir ili 2024 yılı çevre durum raporu.* İzmir.

İZKA. (2023). *İzmir Kooperatif Analizi 2022* (Rapor). İzmir Kalkınma Ajansı. https://izka.org.tr/wp-content/uploads/2023/06/KOOPERATIF-ANALIZI.pdf, Erişim: Aralık 2025.

Karahan, B. C., & Pınar, M. (2023). Climate change and spatial agricultural development in Türkiye. *Review of Development Economics, 27*(4), 2325–2348.

Kendirli, B., Önol, B., & Yılmaz, M. (2010). Kuraklık ve tarımsal etkileri. *Tarım Bilimleri Araştırma Dergisi, 3*(1), 23–30.

Lal, R. (2009). Soil degradation as a reason for inadequate human nutrition. *Food Security*, 1, 45–57.

MGM. (2024). Türkiye 2024 yılı iklim raporu. T.C. Çevre, Şehircilik ve İklim Değişikliği Bakanlığı. https://www.mgm.gov.tr/FILES/iklim/yillikiklim/2024-iklim-raporu.pdf, Erişim: Aralık 2025.

MGM. (2023). Türkiye 2023 yılı iklim raporu. T.C. Çevre, Şehircilik ve İklim Değişikliği Bakanlığı. https://www.mgm.gov.tr/FILES/iklim/yillikiklim/2023-iklim-raporu.pdf, Erişim: Aralık 2025.

OECD. (2021). *Building the resilience of Türkiye's agricultural sector to droughts*. OECD Publishing.

Plevneli, T., et al. (2023). Investigation of climate change impacts on agricultural production in 25 river basins of Türkiye. *Agricultural Water Management, 278*, 108150.

Tarım ve Orman Bakanlığı. (2024). *Tarımsal amaçlı örgütler: 2024 istatistik bülteni* (KoopBİS verileri). Tarım ve Orman Bakanlığı.

TAGEM. (2023). *Türkiye tarımsal kuraklık raporu (2020–2022)*. T.C. Tarım ve Orman Bakanlığı.

Taş, I., Gökalp, Z., Özkay, F., Yıldırım, Y. E., Kodal, S., Tüzün, M., & Akgül, S. (2011). Tarımsal sulamalarda su tasarrufu. *GAP VI. Tarım Kongresi Bildiriler Kitabı* (ss. 557–562).

TGDF. (2017). *İklim değişikliği ve tarımda sürdürülebilirlik raporu*. https://www.tgdf.org.tr/wp-content/uploads/2017/10/iklim-degisikligi-rapor, Erişim: Aralık 2025.

Türkeş, M. (2019). Türkiye'de iklim değişikliği ve kuraklık. *Türkiye Bilimler Akademisi Raporu, 2*(3), 5–20.

Türkeş, M., Sümer, U. M., & Çetiner, G. (2000). *Küresel iklim değişikliği ve olası etkileri*. Birleşmiş Milletler İklim Değişikliği Çerçeve Sözleşmesi Seminer Notları (ss. 7–24). Çevre Bakanlığı, Çevre Koruma ve Kontrol Genel Müdürlüğü, Ankara.

TÜİK (Türkiye İstatistik Kurumu). (2024). *Türkiye tarımsal üretim istatistikleri*. Türkiye İstatistik Kurumu. https://data.tuik.gov.tr, Erişim: Aralık 2025.

Uysal, H., & Yıldız, D. (2025). *Sustainable water management and irrigation cooperatives*. https://www.hidropolitikakademi.org/en/article/31423/sustainable-water-management-and-irrigation-cooperatives, Access date: December 2025.

Ünver, A. (2016). *Su kaynaklarının yönetimi ve çevresel sürdürülebilirlik açısından sulama kooperatifleri* (Yüksek lisans tezi). Namık Kemal Üniversitesi.

Vu, T.H., Hong Phi, T.D., Nguyen, D.H., & Trung Tran, Q. (2023). Agricultural cooperatives and climate change adaptation - Case study in Son La, Vietnam. The VMOST *Journal of Social Sciences and Humanities*, 65(1), 41-53.

Wang, G., & Xu, M. (2025). Effect of cooperative membership on farmers' technology adoption based on the mediating effects of technology cognition. Heliyon, 11(2), e42130. https://doi.org/10.1016/j.heliyon.2025.e42130.

World Bank. (2023). *Towards a greener and more resilient Türkiye*. https://www.worldbank.org/en/country/Türkiye/brief/towards-a-greener-and-more-resilient-turkiye, Access date: December 2025.

Yılmaz, F., Osborn, D., & Tsamados, M. (2025). *Strengthening Türkiye's drought management: insights from international practices (Netherlands, UK and USA)*. Frontiers in Climate, 6, Article 1504779. https://doi.org/10.3389/fclim.2024.1504779.

Zobar, M., Sever, H., & Kaya, E. (2025). Kuraklık ve tarımsal üretim ilişkisi: Yeni bulgular. *Türk Tarım Bilimleri Dergisi, 11*(1), 33–48.

Chapter 2

MODERN APPROACHES TO THE MANAGEMENT OF HEAT STRESS IN GREENHOUSE VEGETABLE CULTIVATION

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INTRODUCTION

Vegetables, which are among the most important nutritional components for human health, must be produced continuously when considered from a production perspective. The most significant climatic factor limiting this continuity is known to be temperature (Abevoy 2018). Greenhouse production systems are an important production method that allows the control of climatic factors and enables cultivation outside the natural growing season (Jalwania et al. 2025).

Temperature is one of the key external factors required for plants to carry out essential cellular and biochemical processes (Li et al. 2018). When the optimum temperature range is exceeded, these processes are reduced or may not occur at all. This situation is referred to as "temperature stress" (Wang et al. 2024). Temperature stress is among the most widespread and economically critical abiotic stress factors in protected vegetable cultivation (Hoshikawa et al. 2021). Climate change driven by global warming leads to more frequent and severe temperature extremes in greenhouse cultivation. In particular, when the desired temperature conditions are not met, reductions in photosynthetic activity, flowering, and yield are observed in plants (Balfagón et al. 2020).

In conventional production systems, farmers often confront this stress and attempt to manage it in a reactive manner. However, these methods are limited in their ability to provide immediate responses and to facilitate early intervention (Kittas and Bartzanas 2007).

In greenhouse cultivation, minimizing or eliminating the negative impacts of temperature stress throughout the entire crop life cycle, from sowing to harvest, is therefore crucial. Accordingly, this chapter proposes an approach that focuses on proactive methods currently used to mitigate this stress factor and discusses how these methods can be integrated.

1. PHYSIOLOGICAL BASICS OF HEAT STRESS

Temperature is a fundamental environmental factor required for living organisms to carry out their life functions. Cellular metabolic activities, enzymatic reactions, energy transformations, and other biological processes occur only within an appropriate temperature range. When conditions exceed this range, adverse effects such as protein denaturation, disruption of biochemical reactions, and loss of cell viability may be observed (Zhang et al. 2020 Mittler 2002). This applies to the vital activities of all living organisms, whether they are eukaryotic or prokaryotic in structure.

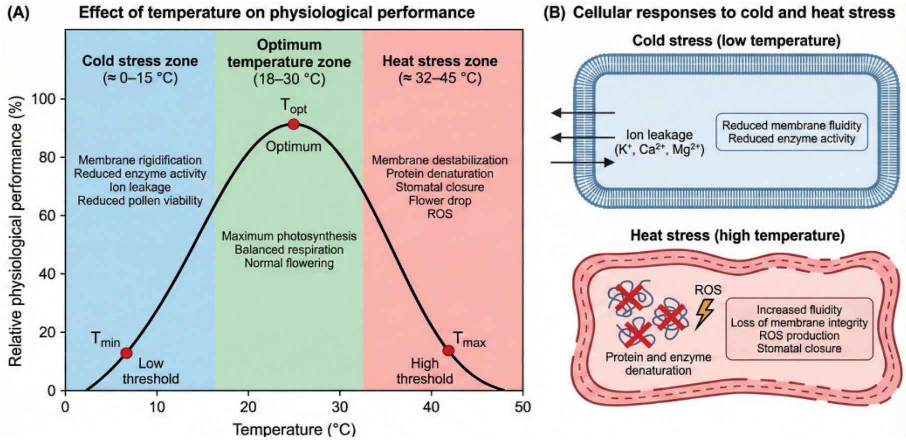

Figure 1: *Impact of Temprature Stress on Plant Physiology and Cellular Structure. This schematic representation has been prepared as an illustrative example based on previously published studies (Mahajan and Tuteja 2005, Blum 2017, Wien 1997, Hasanuzzaman et al., 2013)*

In plants, each stage of the life cycle—germination, flowering, pollination, fruit set, photosynthesis, and respiration—occurs most efficiently within a particular temperature range. When temperatures fall outside these ranges, they are considered a stress factor (Wahid et al. 2007; Hasanuzzaman et al., 2013; Taiz and Zeiger, 2010). These temperatures are limited to minimum and maximum values at which life processes are suspended. The temperature that yields the highest efficiency in each physiological event is called the optimum temperature (Went 1953). Optimum temperature values may change depending on plant species and varieties, as well as the developmental stage and age of plant tissues and organs. In general, optimum temperatures for greenhouse vegetable species are accepted to be in the range of 18-30°C (Wien 1997, Hasanuzzaman et al., 2013)(Figure 1).

When temperatures fall below minimum values, various structural and functional abnormalities occur in plants. The fluid phospholipid structure of the cell membrane solidifies, its flexibility is impaired, its semi-permeability is lost, and as a consequence, substance exchange cannot occur (Ruelland et al. 2009; Theocharis et al. 2012). As a result, the cell membrane causes ions (K+, Ca2+, Mg2+) inside the cell to leak out, disrupting the osmotic pressure balance within the cell (Figure 1). This leakage reduces turgor pressure due to the imbalance in osmotic pressure, causing the cell to lose water (Mahajan and Tuteja 2005, Blum 2017). Leaves wilt and then dry out due to plasmolysis. In addition, enzymes do not function at minimum temperatures. Enzymes involved in photosynthesis, respiration, and protein synthesis, in particular, cannot function. Plant growth and development, energy production, and other vital processes cannot occur (Theocharis et al. 2012). Another significant effect of cold stress is the disruption of chlorophyll structure. Mg^{2+} and nitrogen absorption decreases due to low temperatures, leading to reduced chlorophyll synthesis and yellowing (chlorosis) of leaves (Hussain et al., 2018). Under greenhouse conditions, night temperatures falling below 9–12 °C, in particular, cause significant cold stress in warm-climate vegetable species such as tomatoes, peppers, eggplants, and cucumbers (Kläring et al. 2015, Pressman et al. 2006, Lopez et al. 2007, An et al. 2021). Under these conditions, water and nutrient absorption in the root zone slows down, growth in young leaves and shoots declines, pollen viability decreases, and consequently, reductions in flowering and fruit set are observed. As the duration of cold stress increases, anthocyanin formation increases in the stem, fruit, and tips. Curling of terminal shoots and chlorosis in leaves are observed (Pressman et al. 2002).

Temperatures higher than the maximum tolerable value are a significant factor of stress for plants. At high temperatures, unlike at temperatures below the minimum, cell membrane fluidity increases. However, this excessive fluidity leads to a weakening of membrane stability. The intracellular-extracellular ion balance is disrupted. Furthermore, high temperatures cause denaturation of proteins and enzymes, inhibiting biochemical processes (Wahid et al. 2007, Hasanuzzaman et al. 2013). Due to the increase in respiration speed, the photosynthesis-respiration balance is disrupted in favor of respiration. Therefore, assimilation products that could be used for growth are consumed more in respiration, and net carbon yield and growth rate decrease (Posch et al., 2019). High temperature stress, especially during flowering and pollination, can significantly reduce fruit set rates by decreasing pollen viability and germination ability (Pressman et al. 2002, Kawasaki 2014). In greenhouse vegetable crops such as tomatoes, peppers, and cucumbers, temperatures above 35°C, flower loss, formation of hollow fruit and deformities, and drying and burning at the tips of plants are observed (Bhattarai et al. 2021, Lee et al. 2023, Sato et al. 2000). Under high temperature and drought conditions, plants close their stomata either partially or completely to limit excessive water loss. Stomatal closure reduces transpiration rate, thereby decreasing water loss from the leaf surface, but it also limits the mass flow that transports water and dissolved nutrients from the roots (Arve et al. 2011). Consequently, water and nutrient uptake from the soil slows down, and the disruption of water balance within the plant can negatively affect growth and development. As a result, yield and quality losses increase under high-temperature conditions.

2. TEMPERATURE MANAGEMENT PRACTICES IN GREENHOUSE VEGETABLE CULTIVATION

The previous section discussed the physiological basis of heat stress in greenhouse vegetable cultivation. This chapter examines how heat stress can be managed during the production period. Increasing environmental risks due to climate change require planned and monitoring-based integrated approaches rather than traditional reactive methods. In this regard, greenhouse climate control, the use of biostimulants, and sensor-supported digital control systems are modern practices that stand out.

2.1. Climate and Temperature Management Applications

2.1.1. Greenhouse Structural Design and Climate Control

The temperature must be maintained at optimal levels to reduce yield losses in greenhouse production due to cold and heat stress. However, the manual and reactive interventions commonly used today are often insufficient to maintain optimal temperature levels. The majority of producers in traditional greenhouse cultivation rely on trial and error to regulate the temperature and humidity inside the greenhouse without the use of a device. Depending on how hot or cold the air feels, ventilation is opened or closed. However, such a practice negatively impacts the quality and yield of production. This situation creates an environment conducive to the spread of diseases and pests. For this reason, sensor-supported monitoring and automation-based climate management are now taking the place of manual and reactive interventions. These systems are mostly used in modern, large-scale greenhouses. However, their adoption in small-scale operations is also important to prevent yield losses.

Temperature and relativity humidity (RH) sensors positioned at plant level inside the greenhouse and under the roof enable continuous monitoring of the microclimate. The system automatically activates climate control equipment such as ventilation, heating, shading, or fogging when predefined threshold values are exceeded (Subahi and Bouazza 2020, Rezvani et al. 2020)(Figure 2). This reduces the need for manual intervention. It keeps both the day/night temperature difference and short-term temperature fluctuations under control.

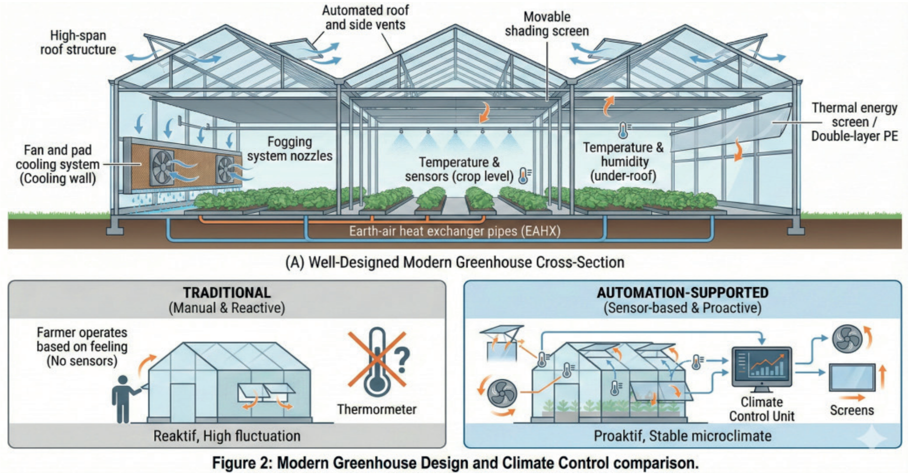

Figure 2: *Modern greenhouse design and climate control comprasion. This schematic representation has been prepared as an illustrative example based on previously published studies (Subahi and Bouazza 2020, Rezvani et al. 2020, McCartney et al. 2018, Zhang et al. 2022, Kim 2024, Bonuso et al. 2020, Costantino et al. 2021, Soussi et al. 2022, Akpenpuun et al. 2021)*

Using these automated systems alone is not sufficient. The correct structural design is also critical in ensuring the right temperature in the greenhouse. Research shows that the shape, size, orientation, and covering material of the greenhouse are decisive factors in the distribution of indoor temperature and humidity. Without an appropriate design, automated systems may be insufficient in providing the required microclimate (Ghani et al. 2019, Soussi et al. 2022, Ghoulem et al. 2019). Sufficient roof height and ventilation openings, appropriate greenhouse orientation, and the use of covering materials that allow diffuse light transmission contribute to reducing leaf surface temperature, particularly during the summer months. Shading curtains help maintain minimum temperatures by limiting excessive daytime heating while also reducing nighttime heat loss. Double-layer polyethylene (PE) covers and thermal curtains can significantly reduce heat loss at night and improve energy efficiency (Akpenpuun et al. 2021). In one study, a cover containing ethylene vinyl acetate (EVA) film provided the best balance between temperature and photosynthetically active radiation (PAR) transmittance in a tomato greenhouse (Baxevanou et al. 2017).

In controlling greenhouse temperature and relative humidity, various ventilation strategies are used alongside the choice of covering material. Natural ventilation mainly relies on cross-ventilation created by airflow through sidewall and roof openings. When this natural airflow is combined with evaporative cooling devices, such as misting systems, the resulting configuration is generally referred to as a hybrid system (NVAC) (McCartney et al. 2018, Zhang et al. 2022, Kim 2024) (Figure 2). Mechanical ventilation, by contrast, makes use of fan-and-pad systems, fan-only ventilation, and earth–air heat exchangers (EAHX) (Bonuso et al. 2020, Costantino et al. 2021, Soussi et al. 2022) (Figure 2). The position and size of sidewall and roof vents have a direct influence on ventilation efficiency. In multi-span or multi-vent greenhouses, using sidewall and bidirectional roof vents together has been shown to improve the distribution of temperature and humidity (Kim 2024). Fan-and-pad systems provide effective cooling by supplying cool, humid air, whereas EAHX systems can contribute to cooling during summer and help reduce heat loss in winter (Bonuso et al. 2020, Soussi et al. 2022).

2.1.2. Cultural Practices and Variety Selection

During periods of frequent temperature variations, cultural practices implemented at the plant level play a significant role in increasing tolerance to heat stress. Selection of vegetable varieties that are more resistant to high temperatures stands out as one of the most effective methods for reducing the negative effects of heat stress. For example, studies on tomatoes have indicated that heat-tolerant varieties such as 'Minichal' experience less yield loss and maintain better fruit quality under high temperature conditions compared to sensitive varieties such as 'Dafnis' (Rajametov et al. 2021)(Figure 3). It has been reported that considering physiological and biochemical parameters such as chlorophyll content, proline accumulation, and membrane stability in the development of heat-tolerant varieties increases the success of breeding programs. Furthermore, evaluating heat tolerance in both the seedling and generative stages is critical for selecting the right variety (Lee et al. 2022, Chaudhary et al. 2022). In addition, controlled heat stress priming applied at the seedling stage has been shown to enhance plant tolerance to high temperatures during later growth stages, helping to maintain yield and seed quality in Brassica species. At the same time, appropriate regulation of plant density, together with cultural practices such as pruning and topping, improves air circulation within the greenhouse. As air movement increases, leaf and fruit temperatures tend to decline, which helps relieve the limitations on airflow and excessive heat buildup associated with dense planting. In this way, these practices support a more stable and favorable greenhouse microclimate (Chaudhary et al., 2022, Delamare et al., 2025) (Figure 3).

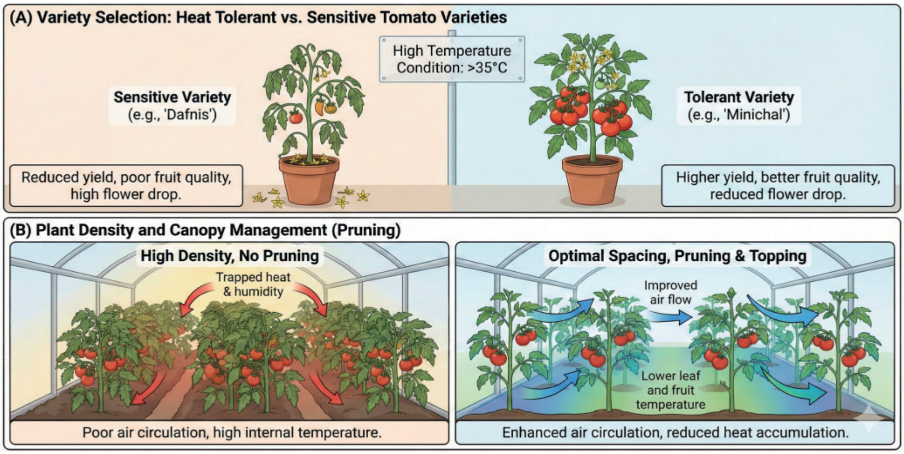

Figure 3: *Cultural measures for temprature stress management in greenhouses. This schematic representation has been prepared as an illustrative example based on previously published studies (Rajametov et al. 2021, Chaudhary et al., 2022, Delamare et al., 2025)*

2.1.3. Root Zone Temperature Management

Water and nutrient absorption in plants is directly linked to root zone temperature. Soil and irrigation water are very important for maintaining root temperature at the optimum level. At temperatures outside the optimum range, root respiration decreases or increases, negatively affecting water and nutrient uptake (Giri et al. 2017). As a result, nutrient deficiency or toxicity occurs. The optimum root temperature required for vegetables is generally between 18-25°C, varying depending on the species (Bai et al. 2016, Giri et al. 2017) (Figure 3). Low temperatures negatively affect osmosis, preventing the transmission of substances to the root hairs. Therefore, yield and quality losses occur in the plant. Low root temperatures, in especially, significantly limit water and carbon transfer and cause drought-like stress symptoms in the plant (Wang and Hoch 2022). On the other hand, high temperatures in the root zone harm the root cells, reduce root metabolism, and decrease oxygen uptake.

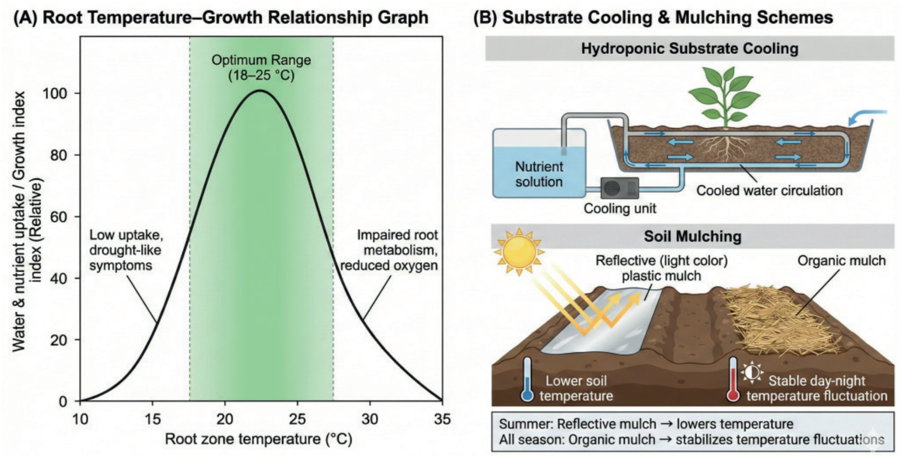

Figure 3: *Root zone temperature management strategies. This schematic representation has been prepared as an illustrative example based on previously published studies (Bai et al. 2016, Giri et al. 2017, Liu et al. 2022, Manni et al. 2021)*

A variety of cooling methods are used to manage root zone temperature. Root zone temperature can be effectively reduced by applying cooled irrigation water and using substrate cooling systems (water-circulating pipes) in soilless farming systems. It has been reported that cooling the root zone temperature to 22-25°C in cucumbers significantly increases growth, yield, and nutrient uptake in hydroponic systems (Liu et al. 2022) (Figure 3).

Also, other methods used to balance soil temperature are mulching and shading practices. Reflective mulches prevent overheating of the soil surface by reflecting sunlight (Manni et al. 2021) (Figure 3). Light-colored plastic mulches reduce soil temperature in summer (Amare and Desta 2021), while organic mulches provide insulation and balance the day-night temperature difference (de Lima et al. 2020).

In conclusion, root zone temperature management is an important practice that must be integrated with greenhouse climate control to maintain yield and quality in greenhouse vegetable production.

2.2. Biostimulants and Antistress Applications Against Heat Stress

Among the strategies developed against heat stress in plants, biostimulant and antistress agents have the potential to maintain yield and quality in protected vegetable cultivation. These biostimulants are defined as products containing seaweed extracts, protein hydrolysates, humic and fulvic acids, free amino acids, arbuscular mycorrhizal fungi, microalgae extracts, phytohormones (salicylic acid, melatonin, etc.), certain microorganisms, and specific mineral elements; they are products that regulate processes such as nutrient uptake, root development, antioxidant defense, and stress tolerance in plants (Di Sario et al. 2025).

Biostimulants are generally applied to leaves, roots, and seeds; the application time and dose vary depending on the plant species (Bulgari et al. 2019, Quan et al. 2022). In a study conducted on cold and drought stress in squash, it was observed that protein hydrolysates and amino acid-based products increased the plant's biomass, chlorophyll/photosynthetic efficiency, and recovery capacity under high-temperature conditions (Navarro-Morillo et al. 2024). Niu et al. (2022) applied the biostimulants Boosten, Megafol, and Isabion to the leaves of tomato seedlings. In their study, their effects were evaluated under different temperature conditions (10°C, 25°C, and 35°C). It was reported that Boosten was the most effective biostimulant under heat stress. In organic hydroponic tomato cultivation, the MycoApply® biostimulant applied over 12 weeks achieved the highest yield (Dash et al. 2025). Another study in tomato reported that Ascophyllum nodosum extract (PSI-494), obtained at high temperature and alkalinity, significantly increased flowering, pollen viability, and fruit yield during the reproductive stage against heat stress, significantly improving tolerance and yield against heat stress (Carmody et al. 2020).

Consequently, when biostimulant applications are integrated with greenhouse climate management, they form an effective complementary strategy against temperature stress.

2.3. Monitoring Temperature Stress and Digital Decision Support Systems

In the greenhouse, temperature and humidity sensors, root zone temperature monitoring systems, and leaf sensors are used to prevent plants from experiencing temperature stress. Automation systems can be integrated with data from these sensors to allow for real-time intervention. With these systems, the labor and time required for manual intervention are saved. In addition, plant health and productivity are increased (Bhujel et al. 2020).

With such systems, data collected from the greenhouse environment is processed, and data analysis and prediction models provide early warnings to the producer. Integrated with weather forecasts, these systems minimize the risks associated with sudden temperature changes. Farmers can monitor greenhouse conditions at any time and can intervene using mobile applications. Recently, artificial intelligence algorithms have been integrated into these systems, allowing the plant's temperature requirements to be easily controlled without the need for farmer intervention (Lee et al. 2024, Hemming et al. 2020). However, while artificial intelligence and sensor-based systems in greenhouse automation offer significant opportunities in terms of efficiency and sustainability, they also carry important drawbacks such as high cost, technical knowledge requirements, data security, and connectivity dependency. In contrast to these disadvantages, IoT-based systems reduce sensor and hardware costs and facilitate remote monitoring and control (Platero-Horcajadas et al. 2024).

Consequently, digital monitoring and decision support systems form the basis of a proactive, data-driven management approach to temperature stress in greenhouse vegetable cultivation. When integrated with greenhouse climate control, root zone management, and biostimulant agents, they offer an effective solution for sustainable and high-yield production.

3. CONCLUSION AND RECOMMENDATIONS

In vegetable cultivation under greenhouse conditions, heat stress is one of the most critical abiotic stress factors directly affecting yield and quality. Increasing sudden temperature fluctuations due to climate change are intensifying the effects of this stress and rendering traditional reactive management approaches inadequate. The physiological principles and modern management practices discussed in this section demonstrate the need for an integrated and proactive approach to successfully manage heat stress.

Greenhouse structural design and climate control systems are fundamental to the effective management of heat stress. Sensor-supported automation systems enable rapid response to sudden temperature fluctuations by optimizing the greenhouse microclimate through real-time data collection and analysis. But technological solutions alone are not sufficient and must be supported by agronomic practices such as heat-tolerant variety selection, root zone temperature management, mulching applications, and the use of biostimulants. Especially maintaining the root zone temperature within the 18-25°C range is critical for optimizing water and nutrient uptake. Biostimulants enhance plants' antioxidant defense systems, increasing stress tolerance, and play a complementary role when integrated with climate management.

Digital decision support systems and IoT-based solutions are shaping the future of heat stress management in greenhouse vegetable cultivation. Supported by artificial intelligence algorithms, these systems provide early warnings using weather forecasts and historical production data, enabling timely preventive measures. However, limitations such as high cost and technical knowledge requirements can hinder the widespread adoption of these technologies, especially in small-scale operations. Therefore, the development of low-cost sensor systems and user-friendly mobile applications will increase the accessibility of the technology.

As a result, the successful management of heat stress in greenhouse vegetable cultivation requires an integrated approach that encompasses the entire production process from seed sowing to harvest. This approach should incorporate greenhouse climate control, agronomic practices, the use of biostimulants, and digital monitoring systems. In the face of uncertainties created by climate change, adopting proactive and data-driven stress management strategies is essential for sustainable and high-yield greenhouse vegetable production. In the future, heat-tolerant variety breeding, energy-efficient cooling technologies, and the development of autonomous systems suitable for small-scale operations will lead to significant advances in heat stress management.

REFERENCES

Abewoy, D. (2018). Review on impacts of climate change on vegetable production and its management practices. *Advances in Crop Science and Technology*, *6*(01), 1-7.

Akpenpuun, T. D., Na, W. H., Ogunlowo, Q. O., Rabiu, A., Adesanya, M. A., Addae, K. S., ... & Lee, H. W. (2021). Effect of greenhouse cladding materials and thermal screen configuration on heating energy and strawberry (fragaria ananassa var.“Seolhyang”) yield in winter. *Agronomy*, *11*(12), 2498.

Amare, G., & Desta, B. (2021). Coloured plastic mulches: impact on soil properties and crop productivity. Chemical and Biological Technologies in Agriculture, 8(1), 1-9..

An, S., Hwang, H., Chun, C., Jang, Y., Lee, H. J., Wi, S. H., ... & Kwack, Y. (2021). Evaluation of air temperature, photoperiod and light intensity conditions to produce cucumber scions and rootstocks in a plant factory with artificial lighting. *Horticulturae*, 7(5), 102.

Arve, L. E., Torre, S., Olsen, J. E., & Tanino, K. K. (2011). Stomatal responses to drought stress and air humidity. In A. Shanker & B. Venkateswarlu (Eds.), *Abiotic Stress in Plants – Mechanisms and Adaptations*. IntechOpen.

Bai, L., Deng, H., Zhang, X., Yu, X., & Li, Y. (2016). Gibberellin is involved in inhibition of cucumber growth and nitrogen uptake at suboptimal root-zone temperatures. *PloS one*, *11*(5), e0156188.

Balfagón, D., Zandalinas, S. I., Mittler, R., & Gómez-Cadenas, A. (2020). High temperatures modify plant responses to abiotic stress conditions. *Physiologia Plantarum*, *170*(3), 335-344.

Baxevanou, C., Fidaros, D., Bartzanas, T., & Kittas, C. (2017). Yearly numerical evaluation of greenhouse cover materials. *Comput. Electron. Agric*., 149, 54-70.

Bhattarai, S., Harvey, J. T., Djidonou, D., & Leskovar, D. I. (2021). Exploring morpho-physiological variation for heat stress tolerance in tomato. *Plants, 10*(2), 347.

Bhujel, A., Basak, J., Khan, F., Arulmozhi, E., Jaihuni, M., Sihalath, T., Lee, D., Park, J., & Kim, H. (2020). Sensor Systems for Greenhouse Microclimate Monitoring and Control: a Review. *Journal of Biosystems Engineering*, 45, 341 - 361.

Blum, A. (2017). Osmotic adjustment is a prime drought stress adaptive engine in support of plant production. *Plant, Cell & Environment*, 40(1), 4–10.

Bonuso, S., Panico, S., Baglivo, C., Mazzeo, D., Matera, N., Congedo, P., & Oliveti, G. (2020). Dynamic Analysis of the Natural and Mechanical Ventilation of a Solar Greenhouse by Coupling Controlled Mechanical Ventilation (CMV) with an Earth-to-Air Heat Exchanger (EAHX). *Energies*, 13, 3676. .

Bulgari, R., Franzoni, G., & Ferrante, A. (2019). Biostimulants application in horticultural crops under abiotic stress conditions. Agronomy, 9(6), 306.

Carmody, N., Goñi, O., Łangowski, Ł., & O’Connell, S. (2020). *Ascophyllum nodosum* extract biostimulant processing and its impact on enhancing heat stress tolerance during tomato fruit set. *Frontiers in plant science*, *11*, 807.

Chaudhary, S., Devi, P., HanumanthaRao, B., Jha, U. C., Sharma, K. D., Prasad, P. V., ... & Nayyar, H. (2022). Physiological and molecular approaches for developing thermotolerance in vegetable crops: a growth, yield and sustenance perspective. *Frontiers in Plant Science*, *13*, 878498.

Costantino, A., Comba, L., Sicardi, G., Bariani, M., & Fabrizio, E. (2021). Energy performance and climate control in mechanically ventilated greenhouses: A dynamic modelling-based assessment and investigation. *Applied Energy*, *288*, 116583.

Dash, P. K., Guo, B., & Leskovar, D. I. (2025). Biostimulants Alleviate Heat Stress in Organic Hydroponic Tomato Cultivation: A Sustainable Approach. *HortScience*, *60*(3), 344-352.

De Lima, J., Da Silva, J., Montenegro, A., Silva, V., & Abrantes, J. (2020). The effect of vegetal mulching on soil surface temperature in semiarid Brazil. *Die Bodenkultur: Journal of Land Management, Food and Environment*, 71, 185 – 195.

Delamare, J., Personeni, E., Guédard, M., Kim, T., Elie, N., Bressan, M., Cantat, O., Dupas, Q., Trinsoutrot-Gattin, I., Prigent-Combaret, C., & Brunel-Muguet, S. (2025). Effects of thermopriming and bacteria-mediated heat-stress acclimation strategies on seed yield and quality criteria in *Brassica napus* cv Aviso and *Camelina sativa* cv Calena.. *Planta*, 261 2, 26 .

Di Sario, L., Boeri, P., Matus, J. T., & Pizzio, G. A. (2025). Plant biostimulants to enhance abiotic stress resilience in crops. *International Journal of Molecular Sciences*, *26*(3), 1129.

Ghani, S., Bakochristou, F., ElBialy, E. M. A. A., Gamaledin, S. M. A., Rashwan, M. M., Abdelhalim, A. M., & Ismail, S. M. (2019). Design challenges of agricultural greenhouses in hot and arid environments A review. *Engineering in Agriculture, Environment and Food*, *12*(1), 48-70.

Ghoulem, M., El Moueddeb, K., Nehdi, E., Boukhanouf, R., & Calautit, J. K. (2019). Greenhouse design and cooling technologies for sustainable food cultivation in hot climates: Review of current practice and future status. *Biosystems Engineering*, *183*, 121-150.

Giri, A., Heckathorn, S., Mishra, S., & Krause, C. (2017). Heat stress decreases levels of nutrient-uptake and-assimilation proteins in tomato roots. *Plants*, *6*(1), 6.

Hasanuzzaman, M., Nahar, K., Alam, M. M., Roychowdhury, R., & Fujita, M. (2013). Physiological, biochemical, and molecular mechanisms of heat stress tolerance in plants. *International Journal of Molecular Sciences*, 14(5), 9643–9684.

Hemming, S., Zwart, F. D., Elings, A., Petropoulou, A., & Righini, I. (2020). Cherry tomato production in intelligent greenhouses—Sensors and AI for control of climate, irrigation, crop yield, and quality. *Sensors*, *20*(22), 6430.

Hussain, H. A., Hussain, S., Khaliq, A., Ashraf, U., Anjum, S. A., Men, S., & Wang, L. (2018). Chilling and frost stress in crop plants: Implications, damage and management strategies: A review. *Agronomy for Sustainable Development*, 38, 54.

Jalwania, R., Kumar, P., Kumar, A., Hansda, S., Pandey, P., Jagadala, K., ... & Verma, S. (2025). Protected Cultivation Technologies for Off-Season Vegetable Production: A Review. *Journal of Scientific Research and Reports*, *31*(5), 470-489.

Kawasaki, Y. (2014). Fruit set and temperature stress. In N. Suzuki (Ed.), *Abiotic Stress Biology in Horticultural Plants* (pp. 87–99). Springer.

Kim, H. K. (2024). Evaluating the ventilation performance of single-span plastic greenhouses with continuous screened side openings. *Agronomy*, *14*(7), 1447.

Kittas, C., & Bartzanas, T. (2007). Greenhouse microclimate and dehumidification effectiveness under different ventilator configurations. *Building and Environment*, 42(10), 3774-3784.

Kläring, H. P., Klopotek, Y., Krumbein, A., & Schwarz, D. (2015). The effect of reducing the heating set point on the photosynthesis, growth, yield and fruit quality in greenhouse tomato production. *Agricultural and Forest Meteorology*, *214*, 178-188.

Lee, C., Harvey, J. T., Nagila, A., Qin, K., & Leskovar, D. I. (2023). Thermotolerance of tomato plants grafted onto wild relative rootstocks. *Frontiers in Plant Science, 14*, 1252456.

Lee, K., Rajametov, S. N., Jeong, H. B., Cho, M. C., Lee, O. J., Kim, S. G., ... & Chae, W. B. (2022). Comprehensive understanding of selecting traits for heat tolerance during vegetative and reproductive growth stages in tomato. *Agronomy*, *12*(4), 834.

Lee, M. H., Yao, M. H., Kow, P. Y., Kuo, B. J., & Chang, F. J. (2024). An Artificial Intelligence-Powered Environmental Control System for Resilient and Efficient Greenhouse Farming. *Sustainability*, *16*(24), 10958.

Li, B., Gao, K., Ren, H., & Tang, W. (2018). Molecular mechanisms governing plant responses to high temperatures. *Journal of integrative plant biology*, 60 9, 757-779.

Liu, X., Yang, S., Chen, X., Liu, S., Zhou, R., Guo, L., ... & Cao, Y. (2022). Performance evaluation of a water-circulating tomato root-zone substrate-cooling system using a chiller and its effect on tomato vegetative growth in Chinese solar greenhouse. *Agronomy*, *12*(8), 1922.

López, J. C., Pérez, C., Pérez-Parra, J. J., Baeza, E. J., Gázquez, J. C., & Parra, A. (2007, October). Heating Strategies for an Eggplant (Solanum melongena L.) Crop on Mediterranean Greenhouses. In *International Symposium on High Technology for Greenhouse System Management: Greensys2007 801* (pp. 1077-1082).

Mahajan, S., & Tuteja, N. (2005). Cold, salinity and drought stresses: an overview. *Archives of biochemistry and biophysics*, *444*(2), 139-158.

Manni, M., Di Giuseppe, A., Nicolini, A., Sciurpi, F., & Cotana, F. (2021). Influences of a highly reflective mulching membrane on heat propagation throughout the soil. *Sustainability*, *13*(17), 9737.

McCartney, L., Orsat, V., & Lefsrud, M. G. (2018). An experimental study of the cooling performance and airflow patterns in a model Natural Ventilation Augmented Cooling (NVAC) greenhouse. *Biosystems Engineering*, *174*, 173-189.

Mittler, R. (2002). Oxidative stress, antioxidants and stress tolerance. *Trends in plant science*, *7*(9), 405-410.

Navarro-Morillo, I., Navarro-León, E., Atero-Calvo, S., Rios, J. J., Ruiz, J. M., & Blasco, B. (2024). Biostimulant-induced mitigation of cold and drought stresses in zucchini plants. *Scientia Horticulturae*, *331*, 113114.

Niu, C., Wang, G., Sui, J., Liu, G., Ma, F., & Bao, Z. (2022). Biostimulants alleviate temperature stress in tomato seedlings. *Scientia Horticulturae*, *293*, 110712.

Platero-Horcajadas, M., Pardo-Pina, S., Cámara-Zapata, J. M., Brenes-Carranza, J. A., & Ferrández-Pastor, F. J. (2024). Enhancing greenhouse efficiency: Integrating IoT and reinforcement learning for optimized climate control. *Sensors*, *24*(24), 8109.

Posch, B. C., Kariyawasam, B. C., Bramley, H., Coast, O., Richards, R. A., Reynolds, M. P., ... & Atkin, O. K. (2019). Exploring high temperature responses of photosynthesis and respiration to improve heat tolerance in wheat. *Journal of experimental botany*, *70*(19), 5051-5069.

Pressman, E., Peet, M. M., & Pharr, D. M. (2002). The effect of heat stress on tomato pollen characteristics is associated with changes in carbohydrate concentration in the developing anthers. *Annals of botany*, *90*(5), 631-636.

Quan, J., Zheng, W., Wu, M., Shen, Z., Tan, J., Li, Z., ... & Zang, Y. (2022). Glycine betaine and β-aminobutyric acid mitigate the detrimental effects of heat stress on Chinese cabbage (Brassica rapa L. ssp. pekinensis) seedlings with improved photosynthetic performance and antioxidant system. *Plants*, *11*(9), 1213.

Rajametov, S. N., Yang, E. Y., Jeong, H. B., Cho, M. C., Chae, S. Y., & Paudel, N. (2021). Heat treatment in two tomato cultivars: A study of the effect on physiological and growth recovery. *Horticulturae*, *7*(5), 119.

Rezvani, S. M. E., Abyaneh, H. Z., Shamshiri, R. R., Balasundram, S. K., Dworak, V., Goodarzi, M., ... & Mahns, B. (2020). IoT-based sensor data fusion for determining optimality degrees of microclimate parameters in commercial greenhouse production of tomato. *Sensors*, *20*(22), 6474.

Ruelland, E., Vaultier, M.-N., Zachowski, A., & Hurry, V. (2009). Cold signalling and cold acclimation in plants. *Advances in Botanical Research*, 49, 35–150.

Sato, S., Peet, M. M., & Thomas, J. F. (2000). Physiological factors limit fruit set of tomato (*Lycopersicon esculentum* Mill.) under chronic, mild heat stress. *Plant, Cell & Environment, 23*(7), 719–726.

Soussi, M., Chaibi, M. T., Buchholz, M., & Saghrouni, Z. (2022). Comprehensive review on climate control and cooling systems in greenhouses under hot and arid conditions. *Agronomy*, *12*(3), 626.

Subahi, A., & Bouazza, K. (2020). An Intelligent IoT-Based System Design for Controlling and Monitoring Greenhouse Temperature. *IEEE Access*, 8, 125488-125500.

Suvorin, O., & Kabachiy, V. (2024). Aı-Drıven Greenhouse Management: Opportunıtıes And Challenges In Automatıon. *Proceedings of XVII International Conference Measurement and Control in Complex System (MCCS-2024)*.

Taiz, L., & Zeiger, E. (2010). Plant physiology (5th ed.). Sinauer Associates.

Theocharis, A., Clement, C., & Barka, E. A. (2012). Physiological and molecular changes in plants grown at low temperatures. *Planta*, 235(6), 1091–1105.

Wahid, A., Gelani, S., Ashraf, M., & Foolad, M. R. (2007). Heat tolerance in plants: An overview. *Environmental and Experimental Botany*, 61(3), 199–223.

Wang, W., & Hoch, G. (2022). Negative effects of low root temperatures on water and carbon relations in temperate tree seedlings assessed by dual isotopic labelling. *Tree Physiology*, *42*(7), 1311-1324.

Wang, Y., Wang, J., Sarwar, R., Zhang, W., Geng, R., Zhu, K. M., & Tan, X. L. (2024). Research progress on the physiological response and molecular mechanism of cold response in plants. *Frontiers in Plant Science*, *15*, 1334913.

Went, F. W. (1953). The effect of temperature on plant growth. *Annual Review of Plant Physiology*, *4*(1), 347-362.

Wien, H. C. (1997). Peppers. In H. C. Wien (Ed.), The physiology of vegetable crops (pp. 259–293). CAB International.

Zhang, A., Zhu, Z., Shang, J., Zhang, S., Shen, H., Wu, X., & Zha, D. (2020). Transcriptome profiling and gene expression analyses of eggplant (Solanum melongena L.) under heat stress. *PLOS ONE*, *15*(8), e0236980.

Zhang, J., Zhao, S., Dai, A., Wang, P., Liu, Z., Liang, B., & Ding, T. (2022). Greenhouse natural ventilation models: how do we develop with Chinese greenhouses?. *Agronomy*, *12*(9), 1995.

Chapter 3

GROWTH AND YIELD PREDICTION USING FOREST GROWTH SIMULATORS AND SUB-MODEL STRUCTURES

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INTRODUCTION

Growth and yield models enable the projection of forest stands under various conditions over time in forest management planning, thereby establishing valuable and essential foundations for these ecosystem-based functional plans (Vanclay, 1994; Pretzsch, 2009). Knowledge of growth and yield relationships is necessary not only for economic utilization of forests, but also for monitoring the economic success of forestry operations. In multipurpose forest management plans, while obtaining optimal solutions by considering economic, ecological, and social functions (Burkhart, 1995; Vanclay, 1994), understanding growth and yield relationships holds critical importance for directing silvicultural interventions and evaluating the effectiveness of these interventions. Therefore, all aspects of the growth and yield relationships required for directing forestry practices must be investigated.

Growth and yield models are defined by Vanclay (1994) as systems of equations that estimate the growth and yield values of forest stands. These models constitute one of the fundamental components in forest management plans and predict the temporal changes in growth and yield elements of forest stands (Gadow and Hui, 1999). In forestry applications, modeling and simplification of complex systems is widely employed to enhance understanding. These growth and yield models serve as indispensable tools for understanding systems and evaluating potential scenarios. In forest systems, these models are extensively utilized to understand system behaviors that change over time and to predict the effects of various interventions. Particularly, considering the long-term negative impacts of inappropriate interventions, modeling methods enable the tracking of outcomes from different intervention scenarios and the determination of optimal intervention strategies. Growth and yield models are of critical importance for understanding forest stand dynamics and tree growth processes. Through different approaches and methodologies, such as empirical growth models and process-based growth models, the accuracy of predictions obtained in forestry applications is improved, and thus sustainable forest management objectives are pursued (Porté and Bartelink, 2002).

The implementation of growth simulators becomes possible through the development of computer programs and interfaces that predict growth and yield characteristics in various forest ecosystems. By simultaneously predicting the growth and yield values of trees along with their mortality status, these simulators gain the capability to determine stand characteristics more successfully. Growth simulators operate processes in which sub-models that predict tree increment, other characteristics, and mortality events function simultaneously (Vanclay, 1994; Bettinger et al., 2017). These simulators reflect the condition of trees within the stand and provide critical information for sustainable forest management.

In countries implementing multipurpose planning, such as the United States, Canada, and European nations, numerous growth simulators have been developed based on data obtained from permanent sample plots, have been used for growth and yield predictions required in planning for many decades, and continue to be used at present (Atar, 2023). These simulators predict growth and yield values based on permanent sample plots established in stands that have undergone specific silvicultural treatment options, thereby providing the opportunity to develop planning strategies and silvicultural treatment alternatives in the planning of forest areas.

Among growth simulators developed in forestry, the Forest Vegetation Simulator (FVS) (FVS, 2022), which is based on the Prognosis simulator whose origins date back to the early 1970s (Stage, 1973), stands out as one of the most widely used simulators with 21 different variants covering the entire United States and certain regions of Canada (a variant of a growth simulator is designated when model parameters are estimated specifically for an ecological region, thereby developing the simulator for that particular region) (Atar, 2023). When this simulator was first developed in the 1970s, it was named Prognosis to reference its predictive function in forestry; however, in the 1990s, its name was changed to Forest Vegetation Simulator (FVS, 2022). Currently, FVS predicts growth and yield values of trees based on the model structure of the Prognosis simulator proposed by Stage (1973) and has furthermore been expanded to include various modules (extensions) related to fire, insects, and other forest pests (Crookston and Dixon, 2005). The Forest Vegetation Simulator possesses a model structure that can fundamentally be classified within the distance-independent single-tree model class (Munro, 1974), and besides containing sub-models that predict diameter increment and mortality probability of trees under various conditions, it also incorporates numerous different models as sub-models or model components, such as diameter-height models, crown ratio models, and two-entry tree volume equations. The simultaneous operation of different model components of the Forest Vegetation Simulator and the prediction of growth and yield in forest stands is accomplished through an interface called "Suppose," which was coded in the C++ computer programming language (Crookston, 1997). Currently, the Forest Vegetation Simulator has been transferred to an R-Shiny interface coded in the R language and is being implemented through this interface. The Forest Vegetation Simulator is used in the preparation of forest management plans in the United States and in the development of management plans for forest pests such as fire, fungal, and insect damage, thereby making it possible to demonstrate the effects of various forestry activities, particularly silvicultural interventions, on stand growth and yield. In this regard, the Forest Vegetation Simulator serves as an important and fundamental foundation in the development of various plans, particularly forest management plans.

Therefore, the Forest Vegetation Simulator, which predicts the growth and yield of forest stands under various conditions, has provided important services as a fundamental foundation in the execution of various forestry activities in American forestry over approximately 50 years and continues to fulfill this role effectively at present.

The development of growth simulators of significant importance for our country's forestry, tailored to our important forestry areas where different tree species are distributed, is of considerable importance. In this context, summary information regarding the equation structure and operational processes of growth simulators will be provided, and prediction procedures will be presented in this study.

Forest Vegetation Simulator and Its General Structure

The Forest Vegetation Simulator (FVS) is a stand growth simulator based on the Prognosis simulator developed in 1973 (Stage, 1973), which has gained widespread application throughout the United States and in certain regions of Canada and, accordingly, supports ecosystem-based functional planning in these regions and serves as a fundamental foundation. The basic modeling unit of this simulator is forest stands. There is a modeling strategy that predicts growth primarily along the diameter increment axis occurring in stands, estimates other characteristics based on this diameter growth, calculates mortality rates in trees, removes some trees from calculations, and thus excludes them from further analysis. By operating this process annually, it bases stand changes throughout the projection period on diameter development and mortality events. Specifically, diameter increment is predicted according to tree-specific characteristics such as initial diameter at breast height and crown ratio at the beginning of the period, as well as competition-related indices such as competitive indices among trees and site productivity characteristics. The predicted diameter increment is added to the initial diameter value to obtain diameter development at the end of the period. Using the predicted diameter values, tree height equations estimate the height values of trees. Based on the diameter and height development thus obtained, tree volume development is predicted using two-entry tree volume equations, and total stand volumes at the end of the projection period, determined annually and at user discretion, are estimated by summing the volume values of individual trees.

In the basic functioning of the Forest Vegetation Simulator, whether based on FVS or other approaches, it becomes possible to simulate stand characteristics by obtaining combined predictions from certain single-tree and stand sub-models and integrating these predictions. In this regard, the forest vegetation simulator comprises several sub-models, and outputs designated as simulations can be obtained by running these models together. The forest vegetation simulator to be developed in this study consists of four different sub-models: a distance-independent single-tree bark diameter increment model with a nonlinear regression model structure, a single-tree mortality model based on logistic function, a stand tree number model, and a generalized diameter-height model. By obtaining predictions concerning single-tree and stand characteristics with these sub-models, or in other words, by running them simultaneously, stand simulations are obtained. Using the models developed and based on the current condition of sample plots, simulations of various stand characteristics such as stand volume, basal area, mean diameter, biomass, and carbon may have been obtained following the Forest Vegetation Simulator (FVS) system, which is an important growth simulator successfully used in the United States and Canada. Explanations regarding the regression model structures fundamental to these sub-models and the model development processes are provided in the following sections.

Individual Tree Diameter Increment Model

When evaluating the working system of the Forest Vegetation Simulator generally, this simulator has two important dynamic sub-models: the diameter increment model and the mortality model. The diameter increment model being the most fundamental sub-model parts from the fact that, as stated in many dendrometric studies, tree diameter measurement is a fast, easy, and least error-prone measurement, and moreover, this characteristic has important and useful aspects in terms of forest inventory as it demonstrates a strong relationship with many other tree characteristics. In single-entry and two-entry tree volume equations that are frequently developed and used in calculating stand volumes, an important topic in forestry, tree diameter at breast height is included as a very important variable along with total tree heights.

The Forest Vegetation Simulator is classified as a simulator within the distance-independent single-tree model class in the classification system of growth and yield models, as it uses distance-independent competition indices to model competition among trees in its diameter increment sub-model, which is its fundamental sub-model (FVS, 2022). In this simulator, the diameter increment model is based on Wykoff (1990)'s multiple linear regression model structure composed of numerous independent variables. However, this study presents and thoroughly explains a nonlinear regression model structure as an example, which may offer improved predictive capability for diameter increments exhibiting a bell-shaped developmental trend relative to conventional linear regression models. A nonlinear regression model produced by Schelhaas et al. (2018) based on the fundamental function of Gompertz (Winsor, 1932) and applied using data from 2.3 million trees of different tree species, including European Beech (Fagus sylvatica L.), may presented as an illustrative example in this study. In the distance-independent single-tree model, which is the core sub-model of FVS; the predicted (dependent) variable is 10-year diameter increment, and the independent variables are tree characteristics such as diameter at breast height, which is known to affect diameter increment of trees, distance-independent competition indices that quantify the competition status of trees with other trees, and stand characteristics such as site index, stand mean diameter (radius of the basal area mean tree), and stand density-related variables. The model can be developed through nonlinear regression analysis based on these variables.

The equation structure of the model employed in this study is as follows, Equation (1)-(3) (Schelhaas et al., 2018);

$$Id = a_1 \cdot d_{1.30} + a_2 \cdot d_{1.30} \cdot Ln(d_{1.30}) \tag{1}$$

$$a_1 = b_1 + \sum_{i=1}^{p} \beta_{i,1} \cdot X_i \tag{2}$$

$$a_2 = b_2 + \sum_{i=1}^{p} \beta_{i,2} \cdot X_i \tag{3}$$

In this distance-independent model with given equation structure, the fundamental growth characteristics affecting tree diameter increment, including tree-specific characteristics such as tree diameter at breast height, the site index variable representing site productivity of the growing environment, the basal area mean tree diameter variable representing stand mean diameter, the stand density ratio representing general stand density, and the competition index variables representing competition among trees with other trees, were included as significant variables at the 95% confidence level ($p<0.05$) (variables symbolized with b_1-b_{10}). Thus, through adjustments made to the basic model provided above using the variables employed in this study, the equation structure given with parameter values below was obtained, Equation (4);

$$Id_{10} = \left[b_1 + (b_2 \cdot SI) + \left(\frac{b_3}{CC1}\right) + \left(\frac{b_4}{Dg}\right) + \left(\frac{b_5}{SDI}\right)\right] * \left(\frac{1}{d_{1.30}}\right) + \left\{\left[b_6 + (b_7 \cdot SI) + \left(\frac{b_8}{CC1}\right) + \left(\frac{b_9}{Dg}\right) + \left(\frac{b_{10}}{SDI}\right)\right] * \left(\frac{1}{d_{1.30}}\right) * LN(d_{1.30})\right\} \tag{4}$$

In this equation, : 10-year diameter increment (cm), $d_{1.30}$: tree diameter at breast height 10 years prior, SI: Site Index value calculated using the site index table, SDI: stand density ratio calculated according to Reineke (1933), D_g: mean diameter calculated using the basal area mean tree approach, CC1: competition index calculated using the approach that relates the diameter at breast height of the subject tree to the diameter of the basal area mean tree of the stand.

In estimating the parameters and various statistics of this nonlinear regression model, which predicts the 10-year diameter increment of trees and whose model structure is provided above, through nonlinear least squares analysis, the "GenSa" library, an optimization library for nonlinear estimation systems developed in the R language, can be employed (R Development Core Team 2024). With this R library, it becomes possible to obtain optimization solutions for the parameters of nonlinear models whose structure will be defined for specific data structures (pools), and thus after the initial values of this nonlinear regression model are determined, nonlinear regression analysis can be applied with the "nls" function, and the parameter values and various statistical values of the model can be obtained. In this study, based on the fundamental Gompertz function (Winsor, 1932), the model structure proposed by Schelhaas et al. (2018) was presented as an illustrative example using independent variables known to be related to diameter increment (diameter at breast height, competition index, site index, stand density ratio, and mean diameter). Initial parameter values associated with these variables were obtained using the GenSA library, and subsequent nonlinear regression analysis was performed using the nls function.

Modeling Tree Mortality Processes

In forest areas, some trees fall behind in the crown and root competition seen within stands, which is actually competition for light, water, and plant nutrients necessary for tree development, and trees that do not exhibit a certain growth potential die and leave the stand (Fırat 1972, Kalıpsız 1998). Mortality of trees within a stand is an important stand dynamic and process and is a model component that must be considered in stand simulation models. In tree mortality modeling, a logistic regression framework is frequently applied, in which dead trees are coded as 0 and living trees as 1. (Yao et al., 2001). In developing the logistic function, which has a nonlinear model structure, the dependent variable (p)—tree survival status—is coded as 0 if the tree has died and as 1 if it is alive, while the predictions of the logistic model are obtained as probability values between 0 and 1. The logistic model structure is expressed below, Equation (5);

$$p(\text{mortality}) = \frac{1}{1+e^{-(\beta_0+\beta_1 \cdot x_1+\cdots+\beta_k \cdot x_k)}} \tag{5}$$

In this model, p represents the mortality status of trees, taking a value of 0 if the tree has died and 1 if it is alive. The variable Xk represents various single-tree and stand characteristics that exhibit statistically significant relationships with tree mortality at the 0.05 significance level and are included in the model, βi represents model parameters, and e represents the natural logarithm. In this study, a logistic model is used to address tree mortality probabilities, and the determination of which trees will die within stands is presented as an illustrative example of an important issue in mortality modeling.

In the growth and yield simulations performed, a threshold value is used to determine whether an individual tree has died or not. For example, Yavuz (1992), in simulations based on stochastic Markov chains of uneven-aged stands, based the assumption that trees reaching 400 years of age and trees with bark-free diameter increment of less than 1 mm would die when determining tree mortality and removal. Erkan (1995) noted that the competition pressure experienced by trees is very important in identifying trees that would leave the stand, and by obtaining critical thresholds for trees experiencing the highest pressure according to age and site index using a function based on competition indices, conducted simulations with the assumption that trees below this critical value should die. However, there is the possibility that predictions regarding total tree numbers in a stand obtained from these mortality predictions made only on a single-tree basis may not be consistent with possible stand tree number values according to the stands' age, site index, and density values. This is because the stand tree numbers obtained by removing trees exceeding a certain threshold or critical value based on the single-tree mortality probabilities predicted at different ages within a stand may differ from the possible tree numbers according to those stands' age, site index, and density values. In this regard, it is necessary to combine mortality conditions on a single-tree basis with stand-level changes in tree numbers according to different age, site productivity, and site index values. In stand simulations conducted by Atar (2023) for Oriental Beech stands in the Western Black Sea region, in the first stage, tree numbers were predicted according to the mean age, site index, and stand density during a certain simulation period; at the end of the relevant simulation period, the current tree number in the sample plot was compared with the tree number predicted according to the stand tree number model, and if the current tree number exceeded the predicted tree number, it was decided that trees with mortality probabilities predicted on a single-tree basis using the logistic model would die, starting from the tree with the mortality probability closest to 0. For example, if the tree number of a stand is predicted to be 600 trees/ha at the end of a period, according to a 600 m^2 sample plot size, this corresponds to 36 trees for the sample plot; if the number of trees in the sample plot is 40, these 4 excess trees are identified as the 4 trees with mortality probability closest to 0. Thus, in relation to the changes in stand tree numbers according to stand age, site index, and density in the stands of the study area, tree mortality processes are presented in a manner consistent with the general trend of stand tree numbers. On the other hand, relying solely on single-tree mortality probabilities and removing trees that do not achieve a certain diameter increment or fall below a critical value can result in obtaining results inconsistent with stand tree number development, such as significant reductions in total tree numbers within the stand or situations where no trees die.

In this study, a predictive model developed to estimate stand tree number based on variables such as stand age, site index, and stand density ratio is introduced as an illustrative example of an important component in modeling tree mortality processes. In this context, different variables were derived from stand age, site index, and stand density ratio variables, and a model structure showing significant relationships at the 5% significance level with these variables was employed. This regression model structure is presented below, Equation (6):

$$N = e^{\left(b_0 + b_1 * \left(\frac{1}{SI}\right) + b_2 * \left(\frac{1}{t}\right) + b_3 \left(\frac{1}{SI * SDI}\right)\right)} \tag{6}$$

where SI represents the stand site index, SDI represents the stand density value, t represents the stand age, and bi represents the coefficients of the regression model.

Development of a Simulation Interface Using Excel Program

The modeling strategy for predicting stand characteristics developed in this study is presented as an illustrative example, based on simulation processes operated through the simultaneous execution of different sub-models. In these simulations, diameter increments of trees under various conditions can be predicted; by adding diameter increment values to previous diameter at breast height values, diameter at breast height values for the next period may be estimated. Based on diameter at breast height values obtained at the end of the simulation period, tree heights can be predicted and using end-of-period diameter at breast height and height values, tree volume values may be obtained using two-entry tree volume equations. Along with growth values obtained through diameter increment and the cumulative accumulation of these increment values, tree mortality events resulting from competition and rivalry among trees within the stand can be modeled using a single-tree mortality model based on the logistic function together with the stand tree number model. In this regard, the two fundamental important components of the simulations conducted van be diameter increments and single-tree mortality conditions.

Discussion

The primary objective of this study is to provide a general and structured overview of forest growth simulators and their underlying sub-model components rather than to develop or recalibrate growth and yield models. Within this framework, the study focuses on explaining how growth simulators are conceptually organized, how their core sub-models function, and how these components interact to represent forest stand dynamics in practical forestry applications.

Growth simulators are not single predictive equations but integrated systems in which multiple sub-models operate simultaneously. This study emphasizes that diameter increment, tree mortality, stand tree number, and diameter–height relationships constitute the fundamental building blocks of most contemporary growth simulators. Understanding the logical structure and functional roles of these sub-models is essential for correctly interpreting simulation outputs and for applying simulators effectively in forest management planning. Within growth simulation systems, diameter increment sub-models serve as the primary driving mechanism of stand development. This study highlights the conceptual importance of diameter growth in determining subsequent tree attributes such as height, volume, and biomass. The widespread use of nonlinear growth functions in simulators reflects an effort to represent biologically realistic growth patterns across varying site conditions and stand structures. Tree mortality is discussed as one of the most complex and influential components of growth simulators. Rather than being treated as an isolated statistical process, mortality in simulators is commonly linked to competition, stand density, and age-related dynamics. This study underscores that the integration of individual-tree mortality probabilities with stand-level constraints is a conceptual strategy widely adopted to maintain consistency between tree-level processes and stand-level development trends, especially in long-term simulations. Stand tree number models and generalized diameter–height relationships are presented as complementary components that support the internal coherence of growth simulators. These sub-models enable the translation of individual-tree growth processes into stand-level structural attributes that are directly relevant for forest management, such as basal area, volume, and yield projections. Their inclusion ensures that growth simulators can produce outputs suitable for planning, evaluation, and scenario analysis.

When the utilization of increment and growth models developed in Türkiye is evaluated, it is observed that yield tables classified within the stand-level model category are frequently employed in forest management plans to define the optimal stand conditions, whereas the application of other model classes, such as individual-tree models, remains rather limited. In this respect, stand models developed in Türkiye and the normal yield tables derived from these models appear to have a restricted application scope, primarily confined to the determination of optimal stand conditions required for the preparation of conventional forest management plans (Yavuz et al., 2005; Ercanlı, 2010). However, in ecosystem-based functional forest management planning that simultaneously considers economic, ecological, and socio-cultural functions, optimal solutions can be achieved through the identification of multiple objectives, constraints, and decision variables, and by employing operations research techniques based on scientific methods such as linear programming or goal programming (Başkent et al., 2001; Başkent and Keleş, 2004). Within this planning framework, the quantification of stand increment and growth components—including tree number, basal area, and volume—through forest inventory data is essential not only for representing the economic dimension of forest plans, particularly timber production, but also for understanding the relationships between these growth attributes, especially stand basal area, and various ecosystem functions such as water yield, soil loss, and carbon sequestration.

In several studies related to functional forest management planning conducted in recent years (Mısır, 2001; Keleş, 2003; Karahalil, 2003), temporal changes in ecosystem functions such as soil conservation and water production in response to silvicultural interventions have been quantified using regression equations that describe statistical relationships between stand basal area and various function-specific indicators. In particular, changes in forest functions have been predicted based on variations in stand basal area resulting from different silvicultural treatments. From this perspective, in the preparation of functional forest management plans, growth models are used to predict the temporal dynamics of stand growth and increment characteristics, thereby enabling the assessment of corresponding changes in forest ecosystem functions. Consequently, growth simulators, which represent an effective application of increment and growth models, can constitute one of the fundamental foundations of ecosystem-based functional forest management planning, as they not only predict changes in stand structure but also implicitly capture the dynamics of forest functions. The predictive consistency and performance of these simulators may therefore substantially influence the overall success of forest management plans.

In Türkiye, however, no growth simulator has yet been developed that plays a prominent role in forestry practices, particularly in forest management planning. This deficiency constitutes a significant obstacle to the development of ecosystem-based functional forest management plans, which have become increasingly prominent in contemporary forest science. Without a growth simulator capable of predicting forest ecosystem increment and growth dynamics under varying conditions—most notably under different silvicultural interventions—it is not possible to develop and implement ecosystem-based functional plans in an effective and consistent manner.

From this perspective, the development of growth simulators, such as an OVS-type system, capable of predicting stand increment and growth under diverse site, stand, and management conditions, represents a critical necessity for national forestry. Such simulators are essential not only for improving the scientific foundation of forest management planning but also for supporting the integrated assessment of economic, ecological, and socio-cultural forest functions.

From a broader perspective, this study underlines that growth simulators should be viewed as decision-support tools rather than purely predictive instruments. Their strength lies in their ability to integrate multiple growth processes and to explore alternative management and silvicultural scenarios over extended time horizons. Consequently, a clear understanding of simulator structure and sub-model logic is as important as statistical accuracy, particularly for practitioners and researchers who rely on these tools for strategic planning. In conclusion, this study contributes by presenting a conceptual and methodological overview of forest growth simulators and their sub-model structures. By clarifying the roles and interactions of key simulator components, it provides a reference framework for understanding how growth simulators operate and how their outputs should be interpreted within the context of sustainable forest management.

References

Atar, D. (2023). Batı Karadeniz Bölgesi Aynı Yaşlı Saf Doğu Kayını (*Fagus Orientalis* Lipsky.) Meşcerelerinin Çeşitli İklim Senaryolarına Göre Meşcere Özelliklerinin Tahmini ve Simülasyonu. Doktora Tezi, Çankırı Karatekin Üniversitesi, 134 sayfa, Çankırı.

Başkent, E., Yolasığmaz, H. A. ve Mısır, M. (2001). Orman Ekosistem Amenajmanı, I. ulusal Ormancılık Kongresi, Mart, 2001, Ankara, Bildiriler Kitabı, 60-74.

Başkent, E. Z. ve Keleş, S. (2004). Ormancılıkta Model ve Modelleme Kavramlarının Kullanımı ve Genel Değerlendirilmesi, Orman Mühendisliği Dergisi, 40, 1: 19-32.

Bettinger, P.; Boston, K.; Siry, J.P.; Grebner, D.L. 2017. Forest Management and Planning: Second Edition; Elsevier Inc., 2017; ISBN 9780128094761.

Burkhart, H. (1995). Modeling Forest Growth, Encyclopedia of Environmental Biology, 2, 535-543

Crookston, N.L. (1997). Suppose: an interface to the Forest Vegetation Simulator. In: Teck, R., Moeur, M., Adams, J. (Comps.), Proceedings: Forest Vegetation Simulator Conference, February 3–7, 1997, Fort Collins, CO. Gen. Tech. Re INT-373. U.S. Department of Agriculture, Forest Service, Intermountain Research Station, Ogden, UT, pp. 7–14.

Crookston, N. L., and Dixon, G. E. (2005). *The Forest Vegetation Simulator: A review of its structure, content, and applications*. Computers and Electronics in Agriculture, 49, 60–80.

Erkan, N. (1995). Kızılçamda Meşcere Gelişiminin Simülasyonu. Doktora Tezi, İstanbul Ünversitesi, 198 sayfa, İstanbul.

Ercanlı, İ. (2010). Trabzon ve Giresun orman bölge müdürlükleri sınırları içerisinde yer alan Doğu Ladini (Picea orientalis (l.) Link)-Sarıçam (Pinus sylvestris l.) Karışık meşcerelerine ilişkin büyüme modelleri. Doktora Tezi, Karadeniz Teknik Üniversitesi, 351 sayfa, Trabzon.

Gadow, K.V. ve Hui, G.Y. (1999). Modelling Forest Development, Kluwer Academic Publishers, Dordrect, 213 s.

Fırat, F. (1972). Orman Hasılat Bilgisi . İ.Ü. Yayın No: 1642, Orman Fakültesi Yayın No:166, 191s., İstanbul.

FVS. (2022). Essential FVS: A user's guide to the Forest Vegetation Simulator, Fort Collins, CO, USA: US Department of Agriculture, Forest Service, Forest Management Service Center.

Kalıpsız, A. (1998). Orman Hasılat Bilgisi, İstanbul Üniversitesi Orman Fakültesi Yayınları, No:4060/448, İstanbul. 349 s.

Karahalil, U. (2003). Toprak Koruma ve Odun Üretimi Fonksiyonlarının Doğrusal Programlama ile Modellenmesi. Yüksek Lisans Tezi, Karadeniz Teknik Üniversitesi, 92 sayfa, Trabzon.

Keleş, S. (2003). Ormanların Su ve Odun Üretimi Fonksiyonlarının Doğrusal Programlama Tekniği ile Optimizasyonu (Karanlıkdere Planlama Birimi Örneği). Yüksek Lisans Tezi, Karadeniz Teknik Üniversitesi, 106 sayfa, Trabzon.

Mısır, M. (2001). Yöneylem Araştırması Teknikleri ve Coğrafi Bilgi Sistemleri Yardımıyla Orman Amenajman Planının Düzenlenmesi. Doktora Tezi, Karadeniz Teknik Üniversitesi, 156 sayfa, Trabzon.

Munro, D. D. (1974). Forest growth models – a prognosis. In: Fries, J. (Ed.), Growth Models for Tree and Stand Simulation. IURFO Working Party S4.01-4, Proceedings of Meetings in 1973. Dept. Of For. Yield Res., For. Res. Note 30, Royal College of Forestry, Stockholm, Sweden, 7–21.

Porté, A. ve Bartelink, H. H. (2002). Modelling Mixed Forest Growth: A Review of Models For Forest Management, Ecological Modelling, 150, 141−188.

R Core Team. (2024). R: A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, Austria.

Pretzsch, H. (2009). Forest dynamics, growth and yield (Vol. 684). Berlin: Springer.

Reineke, L.H. (1933). Perfecting a stand-density index for even-aged forests, Journal of Agricultural Research, 46: 627-638.

Schelhaas, M. J., Hengeveld, G. M., Heidema, N., Thürig, E., Rohner, B., Vacchiano, G., Vayreda, J., Redmond, J., Socha, J., Fridman, J., Tomter, S., Polley, H., Barreiro, S. and Nabuurs, J. N. (2018). Species-specific, pan-European diameter increment models based on data of 2.3 million trees. Forest Ecosystems, 5(21): 1-19.

Stage, A. R. (1973). Prognosis Model for Stand Development, Res. Pa INT-137. U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, Ogden, UT 84401, 32 p.

Winsor, C. P. (1932). The Gompertz curve as a growth curve. Proceedings of the national academy of sciences, 18(1): 1-8.

Vanclay, J.K. (1994). Modelling Forest Growth: Applications to Mixed Tropical Forests, CAB International, Department of Economics and Natural Resource, Royal Veterinary and Agricultural University, Copenhagen, Denmark, Wallingford, UK, 312 s.

Yao, X., Titus, S. J. and MacDonald, S. E. (2001). A Generalized Logistic Model of Individual Tree Mortality for Aspen, White Spruce, and Lodgepole Pine in Alberta Mixedwood Forests, Canadian Journal of Forest Research, 31: 283-291.

Yavuz, H. (1992). Değişik Yaşlı Meşcerelerde Büyümenin Markov Zincirleri Yöntemi ile Analiz Edilmesi. Doktora Tezi, Karadeniz Teknik Üniversitesi, 230 sayfa, Trabzon.

Yavuz, H., Mısır, N., Ercanlı, İ. ve Kahriman, A. (2005). Büyüme Modellerinin Ormancılıktaki Önemi ve Ormancılığımız İçin Öneriler, I. Çevre ve Ormancılık Şurası, 22-24 Mart, Antalya.

Chapter 4

COST ACCOUNTING FOR ANNUAL CROPS IN AGRICULTURAL ENTERPRISES

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1. INTRODUCTION

Agriculture occupies an indispensable position in sustaining human life. Ensuring food security, maintaining rural employment, supporting the integration between agriculture and industry, and strengthening the resilience of national economies depend largely on the continuity of agricultural production. In a global context where the population is rapidly increasing, challenges such as climate change, declining water resources, shrinking agricultural lands, and fluctuations in input prices exert significant pressure on agricultural production systems. These pressures further underscore the strategic importance of cost management in agricultural enterprises (Kıral et al., 1999; Tcacı et al., 2021).

Cost analysis— which is one of the most critical components of agricultural production—serves as a fundamental tool for monitoring profitability, assessing the efficiency of input use, selecting among alternative crops, rationalizing resource allocation decisions, and guiding production planning based on optimization principles. Compared to traditional industries, agricultural production is characterized by higher uncertainty and risk. Variability in natural conditions, biological production cycles, and inadequate record-keeping practices necessitate a more careful and systematic cost analysis approach (Çelik, 2014).

Moreover, the importance of agricultural cost information is not limited to the determination of product-based unit costs but also plays a decisive role in farm management, resource allocation, and decision-making processes. Evaluating cost data within the framework of management accounting enables efficiency and productivity analyses in agricultural enterprises (Govdya et al., 2017).

Difficulties in cost analysis within agricultural enterprises arise from uncertainties in input pricing, challenges in valuing family labor, the allocation of joint costs among multiple products, variations in depreciation calculations across enterprises, and the lack of standardization in agricultural accounting systems (Kumbasaroğlu & Dağdemir, 2010a; Hatunoğlu & Kıllı, 2016). Therefore, cost accounting in agriculture is not merely a bookkeeping activity but rather a multidisciplinary analytical domain encompassing agricultural economics, production economics, accounting standards, and management science.

Annual crops constitute one of the most intensively cultivated groups within agricultural production. Since these crops complete their production cycle within a single vegetative period, require annual sowing, and utilize all inputs within one production season, they offer the clearest and most measurable structure for cost analysis. Wheat, barley, maize, vetch, sunflower, and several similar field crops are of critical importance for human consumption, livestock feed, and agri-food industries. Annual cost estimation for these crops is essential for crop pattern decisions, farmers' production choices, and regional agricultural policy formulation (Kumbasaroğlu & Dağdemir, 2010b; 2010c).

In recent years, sharp increases in the prices of key inputs including but not limited to fuel, fertilizer, seeds, and energy in Türkiye— as evidenced by the continuous upward trend in indicators such as the Producer Price Index (ÜFE) and the Agricultural Input Price Index (TGFE)—combined with farmers' limited bargaining power, have further heightened the importance of cost analysis. The low input demand elasticities reported in the literature imply that farmers cannot significantly reduce input use in response to price increases (Çiftçi, 2009), leading to rigid and rapidly rising cost structures. Similarly, Tcacı et al. (2021) demonstrated through evidence from Moldova that increases in production costs directly reduce profitability.

In this context, conducting accurate, comparable, and scientifically grounded cost estimations for annual crops has become a critical requirement at both the micro level (farm economics, producer decision-making, profitability assessment) and the macro level (agricultural support policies, pricing strategies, supply management, and sectoral planning). In the agricultural economics and accounting literature, the Classical Cost Accounting System is widely used for product-based unit cost calculations and is considered the most appropriate and reliable method for analyzing the cost structure of annual crops.

This book chapter adopts a methodological, systematic, and comprehensive perspective to explain the cost accounting process for annual crops. It provides a step-by-step framework for defining, classifying, and calculating cost components. Drawing on national and international literature on cost accounting methods, input-use structures, and production economics, the chapter tailored for annual crops, thereby supporting both micro- and macro-level decision-making processes.

2. PURPOSE AND IMPORTANCE OF COST ACCOUNTING IN AGRICULTURAL ENTERPRISES

Agricultural production is an economic activity that entails considerably higher uncertainty and risk than other sectors due to its direct dependence on natural conditions and biological processes. These uncertainties—arising from fluctuations in input prices, the unpredictability of climatic conditions, variability in yield levels, and instability in market prices—complicate the accurate determination and monitoring of production costs. Therefore, cost accounting in agricultural enterprises constitutes a fundamental tool for managing the production process and assessing economic performance in a reliable and systematic manner (Kıral et al., 1999).

One of the key functions of cost calculations is their contribution to production planning. Farmers can determine which crops are more profitable, which crop pattern is most suitable, and how existing resources should be allocated only when accurate cost information is available. The ability to compute annual costs clearly in annual crops facilitates planning for subsequent production seasons and helps reduce production risks (Tcacı et al., 2021). Moreover, establishing consistent and comparable cost data over time enables the monitoring of technical and economic developments in agricultural production.

The primary purpose of cost calculations is to make product costs comparable. However, due to regional differences, variations in production techniques, farm sizes, and input-use levels, cost structures in agricultural enterprises can differ significantly. Consequently, cost analyses based on a standardized method allow meaningful comparisons across products and enterprises.

Economic evaluation of agricultural activities also necessitates profitability measurement, which is another critical function of cost analysis. Economic performance in agricultural enterprises is assessed using indicators such as gross profit, gross value added, net profit, and net farm income (Erkuş et al., 1995; Çelik, 2014). Accurate computation of these indicators requires precise determination of all cost components. Particularly, assigning a monetary value to family labor, calculating depreciation, including interest on working capital, and apportioning joint costs appropriately among products ensure the reliability of profitability analyses. Failure to account for these items leads to incomplete cost calculations and misrepresentation of the enterprise's actual economic performance.

The importance of cost accounting in agricultural enterprises extends beyond the farm level; it also carries substantial value for the design and evaluation of agricultural policies. Crop-based cost data serve as essential inputs for developing support policies, establishing price stabilization mechanisms, designing input subsidies, and formulating national agri-food strategies. Especially for annual crops, yearly cost and income analyses constitute key indicators for regional production planning, market responsiveness, and the assessment of international competitiveness.

In conclusion, cost accounting in agricultural enterprises is an indispensable managerial tool for guiding production decisions, measuring resource-use efficiency, comparing product costs, accurately determining enterprise income, and grounding agricultural policies in scientific evidence and transparent cost structures.

3. CHARACTERISTICS AND COST STRUCTURE OF ANNUAL CROPS

Annual crops are plant species that complete their production cycle within a single vegetative period and must be replanted every year. The production process of annual crops consists of clearly defined stages, including soil preparation, sowing, fertilization, maintenance operations, irrigation, hoeing, pesticide applications, harvesting, and marketing. Since all these stages are carried out according to a specific calendar, both the timing of cost occurrence and the quantity of input use can be monitored with relative ease. In addition, most of the inputs used in annual crop production—such as seeds, fertilizers, pesticides, and fuel—are variable in nature and must be procured for each production season. For this reason, variable costs constitute the dominant component of the total production cost in annual crop systems (Kıral et al., 1999).

Significant differences exist between annual and perennial crops in terms of cost structure. Compared to perennial crops, annual crops do not require establishment investments, and depreciation represents a relatively smaller share of total costs. Moreover, input use intensity in annual crops follows yearly cycles. Consequently, variable costs such as fertilizers, seeds, and fuel account for the largest portion of total production expenses, whereas fixed costs—including depreciation and land rent—gain relative importance depending on farm size and operational structure.

The cost structure of annual crops is highly sensitive to production conditions and environmental factors. Yield levels vary considerably with climatic conditions, soil characteristics, irrigation opportunities, and the quality and quantity of inputs used. This variability directly affects unit production costs. For instance, in dry seasons, irrigation costs increase while yield may decrease, resulting in higher unit costs; conversely, in years with adequate rainfall, irrigation expenses decline and higher yields may reduce unit costs. Therefore, annual crops are among the most climate-responsive plant groups—making climate variability a direct and measurable determinant of unit production costs.

As mechanization becomes increasingly prevalent in agricultural production, the structure of labor and machinery use has emerged as another major determinant of costs. In highly mechanized farms, the need for human labor decreases, whereas fuel consumption, repair–maintenance expenses, and depreciation items rise. In contrast, small-scale farms rely more heavily on family labor, creating methodological challenges in assigning monetary value to unpaid labor (Kumbasaroğlu & Dağdemir, 2011) and ensuring comparability across farms. Therefore, accurately estimating the opportunity cost of family labor is a critical requirement for reliable cost analysis.

Another important factor shaping the cost structure of annual crops is the low elasticity of input demand. Inputs such as seeds, fertilizers, pesticides, and fuel are indispensable components of production; therefore, increases in their prices cannot easily be offset by producers. Reducing input use would risk lowering yield, forcing farmers to maintain input quantities. Consequently, production costs display a rigid structure, and increases in input prices are rapidly reflected in total costs (Kumbasaroğlu & Dağdemir, 2010b).

In addition, the value of by-products plays a significant role in cost calculations for annual crops. For instance, straw in wheat production, oilcake in sunflower production, and cob and stalk residues in maize production may possess economic value. In cost accounting, the value of such by-products is deducted from the total production cost of the main product—in order to obtain a more accurate estimation of the net cost attributable to the primary output (Çalıyurt, 2010; Hatunoğlu & Kıllı, 2016).

In conclusion, annual crops require detailed, careful, and multidimensional cost analyses due to their short production cycles, high intensity of variable inputs, sensitivity to climatic and soil conditions, rigidity of input use, and the necessity of incorporating by-product values into cost calculations.

4. CLASSIFICATION OF COST COMPONENTS (ENGLISH VERSION)

In agricultural production, accurate cost determination requires that cost components be classified systematically and on a scientific basis. In annual crop production, the production cycle is short, input intensity is high, and production stages follow a seasonal pattern. For this reason, accurate categorization of each cost item directly affects not only the precision of cost calculations but also the reliability of managerial and policy-oriented decisions derived from them. The classification of agricultural cost components is traditionally based on the Classical Cost Accounting System. Foundational studies by Kıral et al. (1999), Çelik (2014), Hatunoğlu & Kıllı (2016), Kumbasaroğlu & Dağdemir (2010a; 2010c), and Kumbasaroğlu & Aşkın (2022) represent the core references for this methodological framework widely used in the agricultural economics literature.

Accordingly, agricultural cost components are conventionally grouped into two principal categories—variable costs and fixed costs—each reflecting distinct behavioral patterns in relation to production volume and resource use. These cost items are examined in detail in the context of annual crop production, and Table 1 summarizes the fundamental distinctions between these two cost structures as applied to annual crop production.

Table 1. Classification of Cost Components in Annual Crop Production

Variable Costs	Fixed Costs
Seeds	General administrative expenses
Fertilizers	Interest on fixed capital
Pesticides	Depreciation of fixed capital
Labor wages	Land rent
Fuel, lubricants, repair & maintenance expenses for machinery	—
Irrigation water fee	—
Interest on variable costs (working capital interest)	—

Variable Costs

Variable costs are expenditures that vary directly with production volume and cultivated area, reflecting the input-intensive nature of annual crop systems. In annual crop production, they constitute the largest share of total production costs. Since annual crop systems rely heavily on input-intensive agricultural activities, the contribution of variable cost items is considerably high (Kıral et al., 1999). These costs occur within the production period and do not generate expenses when production is not carried out.

The main variable cost items in annual crops are as follows:

- **Seed Costs:** Seeds are the primary input in annual crops, which must be replanted every year. Seed price, variety, certification status, and sowing density are the main factors determining seed expenditure. Costs are calculated by multiplying the required seed quantity with unit prices.
- **Fertilizer Costs:** Plant nutrition in annual crops is carried out entirely within a single production year, making fertilizer one of the major components of variable costs. Soil structure, climatic conditions, and yield expectations influence fertilizer requirements. Fertilizer expenditures are calculated by multiplying the required fertilizer quantities with prevailing unit prices.
- **Pesticide Costs:** Pest management is essential for yield protection. Due to high price volatility, pesticide expenditures may vary significantly across years and can cause notable fluctuations in the overall cost structure.
- **Fuel, Lubricant, and Machinery Maintenance Costs:** In farms where mechanized agriculture is widely adopted, fuel, oil, and repair– constitute a substantial share of variable costs, especially in mechanized farms where field operations are intensive. Increases

in fuel prices quickly reflect on production costs (Kumbasaroğlu & Dağdemir, 2010b).

- **Labor Costs:** Labor costs include the monetary value of seasonal labor used for hoeing, maintenance, harvesting, and other operations. Labor hours used in production are multiplied by prevailing wage rates to determine total labor expenditure.
- **Irrigation Costs:** Irrigation expenses—including electricity, water fees, or contributions paid to irrigation associations—vary depending on seasonal water demand. In dry years, rising irrigation needs significantly increase costs.
- **Harvesting and Post-Harvest Costs:** This cost category includes operations such as combine harvesting, baling, packaging, loading, and transportation.
- **Interest on Working Capital:** Since working capital is used throughout the production year, calculating interest on working capital is an essential component of cost accounting. Although annual crop production has a relatively short production cycle, most inputs are purchased at the beginning of the season, creating substantial financing requirements. The half-year interest calculation method is commonly employed (Kıral et al., 1999). The working capital interest is calculated using Equation 1, which reflects the standard half-year interest method widely adopted in agricultural cost accounting:

$$\text{Interest on Working Capital} = \frac{\text{Variable Costs}}{2} \times \text{Interest Rate} \qquad (1)$$

The applicable interest rate is generally based on the average rates published by the Agricultural Bank of the Republic of Turkey.

Accurate calculation of working capital interest is crucial for ensuring the reliability of total production cost estimation, particularly in annual crops where expenditures must be recorded using the quantity × unit price principle, ensuring consistency and comparability across farms and production seasons.

4.1. Fixed Costs

Fixed costs are expenditures that arise independently of the level of production and must be paid even if no production takes place. They are primarily associated with long-term business assets. Although the proportion of fixed costs in annual crop production is generally lower than that of variable costs, their relative importance increases in capital-intensive farms with large machinery investments.

The major fixed cost components are as follows:

- **General Administrative Expenses:** General administrative expenses correspond to approximately 3% of variable costs during the production period. This 3% coefficient is derived from the Classical Cost Accounting System and is widely applied in agricultural cost studies. These expenses represent the overhead costs necessary for managing and maintaining the operational structure of the farm business.
- **Land Rent or Opportunity Cost of Land Capital:** If the land is leased, the rental payment constitutes the land cost. For owned land, the opportunity cost of capital must be taken into account. In this case, the prevailing rental value of comparable agricultural land in the region is used in the calculation. If the land is leased, the rental payment constitutes the land cost. For owned land, the opportunity cost of capital must be taken into account. In this case, the prevailing rental value of comparable agricultural land in the region is used in the calculation.
- **Machinery Capital Costs and Depreciation Expenses:** Depreciation reflects the annual wear and tear of machinery, tractors, and equipment. Depreciation is calculated based on the economic life and residual value of machinery using standard accounting methods such as the straight-line method, which is predominantly used in agricultural cost studies (Çelik, 2014; Hatunoğlu & Kıllı, 2016).

If a single crop is produced on the farm and the machinery belongs to the farmer, the entire machinery capital and depreciation cost is allocated to that crop. When multiple crops are cultivated, machinery-related costs are distributed proportionally according to the cultivated area of each crop, ensuring that machinery costs are allocated in a manner consistent with field operation intensity.

4.2. By-Product and Residual Value Applications

In the production of annual crops, secondary outputs with economic value are frequently obtained alongside the main product. For instance, straw in wheat production, oilcake in sunflower processing, and stalk–cob residues in maize cultivation hold may hold economic value depending on market conditions. Since these by-products arise naturally and unavoidably from the production process, their treatment within cost analysis represents an important methodological consideration.

The literature generally identifies two main approaches for handling by-product value. The first and most widely adopted method in classical agricultural economics deducts the value of by-products from the total production cost, thereby deriving the net production cost. This approach assumes that by-products are secondary outputs that emerge jointly with the main product without requiring additional input use by the producer. Therefore, income generated from by-product sales is considered a compensating factor that reduces the effective cost of production. This methodology has been extensively used in Turkey's standard cost calculation framework (Kıral et al., 1999) as well as in numerous empirical studies on annual crops (Kumbasaroğlu & Dağdemir, 2010a; 2010c).

The second approach allocates by-product value proportionally among main and secondary outputs; however, this method is less commonly applied in annual crop studies.

Within the context of agricultural cost accounting—where the primary objective is to evaluate production efficiency and profitability—deducting the by-product value from total cost provides a more consistent and realistic basis for unit cost estimation.

In unit cost calculations, the sum of variable and fixed costs constitutes the total production cost. If by-product revenue exists, it is subtracted from the total cost to obtain the net production cost; if not, the full production cost is retained. The net cost value is then divided by the quantity of main product obtained to determine the cost per kilogram.

5. COST CALCULATION IN ANNUAL CROPS

Cost calculation in annual crops is a multi-stage process that involves the systematic identification of all inputs used during the production period, together with their economic valuation. Due to the short production cycle—one of the defining characteristics of annual crops—the consumption of inputs within the same season, and the crucial effect of product value on producer decisions, cost analysis in annual crops plays a significant role in both enterprise management and product-based comparisons.

In this section, a classical agricultural cost accounting approach is adopted, and the cost calculation procedure for annual crops is presented in detail. Each calculation step is explained together with the relevant formulas, definitions, and methodological descriptions to ensure conceptual clarity.

In the literature, alternative costing approaches have also been applied, particularly for agricultural enterprises characterized by multi-product and complex production structures. For instance, Gómez-González and Morini (2009) demonstrated that activity-based costing can provide a more detailed allocation of indirect costs in ornamental plant production systems.

However, due to its high data requirements and implementation complexity, such approaches are not commonly applied in annual field crop production. Therefore, classical cost accounting remains the most practical, transparent, and widely adopted framework for cost calculation in annual crops.

5.1. Determining the Production Unit and the Analysis Period

Cost analysis begins with defining the production unit. In annual crops, the analysis unit is typically one decare or one hectare, depending on the production scale. Since the production period is confined to a single vegetation cycle, the complete use of inputs within the same season enhances the comparability and internal consistency of cost calculations.

Defining the appropriate production unit also ensures methodological consistency and allows meaningful comparisons across different crops, production systems, and regions.

The key variables affecting cost calculations include the type of crop (e.g., wheat, maize, vetch), the production method (dry vs. irrigated farming), and regional agro-ecological conditions.

5.2. Activity-Based Definition of the Production Process

The first step in cost analysis is the identification and categorization of production activities. The typical activity structure for annual crops is presented below.

a) Variable Costs

- **Land Preparation**
  - o Plowing
  - o Planting
  - o Harrowing/Rolling
- **Crop Maintenance**
  - o Fertilization
  - o Hoeing (for industrial crops)
  - o Plant protection (pesticide application)
  - o Irrigation
- **Harvesting and Post-Harvest Operations**
  - o Harvesting

- Bundling or stacking (crop-specific)
- Collecting and sorting
- Bagging
- Threshing
- Straw transportation (when applicable)
- Transportation to storage
- Loading and unloading
- Transportation to market
- Fuel expenses
- Repair and maintenance expenses
- Working capital interest

TOTAL VARIABLE COSTS

b) Fixed Costs

These cost items arise even if no production takes place:

- General administrative expenses
- Land rent
- Machinery and equipment depreciation
- Machinery and equipment interest costs

TOTAL FIXED COSTS

Fixed costs represent long-term expenditures associated with allocating asset value over multiple years of use.

5.3. Depreciation Calculation

Depreciation refers to the systematic allocation of machinery and equipment costs over their economic lifespan. In annual crop production, proper allocation of fixed capital assets is essential for accurately reflecting machinery-related costs in total production expenses. In traditional cost accounting, depreciation is calculated using the straight-line method. Equation 2 presents the standard formula used to calculate annual depreciation:

$$\text{Annual Depreciation} = \frac{\text{Purchase Value} - \text{Salvage Value}}{\text{Economic Life}} \tag{2}$$

In agricultural machinery, the salvage value is generally assumed to be zero. To determine product-based depreciation, the proportion of the machine's annual operating time allocated to each crop must be considered. Equation 3 illustrates the procedure for calculating crop-specific depreciation:

$$\text{Crop-Based Depreciation} = \frac{\text{Annual Depreciation} \times \text{Usage Ratio}}{\text{Cultivated Area}} \tag{3}$$

This method accurately reflects the effect of capital use on production costs, enhances comparability across crops, and ensures methodological robustness. The resulting depreciation value is incorporated into the total production cost of the crop.

5.4. Calculation of Operating Capital Interest

Operating capital interest represents the financing cost associated with variable inputs and reflects the opportunity cost of capital tied up during the production cycle. In agricultural cost accounting, this component ensures that the monetary value of production expenditures is evaluated in line with their timing and financial implications.

Operating capital interest is calculated using Equation 4, which illustrates the half-year interest calculation method widely adopted in Türkiye.

$$\text{Operating Capital Interest} = \frac{\text{Variable Costs}}{2} \times \text{Interest Rate} \tag{4}$$

The applicable interest rate is typically selected within the range of 12–20% under Türkiye's production and financial conditions. The division by "2" accounts for the assumption that production expenditures are made gradually and, on average, remain committed to the production process for half of the year.

5.5. Determination of By-Product Value and Its Deduction from Production Cost

In annual crops, by-products often possess significant economic value. Examples include:

- **Wheat:** straw
- **Maize:** stalks and cobs

- **Sunflower:** oilcake (a valuable processing by-product)

Since these by-products can be sold, their value must be incorporated into the cost analysis. In classical agricultural economics, the standard approach is to deduct the by-product value from the total production cost to obtain the net cost of the main product.

Unit cost is calculated using Equation 5, which presents the standard procedure for deriving the net unit cost after deducting by-product revenue:

$$\text{Unit Cost}\left(\frac{TL}{kg}\right) = \frac{\text{Production Costs} - \text{By-Product Revenue}}{\text{Yield}\left(\frac{kg}{decare}\right)} \tag{5}$$

This approach is well-established in the agricultural economics literature (Kıral et al., 1999; Kumbasaroğlu & Dağdemir, 2010c–2011) and is applicable across all annual crop systems, including wheat, maize, vetch, and potatoes.

5.6. Profitability Analysis

Profitability performance indicators are calculated as follows. Gross margin and net profit are calculated using Equation 6 and Equation 7, respectively:

$$\text{Gross Margin} = \text{Gross Production Value} - \text{Variable Costs} \tag{6}$$

$$\text{Net Profit} = \text{Gross Margin} - \text{Total Production Costs} \tag{7}$$

Gross margin reflects the difference between gross revenue and variable costs, whereas net profit incorporates all cost components, including fixed expenses.

These indicators provide essential insights into the economic efficiency, financial sustainability, and overall viability of annual crop production systems.

6. GENERAL COST CALCULATION TABLES FOR ANNUAL CROPS

Tables 2–5 collectively present a standardized and practical framework for conducting comprehensive cost and profitability analyses of annual crops. This framework is grounded in the classical agricultural cost accounting approach, which clearly distinguishes between variable costs, fixed costs, and profitability indicators, thereby ensuring methodological transparency and consistency.

Table 2 provides a general cost calculation template applicable to cereals such as wheat, barley, and rye, while Table 3 and Table 4 adapt the same methodological structure to crops with different production characteristics, such as potato and vetch. Despite crop-specific differences in production operations, input intensity, and timing, all tables follow an identical accounting logic. This consistency enables direct comparison across crops by modifying only input quantities, unit prices, and yield levels, without altering the underlying calculation methodology.

Within these tables, variable costs include all inputs directly linked to production scale, whereas fixed costs represent expenditures that arise independently of output level. The inclusion of operating capital interest reflects the financing cost of variable inputs, and the deduction of by-product value from total production costs follows a widely accepted and scientifically sound practice in agricultural economics. Unit production cost is calculated by dividing net production cost by yield per decare, providing a critical indicator for evaluating cost efficiency, price competitiveness, and managerial performance.

Finally, Table 5 synthesizes cost and revenue components to derive gross margin and net profit per decare, thereby translating cost calculations into economically meaningful performance indicators. When used together, Tables 2–5 function as an integrated decision-support tool that standardizes cost accounting practices and enhances comparability for researchers, students, extension services, and producers. This structured framework facilitates informed production planning, economic evaluation, and policy-oriented analysis across a wide range of annual crops.

Table 2. *General Cost Calculation Framework for Wheat, Barley, and Rye*

Production Activities	Timing	Labor & Machinery Requirements				Equipment Used	Materials Used			Total Expenses (₺)	%
		Labor		Machinery			Type	Quantity	Cost (₺)		
		(hrs)	Cost (₺)	(hrs)	Cost (₺)						
I. Soil Preparation											
a) First Plowing	September					Plow					
b) Second Plowing	September					Cultivator					
c) Planting	October					Seeder	Seed				
d) Harrowing/ Rolling	October					Harrow					
II. Crop Maintenance											
a) Fertilization 1	October					Fert. Applicator	DAP				
b) Fertilization 2	March					Fert.App	Urea				
c) Pesticide Application	April					Sprayer	Chemical				
d) Irrigation	April						Water				
III. Harvest & Post-Harvest											
a) Harvesting	August					Harvester					
b) Bundling or Stacking	August										
c) Harvesting (Manual/ Mechanical)	August					Thresher					
d) Collecting	August										
e) Straw Transportation	August					Trailer	Bag				
f) Storage Transport	August					Trailer					
g) Market Transport											
h) Fuel Cost							Fuel				
i) Repair–Maintenance											
Subtotal (I+II+III)											
1) Working Capital Interest											

A. Total Variable Costs											
a) General Admin. Expenses (A × 3%)											
b) Land Rent											
c) Machinery Depreciation											
d) Machinery Capital Interest											
B. Total Fixed Costs											
C. Total Production Cost (A + B)											
D. By-Product Revenue											
E. Grain Output (kg/da)											
F. Unit Cost (₺/kg) = (C – D) / E											

Table 3. *General Cost Calculation Framework for Potato*

Production Activities	Timing	Labor & Machinery Requirements				Equipment Used	Materials Used			Total Expenses (₺)	%
		Labor		Machinery			Type	Quantity	Cost (₺)		
		(hrs)	Cost (₺)	(hrs)	Cost (₺)						
I. Soil Preparation											
a) First Tillage	Sep–Oct					Plow					
b) Second Tillage	May					Plow					
c) Ridge Formation	May					Ridge Plow					
d) Fertilization	May						Fertilizer				
e) Planting	May					Plant. Mach	Seed				
II. Crop Maintenance											
a) Fertilization	June					Manual	DAP				
b) Hoeing (2×)	May–Jul					Man. + Tool					
c) Earthing Up	May–Jun					Manual					
d) Pesticide Application	June					Sprayer	Chemical				
e) Irrigation (3×)	Jul–Sep						Water				
III. Harvest & Post-Harvest											
a) Harvesting (Lifting)	September					Man. + Plow					
b) Collecting & Sorting	September					Manual					
c) Bagging	September					Manual	Bag				
d) Loading–Unloading	September					Manual					
e) Transport to Market						Trailer					
f) Fuel Cost							Fuel				
g) Repair–Maintenance											
Subtotal (I + II + III)											
1) Working Capital Interest											
A. Total Variable Costs											
a) General Administrative Expenses (A × 3%)											
b) Land Rent											
c) Machinery Depreciation											
d) Machinery Capital Interest											
B. Total Fixed Costs											
C. Total Production Cost (A + B)											
D. By-Product Revenue											
E. Potato Yield (kg/da)											
F. Unit Potato Cost (₺/kg) = (C – D) / E											

Table 4. General Cost Calculation Framework for Vetch

Production Activities	Timing	Labor & Machinery Requirements				Equipment Used	Materials Used			Total Expenses (₺)	%
		Labor		Machinery			Type	Quantity	Cost (₺)		
		(hrs)	Cost (₺)	(hrs)	Cost (₺)						
I. Land Preparation											
a) First plowing	April					Plow					
b) Second plowing	May					Cultivator					
c) Sowing	May					Seed drill					
d) Rolling	May					Roller	Seed				
II. Crop Maintenance											
a) Fertilization 1	May					Fertilizer spreader					
b) Fertilization 2							Ammonium nitrate				
c) Pesticide application						Sprayer					
d) Irrigation	Jun–Jul										
III. Harvest and Post-Harvest							Water				
a) Harvesting	August					Combine harvester					
b) Baling	August					Baler					
c) Transport to threshing area	August					Trailer					
d) Fuel cost							Fuel				
e) Repair and maintenance											
Subtotal (I + II + III)											
e) Operating capital interest (6.565%)											
A. Total Variable Costs											
A) General administrative expenses (A × 3%)											
B) Land rent											
C) Machinery depreciation											
D) Machinery capital interest											
B. Total Fixed Costs											
C. Total Production Cost (A + B)											
D. By-product revenue											
E. Vetch yield (kg/da)											
e) Repair and maintenance											

Table 5. *Gross and Net Profit per Decare Obtained from Production*

No.	Cost and Revenue Items	Calculated Value
1	Variable costs (₺/da)	
2	Fixed costs (₺/da)	
3	Total production costs (1 + 2) (₺/da)	
4	Selling price (₺/kg)	
5	**Gross Production Value (₺/da)**	
	a. Product revenue* (₺/da)	
	b. By-product revenue (₺/da)	
6	Unit product cost (₺/kg)	
7	**Gross margin (5 − 1) (₺/da)**	
8	**Net profit (5 − 3) (₺/da)**	
9	Yield (kg/da)	

Notes:

* **Product revenue** = *Yield (kg/da) × Unit price (₺/kg)*

By-product revenue = By-product quantity (kg/da) × Unit price (₺/kg)

7. CONCLUSIONS AND RECOMMENDATIONS

Cost calculation in annual crops plays a crucial role in revealing the economic dimension of agricultural production and enabling producer decisions to be evaluated on a rational basis. Due to the short production cycle, the concentration of input use within a single season, high sensitivity to climatic and market conditions, and the direct impact of by-product revenues on total costs, cost analysis in annual crops constitutes a critical economic and managerial tool. The classical agricultural cost accounting approach adopted in this chapter represents a comprehensive methodology widely used in Türkiye for estimating crop production costs. This approach is based on the distinction between variable and fixed costs and explicitly incorporates operating capital interest and by-product value. The literature consistently indicates that this framework is the most appropriate for annual crops due to its practical applicability and its ability to generate comparable results across different products (Kıral et al., 2003; Çelik, 2014; Kumbasaroğlu & Dağdemir, 2010b–2011; Kumbasaroğlu & Aşkan, 2021).

Within this chapter, all essential steps required for cost analysis in annual crops have been presented in detail, covering the identification of variable and fixed costs, the calculation of operating capital interest, the treatment of by-product values, and the estimation of unit costs and profitability indicators. To standardize the calculation process, a general cost calculation table and a conceptual structure were provided. This framework should be regarded not only as an academic approach but also as a practical decision-support model that can be directly applied in farm management and production planning.

The importance of cost analysis in annual crops has become even more pronounced in today's agricultural sector. Rapid increases in input prices, exchange rate volatility, growing uncertainty driven by climate change, and rising production costs have intensified the need for economically sustainable production models. Declining profitability levels or situations in which production costs approach market prices have the potential to significantly alter producers' crop choices. Under these conditions, it is essential that cost analyses are conducted using accurate methodologies and updated on a regular basis.

Beyond the farm level, cost analyses also play a critical role in shaping regional and national agricultural policies. The evaluation of the profitability effects of crop-based support schemes, the assessment of agricultural insurance mechanisms, and the effectiveness of input subsidy policies can be more reliably examined when grounded in systematic cost data. The academic literature emphasizes that transparent and regularly collected cost information substantially enhances the quality and reliability of agricultural economics analyses (Gül et al., 2016; Uzundumlu et al., 2012; Atay & Kartal, 2020; Erbaş, 2025).

Within this context, based on the overall framework and evaluations presented in this chapter, several key recommendations can be summarized as follows.

7.1. Recommendations for Producers

- Producers should regularly record their actual production costs and systematically monitor changes in input prices. Accurate cost records enable producers to evaluate profitability more realistically and support informed decision-making.
- If by-products have an economic value, this value must be deducted from total production costs; otherwise, unit costs will be overestimated.
- Cost analyses that exclude operating capital interest fail to reflect the true level of profitability, particularly in input-intensive annual crop production systems.
- Since yield records constitute the basis of unit cost calculations, they should be maintained carefully and consistently to ensure reliable cost assessments.

7.2. Recommendations for Researchers

- In cost analyses of annual crops, the use of the classical agricultural cost accounting method enhances comparability across products, regions, and time periods.
- Cost studies should explicitly account for regional differences in yield levels, production techniques, and input-use structures to avoid misleading conclusions.
- High-quality and systematically collected cost data play a key role in explaining product-based competitiveness, export potential, and price formation mechanisms in agricultural markets.

7.3. Recommendations for Policymakers

- The effectiveness of agricultural support policies should be evaluated using comprehensive cost analysis frameworks.
- Product-based cost maps that account for regional differences can be developed to support more targeted and efficient policy design.
- Policies aimed at reducing volatility in input prices are essential for ensuring cost stability, improving producer welfare, and sustaining agricultural production.
- Agricultural insurance schemes may be more effectively structured by incorporating cost-based risk groups derived from systematic cost analyses.

7.4. General Evaluation

Cost analysis in annual crops represents a fundamental tool for evaluating agricultural production at both micro and macro levels. The methodological framework and application examples presented in this book chapter contribute to the standardization of cost calculations and provide a common reference for researchers, practitioners, and policymakers.

The overall approach adopted in this chapter aims to support improvements in economic efficiency, enhance managerial decision-making, and strengthen the scientific foundation of agricultural policy design.

REFERENCES

Atay, M. S., & Kartal, C. (2020). Agricultural product marketing and accounting of agricultural transactions. Journal of the Faculty of Economics and Administrative Sciences of Süleyman Demirel University, 25(2), 185–201. [in Turkish]

Çalıyurt, K. T. (2008). Production process and calculation of by-product costs in sunflower oil industry enterprises. Journal of Accounting and Finance, (39), 84–91. [in Turkish]

Çelik, Y. (2014). Cost and income calculation methods in agricultural enterprises in Türkiye according to different accounting systems. Journal of Agricultural Economics, 20(1–2), 41–52. [in Turkish]

Çiftçi, O. (2009). *Demand analysis of agricultural products* (Master's thesis, Marmara University, Türkiye). ProQuest Dissertations & Theses Global. (Publication No. 28526690) [in Turkish]

Erbaş, N. (2025). Production and comparative cost, income, and profit analysis of major field crops grown in Yozgat Province. Journal of Agricultural Economics, 31(1), 149–158. [in Turkish] https://doi.org/10.24181/tarekoder.1640889

Erkuş, M., Cumurcu, S., **Şahin**, A., Cirik, M., & Bayol, Ü. (1995). Comparison of imprint cytology and frozen section methods in intraoperative diagnosis: 381 cases. [in Turkish]

Gül, M., Kart, M. C. O., & Sirikci, B. S. (2016). Determining costs and profitability of lavender farms in Isparta province of Turkey. Journal of Essential Oil Bearing Plants, 19(3), 686-692. https://doi.org/10.1080/0972060X.2014.971074

Hatunoğlu, Z., & Kıllı, M. (2016). Accounting for agricultural production costs within the framework of TMS 41 in agricultural enterprises. Journal of Social Sciences, Kahramanmaraş Sütçü İmam University, 13(1). [in Turkish]

González-Gómez, J. I., & Morini-Marrero, S. (2009). A model for cost calculation and management in a multiproduct agricultural framework. The case for ornamental plants. Spanish journal of agricultural research, 7(1), 12-23. https://doi.org/10.5424/sjar/2009071-394

Govdya, V. V., Khromova, I. N., Vasilieva, N. K., Sigidov, Y. I., & Polutina, T. N. (2017). Decomposition approach to formation of accounting and analytical system of cost management in agricultural enterprises. http://dx.doi.org/10.18006/2017.5(6).818.830

Hudáková Stašová, L. (2020). Statistical analysis of suitability of the activity based costing method in agricultural enterprises. Agricultural and Resource Economics: International Scientific E-Journal, 6(4), 20-42. https://doi.org/10.22004/ag.econ.308584

Kıral, T., Kasnakoğlu, H., Tatlıdil, F. F., Fidan, H., & Gündoğmuş, E. (1999). Methodology and database guide for cost calculation of agricultural products. Agricultural Economics Research Institute Project Report, 1999-13. Ankara. [in Turkish]

Kumbasaroğlu, H., & Dağdemir, V. (2010a). A study on input demands for wheat, barley and rye production in Erzurum province. Journal of Agricultural Sciences, 16(3), 194–204.

Kumbasaroğlu, H., & Dağdemir, V. (2010b). Production costs of potato, sugar beet, and sunflower in farms with and without agricultural machinery in Erzurum province. Adnan Menderes University Journal of the Faculty of Agriculture, 7(2), 15–24. [In Turkish]

Kumbasaroğlu, H., & Dağdemir, V. (2010c). Production costs of wheat, barley, and rye in farms with and without agricultural machinery in Erzurum province. Tarım Ekonomisi Dergisi (Journal of Agricultural Economics), 16(1–2), 7–17. [In Turkish]

Kumbasaroğlu, H., & Dağdemir, V. (2011). Production cost of alfalfa, sainfoin, vetch, and meadow in farms owning agricultural machinery and renting machinery in Erzurum province. Selcuk Journal of Agriculture and Food Sciences, 25(4), 91–102.

Kumbasaroğlu, H., & Aşkan, E. (2022). A study on the determining silage corn production cost: the case of Van Province, Turkey. Custos e Agronegocio, 18(3).

Moshchenko, O. V., Matveeva, V. A., Rokotyanskaya, V. V., Maryanova, S. A., & Romanova, S. V. (2020). Main areas of improvement in losses accounting and cost calculation in agricultural production. Revista Gênero e Direito, 9(S3), 714-725.

Selvi, E., & Dağdemir, V. (2022). Production cost of conventional and organic silage maize in Kelkit district of Gümüşhane province. Anadolu Journal of Agricultural Sciences, 37(1). [In Turkish] https://doi.org/10.7161/omuanajas.913874

Tcaci, N., Tcaci, A., & Dombrovschi, I. (2021). The analysis of cost structure and the impact on the profitability of agricultural products in the Republic of Moldova.

Uzundumlu, A. S., & Topçu, Y. (2012). Production cost of confectionary sunflower in Erzurum province. Journal of the Institute of Science and Technology, 2(2, Special Issue A), 33–40. [In Turkish]

Chapter 5

EXAMINING THE PRESENCE OF NOISE IN GREEN AREAS

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Introduction

Green spaces are parks, woodlands and other natural areas that are crucial for improving air quality and promoting healthier populations. Some of the studies on noise and its effects in city parks and forest areas were examined. A noisy environment can cause physical effects such as temporary or permanent hearing loss, physiological effects such as increased blood pressure, changes in heart rate and blood circulation, psychological effects such as nervous breakdown, fear, anxiety, and decreased performance in areas such as work efficiency, learning, and reading.

Noise is one of the most significant sources of stress for people. Sudden exposure to noise levels can cause changes in a person's heart rate, respiratory rate, blood pressure, metabolism, visual acuity, and even the electrical resistance of their skin. Insomnia is one of the most common disorders caused by noise. It is stated that when environmental noise is 60 dB, catecholamine and cortisol levels increase, which causes distraction, communication and sleep disorders in humans (Environmental Atlas of Turkey, 2004; Çetin, 2010). According to studies conducted in recent years, noise exposure affects hearing loss as well as cortisol and epinephrine levels. It has been reported that when environmental noise reaches 60 dB, catecholamine and cortisol levels increase, leading to concentration, communication, and sleep disorders in humans. Furthermore, noise affects neuroendocrine patterns during sleep (Güler et al.,1994; Last et al., 1998). As industrialization and urbanization increase, noise has become a significant factor in environmental pollution. Although noise negatively affects human health in many ways, it is still not perceived as a risk in our society. However, it is also known that the most effective way to protect against these negative effects of noise is to control the noise source.

Traffic noise, one of the noises originating from transportation, has a large share in the formation of noise pollution. Traffic noise consists of the sum of the noises created by motor vehicles alone. The most important noise factors caused by the park's proximity to the transportation line are the sounds of horns, the sounds of vehicles stopping and starting, and the sounds of moving vehicles (Ünver, 2008; Solak et al., 2023). The rapid increase in the number of motor vehicles also causes a rapid increase in noise levels. The density of motor vehicles, which causes an increase in the noise level in parks, causes a decrease in the comfort of the parks and a decrease in the satisfaction of the people visiting the park.

Noise impact in city parks

Parks play a vital role in urban ecosystems in terms of recreation, ecological balance, and human health. However, parks located near urban road traffic are exposed to high levels of environmental noise. Some studies have examined the relationship between road distance to parks and noise levels.

There are various studies on the impact of noise pollution on parks, determining noise levels and offering solutions. Noise measurements were made in heavily used urban parks in the Trabzon city center by Bayramoğlu et al. (2014). The measurement values were above the required noise level according to the Noise Control Regulation. In another study conducted by Ünver (2008), noise pollution originating from traffic and recreational use in Tekirdağ Çorlu District was investigated and the measurement values were found to be above the desired noise level according to the Noise Control Regulation.

It has been determined that the noise measurements carried out to determine the level of noise pollution in the parks far exceed the limit values allowed by the International Organization for Standardization (ISO) and the Regulation on Assessment and Management of Environmental Noise. It was concluded that the noise in the parks was caused by the park being surrounded by roads and heavy vehicle traffic. It has been stated that in order to prevent noise pollution, it will be important to leave the noise barrier within the park as wide as possible and to use the right plants. In another study conducted to determine the noise level in Yakutiye Park, which is the garden of a historical building in the city center of Erzurum, it was determined that the noise measurement results did not reach the limit value allowed in the Regulation on Assessment and Management of Environmental Noise (Official Gazette, 2010). The reason for this is that large vehicles, especially those excluding municipal buses, are prohibited from entering Cumhuriyet Avenue, which forms the perimeter of Yakutiye Park, and vehicle speeds are low due to the street's traffic density.

The relationship between the distance of parks within the city from roads and measured environmental noise levels was investigated. Traffic noise has significant effects on human health and comfort, especially in urban living spaces. While parks are designed as escape areas from noise within the city, their proximity to roads may not always provide the desired level of silence. Distances range from 10–200 m, and noise levels are in the range of 48–79 dB (Tunay, 2023). A synthetic dataset consisting of 40 observations was created to examine the relationship between road distance to parks and noise levels. Distances were randomly distributed between 10 and 200 meters, and noise levels were modeled to represent a tendency to decrease depending on traffic. Correlation, regression, and residual tests were applied in the analyses. A strong negative correlation was found between distance and noise at the level of $r = -0.952$. The regression value is -0.148 and the 95% confidence interval is [-0.1635, -0.1323]. The residuals are normal and the model assumptions are satisfied. Traffic noise is a key factor determining the acoustic environment of parks. The results are consistent with the literature, and noise decreases linearly as distance increases. The analysis offers important implications for park planning and urban design: Parks located 5–10 meters from the roadside have significantly higher noise levels. Ideal noise reduction for parks is observed at distances of 20 meters and above. In park design, seating areas, children's playgrounds, and rest areas should be located on the opposite side of the road or at least 20 meters away. Afforestation and green barriers can further support noise reduction.

Table 1. Distance and noise levels

Variable	Mean	SD	Min	Max
Distance (m)	96.69	56.18	13.91	194.28
Noise (dB)	62.26	8.73	48.23	79.08

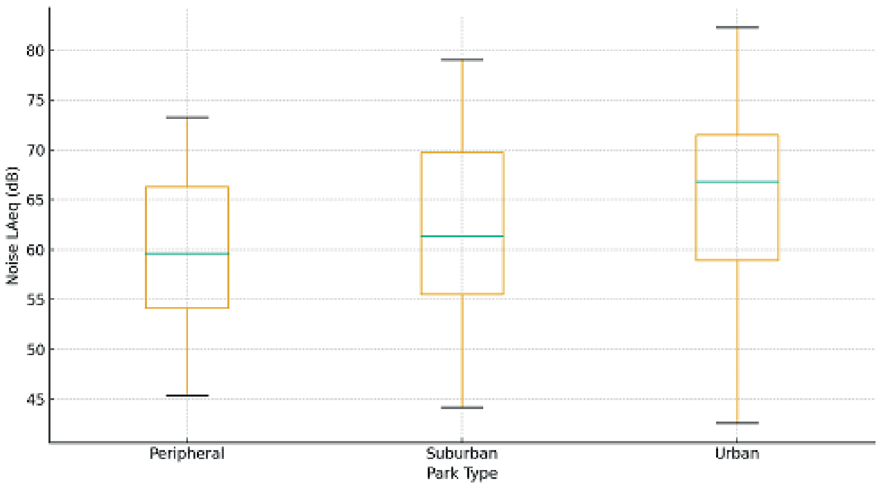

Figure 1. Noise by park type

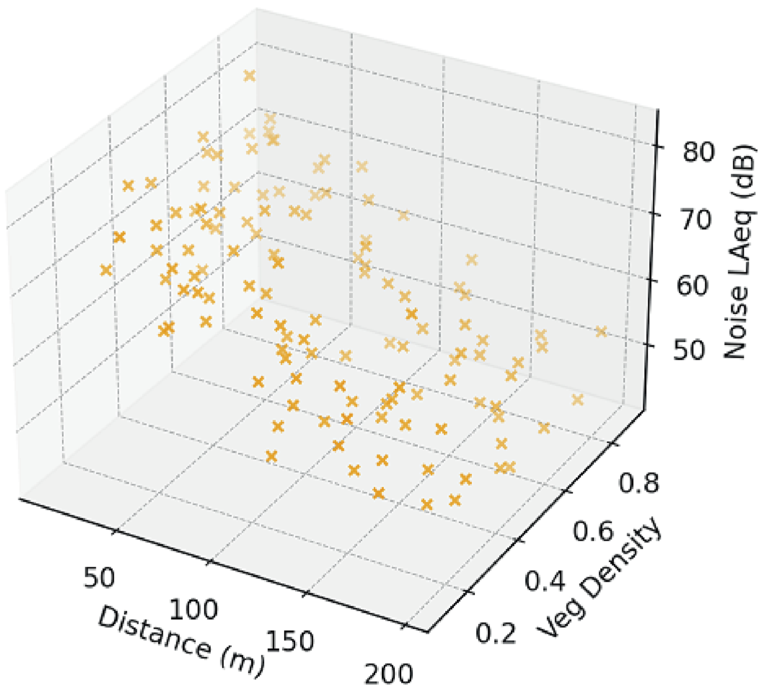

Figure 2. 3d scatter: distance, vegetation vs noise

The dataset used in the analysis consists of the distances of the parks from the road (in meters) and the noise levels (dB) measured at the same points. Distance was treated as the independent variable, and noise level as the dependent variable. The results show a strong, negative correlation between distance and noise. In other words, noise decreases significantly as the park moves further away from the road. The analysis results show that noise levels increase significantly when parks are close to the roadside, and decrease steadily as the distance increases. The effect of distance on noise is consistent with traffic-related noise models in the literature.

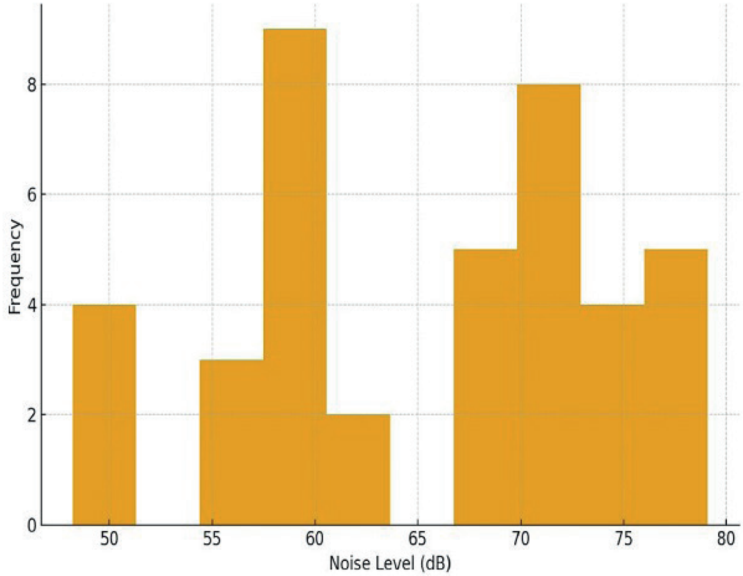

Figure 3. Noise distribution histogram

The analysis results show that traffic-related noise has a very strong effect on the perceived acoustic environment in parks. Although the distance of the park from the road was considered as the only parameter, the model exhibited: strong correlation, significant slope, appropriate residual distribution. These findings support the idea that road traffic is the primary determinant of park noise. Furthermore, the obtained slope is consistent with the findings in the literature of "a decrease of 12–15 dB for every 100 m distance".

A feasible action plan for noise control in parks

Parks are spaces for rest, recreation, and social interaction in urban life. However, uncontrolled noise disrupts the peaceful atmosphere of parks, negatively impacting both visitors and the surrounding ecosystem. In order to create a sustainable and peaceful environment in park areas, municipalities need to develop a noise management plan for both visitor comfort and environmental sustainability. The purpose of this action plan;

-To reduce noise sources in and around the park,

-To manage noise levels in accordance with regulations,

-To create healthy and peaceful environments for park users,

-To reduce noise pressure on the ecosystem.

Noise control in parks is very important both to protect the peace of visitors and to protect the surrounding ecosystem (especially birds and other wildlife). Noise control in parks is regulated within the scope of the Regulation on Assessment and Management of Environmental Noise (Official Gazette, 2010). Parks are considered quiet areas. The most important source of noise in parks is the motor vehicle traffic in the immediate vicinity. Typical limit for inside the park: 55–60 dB (45–50 dB at night). The Regulation on Assessment and Management of Environmental Noise and the Environmental Law No. 2872 grant municipalities broad authority in noise control. Physical and Infrastructure Measures for Noise Control in Parks;

-Dense greenery and tree buffers can reduce noise by 20–30%.

-Acoustic barriers (natural or artificial) can be used.

-Sound propagation can be controlled through the strategic placement of playgrounds, sports -fields, and quiet areas.

-Motorized maintenance vehicles can be replaced with quieter vehicles.

-It is recommended that parks be located at least 80–100 meters away from roads.

In urban parks exposed to traffic-related noise, large vehicles should be prevented from passing around the park as much as possible, directed to alternative routes, and vehicle speeds should be reduced on the roads surrounding the parks. There are no shrubs, coniferous and leafy trees on the edges of the parks, which are important for noise barriers (Kılıç and Abuş, 2018). Therefore, the heavy traffic noise on the roads is also felt in the park. For this reason, noise-blocking barriers made of plant materials should be added to the edges of the park.

Noise impact in woodlands

The high noise level on the straight sections of the intercity highway within the forest affects the habitats of wild animals and access to water resources in some sections of the road. When motor vehicles slow down and then accelerate at points where there are vertical curves, noise levels, especially from the engine and exhaust, reach 65-78 decibel.

In a study conducted on the Bartın-Karabük highway located in the forest area, environmental noise measurements were done at such points as especially turns, long plains and vertical curve turns where noise level would be different. Furthermore, for the average inner-woods noise level, environmental noise measurements were done during the day in different parts of a forest isolated from the highway (Atesoglu et al., 2016).

Figure 4. Noise measurement points in woodland

In the straight parts of the road, it was detected that the noise level 76-78 dB as a result of cars' increasing their speed, motors and exhaust sounds. The noise level is quite high on the flat sections of the Bartın-Karabük highway within the forest, affecting the habitats of wild animals and their access to water sources located in some parts of the road. It has been observed that the existing trees reduce the noise to varying degrees depending on the slope.

Noise is one of the important industrial and environmental problems of our time. Unless sufficient and effective measures are taken, the noises made by industrial machines may do serious harm to workers. Environmental noise affects humans both physically and psychologically (Durgut and Celen, 2004). The human ear attempts to adapt to noise up to a certain level. However, this adaptation is not sufficient to eliminate industrial noise. In a study conducted to ergonomically examine the noise generated by loading machines used in forestry activities in forest areas, the equivalent noise levels to which operators are exposed during the operation of loading machines and the factors affecting these noise levels were determined using regression analysis (Melemez and Tunay, 2010).

Figure 5. Original cabin-equipped loading machine working in the forest

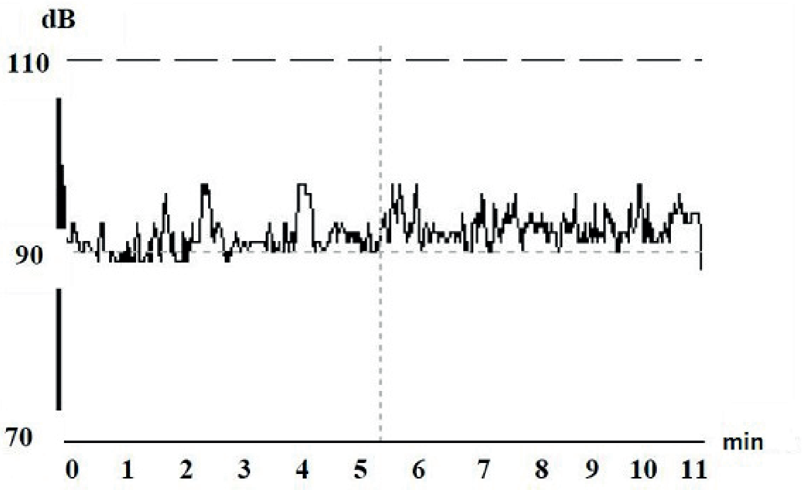

Figure 6. Noise levels to which the operator is exposed during work

It has been determined that the noise levels to which loading machine operators are exposed during their work range from 85.4 to 104.7 dB. The equivalent noise level to which the operator is exposed is 92.9 dB. This value is above the danger limit of 90 dB specified in international standards. Regression analysis was conducted to determine the factors affecting the noise levels experienced by operators working with loading machinery in forested areas. The most influential variable on the noise level transmitted to the operator is whether the loading machine has its original cab or not.

Table 2. Average noise levels

Loading machine	**Mean**	**SD**	**Min**	**Max**
All tractors	91.80	6.10	75.60	105.00
Without a cabin	93.45	3.88	83.50	105.00
Original with cabin	77.53	1.45	75.60	78.90

In forestry operations with loading machines, the minimum equivalent noise level for all tractors has been determined as 76 dB, and the maximum equivalent noise level as 105 dB. The most ergonomic way to control noise in tractors is to use a good cabin. Cabs can reduce tractor noise levels by 2-10 dB. The average noise level experienced by operators of cabless tractors with loading equipment mounted has been found to be considerably higher than that experienced by operators of original cabbed loading machines. After determining the effects of noise on hearing, research has focused on other physiological effects caused by noise. Prolonged exposure to noise has been shown to affect heart rate, blood pressure, respiration, and uric acid levels in the blood (Sabancı, 1999). As noise levels increase, so does heart rate, which is also an indicator of increased energy consumption. Therefore, as noise increases, fatigue increases and work performance decreases. The most influential factors on the equivalent noise levels experienced by loading machine operators during their work were found to be machine cab condition, ground roughness, machine operating time, and terrain slope. Considering these factors, it can be said that, in general, machine and ground characteristics have an impact on noise levels. The slope and roughness of the terrain in forest areas are related to the soil characteristics. The more suitable these characteristics are, the lower the noise level transmitted to the operator will be.

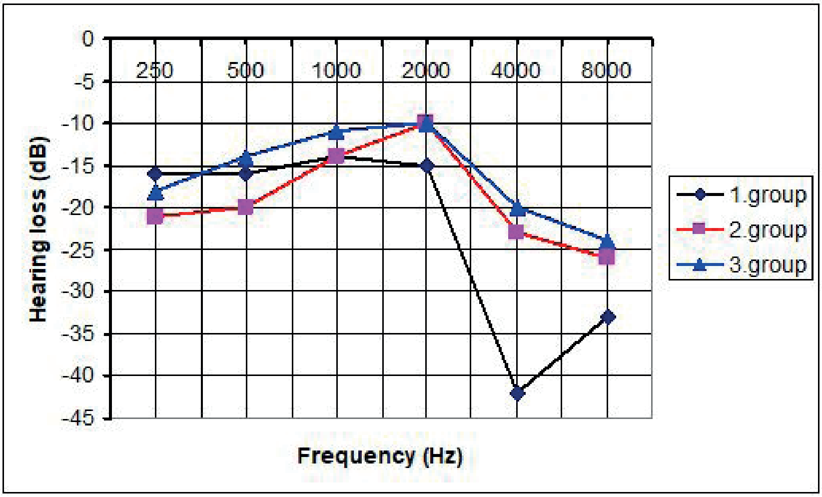

Figure 7. Hearing loss values in six frequencies

To determine noise-induced hearing loss among forestry workers in the Zonguldak region, the workers were divided into three groups: chainsaw operators, tractor operators, and other forestry workers (Tunay and Melemez, 2008). The average noise level to which workers, especially those operating chainsaws, are exposed ranges between 90-105 dB. Audiogram testing performed on the forest worker revealed bilateral very mild (41-55 dB) sensorineural loss in both ears and bilateral moderate (56-70 dB) loss in the 2000-4000-8000 Hz range. Figure 7 shows the distribution of hearing loss values at six frequencies for three worker groups, according to audiometric analysis. The most noticeable difference was observed in chainsaw operators at the 4000 Hz frequency. High noise levels are a significant factor causing hearing loss. Chainsaw operators exposed to high noise levels above 90 dB in forested areas have been found to experience significant hearing loss at the 4000 Hz frequency. Forestry workers who use chainsaws should be informed and should use protective equipment.

References

Ateşoğlu A., Tunay M., Arıkan T.B., Yıldız S., Kahraman H., (2016). Noise Effects of Roads on Wildlife using GIS, *European Journal of Advances Engineering and Technology*, 3(7).

Bayramoğlu E., Özdemir B., Demirel, Ö. (2014). Gürültü Kirliliğinin Kent Parklarına Etkisi ve Çözüm Önerileri: Trabzon Kenti Örneği. *Inönü University Journal of Art and Design*, 4(9).

Çetin F., (2010). Denizli İli trafik gürültü kirliliği haritası. Celal Bayar Üniversitesi Sağlık Bilimleri Enstitüsü, Manisa.

Durgut M.R., Celen İ.H., (2004). Noise levels of various agricultural machineries. *Pak. Journal of Biological Sciences* 7(6).

Environmental Atlas of Turkey, (2004). Türkiye Çevre Atlası, ÇED ve Planlama Genel Müdürlüğü. Çevre Envanteri Dairesi Başk. T.C. Çevre ve Orman Bakanlığı, Ankara.

Güler Ç., Çobanoğlu Z., (1994). Gürültü: Çevre Sağlığı Temel Kaynak Dizisi No: 19 Ankara.

Kılıç M.Y., Abuş M.N., (2018). Assessment of Noise in Urban Parks: Hüdavendigar Park Example. *Iğdır University J. Inst. Sci. & Tech.* 8(3).

Last J.M., Wallace R.B. (1998). *Public health and preventive medicine*. ISBN: 0838561888, Norwalk, Conn. : Appleton & Lange, 1998.

Melemez K., Tunay M., (2010). The investigation of the ergonomic aspects of the noise caused by agricultural tractors used in Turkish forestry. *African Journal of Agricultural Research*, 5(4).

Official Gazette (2010). Çevresel Gürültünün Değerlendirilmesi ve Yönetimi Yönetmeliği, *Resmi Gazete*, Sayı 27601.

Sabancı A., (1999). *Ergonomi*, Baki Kitabevi, Yayın No: 13, s.592. Adana.

Solak E.B., Şahin C., Onay B., Sava B., (2023). Parklardaki gürültünün değerlendirilmesi: Isparta ili örneği, Mehmet Akif Ersoy Üniversitesi Fen Bilimleri Enstitüsü Dergisi 14(2).

Tunay M. (2023). *Investigation of Noise Level in Some Parks in Bartın City Center*. International Research and Reviews in Agriculture, Forestry and Aquaculture Sciences, ISBN: 978-625-6760-74-5 Serüven Publishing, Ankara.

Tunay M., Melemez K., (2008). Noise Induced Hearing Loss of Forest Workers in Turkey. *Pakistan Journal of Biological Sciences* 11(17).

Ünver, E., (2008). Trafik ve rekreasyonel kullanım kaynaklı gürültü kirliliğinin belirlenmesi: Çorlu örneği. Namık Kemal Üniversitesi, *Fen Bilimleri Enstitüsü Yüksek Lisans Tezi, Tekirdağ.*

Chapter 6

GEOSPATIAL ARTIFICIAL INTELLIGENCE (GeoAI): A LITERATURE REVIEW

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1. Introduction

1.1. The convergence of geographic information systems (GIS) and artificial intelligence (AI)

The integration of Geographic Information Systems (GIS) with Artificial Intelligence (AI) represents a significant advancement in spatial technology and geographic information science in the 21st century (Li et al., 2024; Mai et al., 2025). This confluence has resulted in the formation of an interdisciplinary domain known as Geospatial Artificial Intelligence (GeoAI), which profoundly transforms our understanding, analysis, and engagement with spatial data and geographic events. Janowicz et al. (2020) observed in their seminal special issue on GeoAI that this integration has resulted in a significant transition from static, descriptive mapping to dynamic, predictive, and autonomous spatial intelligence systems.

This alteration is significant and should not be underestimated. Conventional GIS was mostly developed for the storage, management, and visualisation of spatial data (Goodchild, 2010). It was groundbreaking in its own regard. GeoAI enhances these capabilities by employing machine learning techniques, deep learning frameworks, and high-performance computing to extract insights from increasingly complex spatial large data (VoPham et al., 2018). This evolution enables academics, practitioners, and decision-makers to understand historical events and their locations, as well as to predict future occurrences and their underlying causes across diverse spatial and temporal dimensions.

There is no universally accepted definition of GeoAI; nonetheless, researchers have proposed various perspectives that emphasise distinct aspects of this transdisciplinary domain. GeoAI fundamentally has three principal components that function in unison:

1. The spatial science foundation**:** VoPham et al. (2018) describe GeoAI as “an emerging scientific discipline that integrates advancements in spatial science, artificial intelligence techniques in machine learning (e.g., deep learning), data mining, and high-performance computing to derive insights from spatial big data” (p. 2). This definition emphasises the field’s roots in geographic information science and its commitment to understanding spatial phenomena through computer methods.

2. The AI methodological component¿ The methodological component of AI? GeoAI integrates artificial intelligence techniques, particularly machine learning and deep learning, with geographic information systems to facilitate intelligent, automated spatial analysis (Li et al., 2024). Machine learning is a kind of artificial intelligence that concentrates on instructing computers to learn from unprocessed geographical data by identifying patterns and utilising them to extract additional information. Deep learning, the most sophisticated variant of machine learning, employs neural network designs capable of assimilating intricate spatial notions by hierarchically integrating simpler components (LeCun et al., 2015).

3. The application-oriented dimension: The practical aspect: GeoAI is defined as "a fusion of narrow artificial intelligence and applied spatial science" (Esri Canada, 2024), with narrow AI pertaining to systems that concentrate on particular geographical tasks rather than broad intelligence. This perspective emphasises the potential of GeoAI to address real-world challenges across various domains, including urban planning, environmental monitoring, disaster management, and public health (Kamel Boulos et al., 2019).

A comprehensive definition of GeoAI is: "The integration of AI methodologies and technologies with high-quality geospatial data and analysis, amalgamating the advantages of AI and geographic information systems to extract valuable insights from spatial data via automated analysis, pattern recognition, and predictive modelling" (Spyrosoft, 2024).

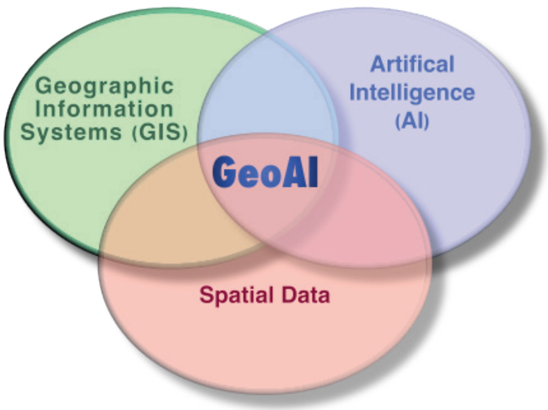

Figure 1. *Conceptual Framework of Geospatial Artifical Intelligence (GeoAI) (Source: Adapted from VoPham et al. (2018) and Li et al. (2024)*

This thorough comprehension establishes GeoAI not merely as a technical tool, but as an avant-garde scientific framework for the acquisition of spatial knowledge and decision-making in an era marked by unprecedented data proliferation and computational power (Li et al., 2024).

GeoAI possesses some distinctive characteristics that differentiate it from conventional GIS and general-purpose AI systems. These attributes arise from the integration of spatial cognition with artificial intelligence.

Clarity in Spatial Context. GeoAI incorporates spatial autocorrelation and spatial heterogeneity—two fundamental attributes of geographic phenomena—into AI modelling (Li et al., 2024). Tobler's First Law of Geography articulates spatial autocorrelation, the principle that proximate entities are more likely to exhibit similarities (Tobler, 1970). This approach guides the creation of GeoAI models, enabling them to leverage geographical linkages that traditional AI methods would neglect. Spatial heterogeneity acknowledges that interactions and processes vary across different locations, requiring models that can adapt to particular geographic contexts rather than assuming global uniformity.

Table 1. *Conceptual Framework of Geospatial Artificial Intelligence (GeoAI)*

Characteristic	Traditional GIS	GeoAI
Primary fonction	Data storage management and visualization	Automated analysis, pattern recognation, and prediction
Data processing	Manual or semi automated analysis workflows	Automated future extraction and classification
Analysis approach	Rule-based and expert-driven spatial queries	Data-driven machine learning and deep learning models
Pattern discovery	Requires explicit programming of spatial relationships	Autonomous pattern detection from training data
Prediction Capability	Limited to interpolation and basic statistical models	Advanced predictive modeling across space and time
Data Volume Handling	Challenged by big data; requires data reduction	Designed for big spatial data; scalable architectures
Computational Requirements	Moderate; desktop or server-based	High; GPU acceleration and cloud computing
Expertise Required	GIS specialist knowledge and domain expertise	Combination of GIS, data science, and programming skills
Temporal Analysis	Static snapshots or simple time series	Dynamic spatiotemporal modeling and forecasting
Update Frequency	Periodic manual updates	Near real-time automated updates possible
Interpretability	Transparent rule-based processes	Variable; some methods are "black boxes"
Application Examples	Map production, spatial queries, overlay analysis	Object detection in imagery, traffic prediction, land use classification
Emergence Period	1960s-present	2012-present (formally recognized field)
Key Technologies	Spatial databases, cartographic visualization, geoprocessing	CNNs, transformers, ensemble methods, foundation models

Scale-Aware Intelligence. GeoAI must operate over many spatial scales, including local, regional, and global, as well as diverse temporal scales, such as real-time, historical, and predictive (Mai et al., 2022). This differs from conventional AI systems. This multi-scale intelligence is crucial for addressing complex spatial issues such as climate change, urban expansion, and disease proliferation, because processes at varying scales influence one another and the outcomes.

Geospatial Data Integration. GeoAI systems are designed to process geospatial data in various formats (raster, vector, point clouds), sourced from diverse origins (satellites, drones, IoT sensors, volunteered geographic information), and utilising many modalities (optical, radar, thermal, multispectral) (Wu, 2025). The capacity to integrate data from several sources enhances the comprehension of geographic phenomena beyond what a single data source might provide.

Actionable Spatial Intelligence. The primary objective of GeoAI is to analyse spatial patterns in order to generate actionable insights that assist individuals in making informed decisions and addressing geographic challenges proactively (Gao et al., 2023). GeoAI distinguishes itself from other methodologies for analysing geographic information by emphasising action.

1.2. The modern GeoAI ecosystem

Contemporary GeoAI constitutes a complex ecosystem comprising technology, data sources, platforms, organisations, and communities. To comprehend the present condition of the field and its trajectory, one must grasp the functioning of this ecosystem.

The technical foundation of contemporary GeoAI is established on many essential technologies that function together.

Architectures for artificial intelligence: GeoAI transcends conventional statistical techniques by employing sophisticated machine learning approaches, including supervised learning for classification and regression, unsupervised learning for clustering and pattern recognition, and reinforcement learning for optimisation and decision-making in uncertain environments. Ensemble approaches, like random forests and gradient boosting, remain preferred for their robustness and transparency (Choi, 2023).

Analysing geospatial information: Specialised tools and libraries have been created to address the distinct requirements of geospatial data. The GeoAI Python module (Wu, 2025) features high-level APIs that simplify complex machine learning operations while providing expert users considerable flexibility. It is capable of reading and writing several data types, including GeoTIFF, JPEG2000, GeoJSON, Shapefile, and GeoPackage. It autonomously regulates equipment to enhance processing efficiency.

Infrastructure for cloud computing: Contemporary GeoAI applications utilise cloud platforms such as Google Earth Engine, AWS, and Azure for the storage and processing of substantial data volumes. This enables researchers lacking local high-performance computing facilities to conduct advanced research by providing universal access to computational resources and extensive geospatial datasets (Gorelick et al., 2017).

The efficacy of GeoAI is significantly influenced by the quality and accessibility of geospatial data, which is acquired from several origins.

Satellite-based remote sensing: Diverse categories of Earth observation satellites provide data at varying spatial resolutions (ranging from sub-meter to kilometres), temporal frequencies (from continuous to monthly), and spectral bands (including visible, thermal, and radar wavelengths). Open data rules for missions such as Landsat and Sentinel have significantly increased data availability (Wulder et al., 2022).

Aerial platforms: Unmanned Aerial Vehicles (UAVs or drones) connect satellite and terrestrial observations, providing exceptionally high-resolution imagery and LiDAR data for localised and regional studies (Manfreda et al., 2018).

Ground-based sensors: IoT networks, environmental monitoring stations, traffic cameras, and mobile sensors continuously provide streams of georeferenced data. This data is compatible with aerial observations from satellites and aircraft.

Data from numerous individuals: Volunteered Geographic Information (VGI) via platforms such as OpenStreetMap, citizen science initiatives, and social media provides valuable ground truth and real-time updates; yet, it presents challenges with quality control (Goodchild, 2007).

Derived and modelled data: GeoAI generates novel spatial datasets through classification, prediction, and simulation of data. These datasets can subsequently serve as inputs for further analysis, so establishing a virtuous cycle of knowledge generation.

The GeoAI ecosystem comprises both commercial and open-source platforms.

Commercial frameworks: The ArcGIS platform by Esri incorporates numerous integrated AI functionalities, including tools for object detection, classification, grouping, and prediction. These technologies integrate traditional GIS workflows with contemporary ML frameworks, enabling anyone with limited technological knowledge to utilise GeoAI methodologies (Esri, 2024b).

Open-source frameworks: TensorFlow and PyTorch are fundamental deep learning frameworks. Rasterio, Geopandas, and the GeoAI package exemplify specialised libraries that enhance geospatial functionalities. This open-source ecosystem fosters innovation and ensures universal accessibility.

Cloud-based services: Google Earth Engine, Sentinel Hub, and analogous systems provide cloud-based data and computational resources, hence alleviating the necessity for numerous applications to download and analyse data locally on their devices.

GeoAI is applicable in nearly every domain where location holds significance: Environmental monitoring and conservation (Pettorelli et al., 2014); urban planning and smart cities (Batty, 2018); disaster management and humanitarian response (Ghaffarian et al., 2023); agriculture and food security (Kamilaris & Prenafeta-Boldú, 2018); public health and epidemiology (Kamel Boulos et al., 2019; VoPham et al., 2018); transportation and logistics (Ermagun & Levinson, 2018); climate science and Earth system modelling (Reichstein et al., 2019).

Each discipline has unique challenges and opportunities, driving the evolution and enhancement of GeoAI methodologies and applications.

2. Technical basis of GeoAI

Geospatial Artificial Intelligence (GeoAI) possesses the potential to transform the world, as it integrates a sophisticated array of technologies encompassing computer science, statistics, and geographic information science. This chapter examines the primary technical components that enable GeoAI systems to extract information from spatial data, predict future occurrences of geographic phenomena, and automate complex spatial analysis tasks.

The technical domain of GeoAI encompasses three interrelated components: (1) machine learning algorithms that discern patterns from both labelled and unlabelled spatial data; (2) deep learning architectures tailored or modified for geospatial data; and (3) specialised computational frameworks and tools that facilitate the practical application of these methodologies (Choi, 2023; Li et al., 2024). Contemporary spatial intelligence systems must achieve a balance among many objectives. For instance, they must accurately identify patterns, do extensive analyses rapidly, be comprehensible to instill trust among decision-makers, and manage the vast quantities of Earth observation data received daily (Esri, 2024b).

2.1 Basic ideas about machine learning in GIS

Machine learning (ML) represents a significant shift from rule-based spatial analysis to data-driven pattern detection. Rather than explicitly programming the rationale for spatial relationships, machine learning algorithms derive these correlations from training data. This enables children to utilise their acquired knowledge in unfamiliar contexts (Chege-Tierra, 2024).

2.1.1 Distinctive attributes of spatial data

Spatial data possesses distinct characteristics that must be considered, in contrast to the tabular data commonly employed in conventional machine learning applications (Analytics Vidhya, 2021):

Spatial autocorrelation: refers to the spatial dependency of geographic phenomena, suggesting that nearby observations tend to be more similar than those that are farther apart, as articulated in Tobler's First Law of Geography (Tobler, 1970). This contradicts the concept of independence upon which several conventional statistical methods rely.

Spatial heterogeneity: The associations among variables sometimes vary across geographic regions rather than being globally uniform. Machine learning models must be flexible to local situations or incorporate geographical context as explicit attributes (Fotheringham & Oshan, 2016).

Multi-scale structure: Geographic processes occur simultaneously across multiple spatial scales. Goodchild (2011) asserts that machine learning for geographic information systems must effectively capture these nested scale interactions.

Diverse categories of data: Geospatial data can be represented through various formats, including vector geometries, raster grids, point clouds, and networks. Each category requires distinct preprocessing and feature engineering (Analytics Vidhya, 2021).

2.1.2 Supervised learning in GeoAI

Supervised learning algorithms acquire mappings from input features to output labels utilising training datasets in which both inputs and corresponding outputs are known (LinkedIn, 2023).

Key Classification Algorithms:

Linear and Logistic Regression: Despite their simplicity, regression-based methodologies retain significance in GIS applications where interpretability and computational speed are paramount. Geographically Weighted Regression (GWR) permits regression coefficients to fluctuate spatially, hence encapsulating spatial heterogeneity (Brunsdon et al., 1996; Fotheringham et al., 2002).

Random Forests: Introduced by Breiman (2001), random forests consolidate predictions from ensembles of decision trees, significantly enhancing generalisation performance. Spatial extensions clearly integrate spatial context via spatial leave-one-out cross-validation or spatial blocking methodologies (Brenning, 2012; Meyer et al., 2018).

Support Vector Machines (SVM) provide ideal hyperplanes that maximise the margin between classes in high-dimensional feature spaces (Cortes & Vapnik, 1995). Support Vector Machines (SVMs) have demonstrated remarkable efficacy in hyperspectral image classification within remote sensing applications, adeptly managing high-dimensional data without necessitating substantial training samples (Mountrakis et al., 2011).

Regression for Spatial Prediction: Contemporary machine learning regression enhances the functionalities of kriging by accommodating intricate nonlinear interactions and multivariate factors. Gradient boosting machines (Friedman, 2001) and neural network regressors frequently surpass conventional geostatistical methods when ample training data is accessible (Hengl et al., 2018). Empirical Bayesian Kriging (EBK) is a hybrid methodology that integrates geostatistical principles with automated model selection via simulation (Krivoruchko & Gribov, 2019).

2.1.3 Unsupervised learning in GeoAI

Unsupervised learning identifies patterns, structures, or clusters in data devoid of specified labels, rendering it advantageous for exploratory spatial analysis, data reduction, and anomaly identification (LinkedIn, 2023).

Clustering Algorithms:

K-Means Clustering: Despite its straightforwardness, k-means continues to be extensively utilised for spatial segmentation applications. Spatial variants integrate geographic limitations by emphasising spatial proximity in conjunction with feature similarity or necessitating cluster compactness (MacQueen, 1967; Chavent et al., 2018).

DBSCAN: Density-Based Spatial Clustering detects clusters as dense regions delineated by sparse areas, autonomously deciding the number of clusters and identifying outliers (Ester et al., 1996). In contrast to k-means, DBSCAN accommodates clusters of arbitrary shapes, which is advantageous for spatial data because natural regions may exhibit irregular forms.

Dimensionality Reduction: Principal Component Analysis (PCA) converts correlated variables into uncorrelated principal components (Jolliffe, 2002). PCA decreases dimensionality in hyperspectral remote sensing data comprising numerous associated spectral bands, while preserving the majority of information. Contemporary nonlinear techniques such as t-SNE (van der Maaten & Hinton, 2008) and UMAP (McInnes et al., 2018) are proficient in maintaining local data structure within low-dimensional embeddings.

2.2 Deep learning architectures for geospatial analysis

Although standard machine learning techniques are still useful for numerous GIS applications, deep learning (DL) has become the prevailing approach for analysing high-dimensional spatial data, especially images obtained from satellites, aircraft, and drones. Deep neural networks autonomously acquire hierarchical feature representations from unprocessed data, obviating the necessity for manual feature engineering (LeCun et al., 2015; Reichstein et al., 2019).

2.2.1 The deep learning revolution in remote sensing

The utilisation of deep learning in remote sensing accelerated with the 2012 ImageNet breakthrough, during which AlexNet attained unparalleled image classification accuracy (Krizhevsky et al., 2012). Deep learning provides numerous benefits for remote sensing, including automatic feature extraction, hierarchical abstraction, end-to-end learning, and scalability (Ball et al., 2017; Zhang et al., 2023). Nonetheless, deep learning has obstacles, including considerable requirements for labelled data, extensive processing costs, sensitivity to hyperparameters, and restricted interpretability.

2.2.2 Convolutional Neural Networks (CNNs)

Convolutional neural networks constitute the foundation of deep learning for geographic data processing. Convolutional Neural Networks (CNNs) leverage the spatial organisation of pictures via specialised processes—convolution, pooling, and hierarchical composition—that effectively acquire translation-invariant feature detectors (LeCun et al., 1998, 2015).

Fundamentals of CNN Architecture:

Convolutional Layers: Convolution operations utilise learnt filters that traverse input feature maps, identifying specific patterns such as edges, textures, and forms. The convolution operation for two-dimensional spatial data is expressed as:

where I represents the input, K denotes the learnable kernel, and S signifies the output.

Pooling Layers: Pooling processes downsample feature maps by consolidating values within local neighbourhoods, hence decreasing computational expense and enlarging the receptive field size.

Activation Functions: The Rectified Linear Unit (ReLU), defined as has emerged as the preferred option owing to its processing efficiency and its efficacy in alleviating vanishing gradient issues (Glorot et al., 2011).

Prominent CNN Architectures:

VGGNet: Established that very deep networks utilising modest (3×3) convolutional filters could attain exceptional performance (Simonyan & Zisserman, 2015). The straightforward, modular architecture of VGG has rendered it favoured for transfer learning in remote sensing.

ResNet: Deep Residual Networks implemented skip connections, facilitating the training of extremely deep architectures (50-200+ layers) without performance deterioration (He et al., 2016). The residual connection formulation $y = F_{(x)} + x$ enables networks to learn residual mappings, hence enhancing optimisation.

DenseNet: Enhances ResNet by linking each layer to all following layers within dense blocks, hence increasing gradient flow and promoting feature reutilization (Huang et al., 2017).

EfficientNet: Methodically adjusts network depth, width, and input resolution using compound scaling, attaining exceptional accuracy-efficiency balances beneficial for extensive remote sensing applications (Tan & Le, 2019).

Specialized Remote Sensing Architectures:

Multi-source Fusion Networks: Consolidate data from several sensors (optical, SAR, LiDAR) by multi-stream processing, dynamic group convolutions, or attention-based fusion techniques (Chen et al., 2020; Zhang et al., 2024).

Lightweight Architectures: Utilise depthwise separable convolutions, pruning, and quantisation to diminish computing demands for real-time or resource-limited applications (Liu et al., 2025; Scientific Reports, 2025).

Attention-Enhanced CNNs: Attention mechanisms dynamically highlight significant geographical regions or feature channels, hence enhancing performance on tasks like as building extraction and land cover classification (Woo et al., 2018; Alhichri et al., 2021).

2.2.3 Advanced deep learning paradigms

Semantic Segmentation Networks: Semantic segmentation allocates class labels to each pixel, generating dense predictions crucial for land cover mapping and building footprint extraction (Long et al., 2015).

U-Net: The established standard for remote sensing segmentation, U-Net's encoder-decoder architecture with skip links maintains intricate spatial features while encompassing semantic context (Ronneberger et al., 2015). Various variants improve performance via inception modules, attention gates, residual connections, and multi-scale fusion (Discover Computing, 2025; Khan & Jung, 2024).

DeepLab: Utilises atrous convolutions and atrous spatial pyramid pooling (ASPP) to capture multi-scale context and generate precise object boundaries (Chen et al., 2018).

Vision Transformers (ViTs) utilise the transformer architecture from natural language processing for image analysis, incorporating self-attention mechanisms that effectively represent long-range relationships throughout complete images (Dosovitskiy et al., 2021). Transformers provide benefits in remote sensing by effectively capturing global spatial context, although they generally necessitate larger training datasets compared to CNNs.

Hybrid CNN-Transformer Architectures: Integrate convolutional neural networks for local feature extraction with transformers for global context modelling, utilising their complimentary strengths (Nature, 2025; Zhang et al., 2024). The Enhanced Hybrid CNN and Transformer Network (EHCTNet) exhibits this methodology by merging spatial and channel attention alongside multi-scale feature fusion (Nature, 2025).

Recurrent Neural Networks (RNNs): Long Short-Term Memory (LSTM) networks are proficient at handling sequential data by preserving an internal state that encapsulates temporal dependencies (Hochreiter & Schmidhuber, 1997). In GeoAI, recurrent neural networks facilitate the study of satellite image time series, the identification of temporal changes, and the forecasting of spatial activities. Bidirectional LSTMs have demonstrated efficacy in hyperspectral image categorisation (Mou et al., 2017).

2.3 Training, optimization, and regularization

The successful implementation of machine learning and deep learning in GeoAI necessitates meticulous consideration of training methodologies, optimisation tactics, and regularisation methods that avert overfitting while ensuring robust generalisation.

Loss Functions: for classification tasks utilise cross-entropy loss, regression tasks implement mean squared error (MSE) or mean absolute error (MAE), and segmentation tasks may adopt specialised losses that tackle class imbalance, including Dice loss, Focal loss, or Tversky loss (Salehi et al., 2017; Lin et al., 2017).

Optimization Algorithms: tochastic gradient descent (SGD) with momentum enhances convergence speed. Adam (Kingma & Ba, 2015) adjusts learning rates for each parameter by utilising first and second moment estimations. Learning rate scheduling—diminishing learning rates as training advances—mitigates oscillation and facilitates fine-tuning (Smith, 2017).

Regularization Techniques: Regularisation Weight decay (L2 regularisation) imposes a penalty on substantial parameter values. Dropout randomly disables neurones during the training process (Srivastava et al., 2014). Data augmentation artificially enlarges training datasets by changes such as rotation, flipping, and scaling. Early stopping terminates training when validation performance stabilises. Batch normalisation standardises activations, hence stabilising the training process (Ioffe & Szegedy, 2015).

Transfer Learning and Domain Adaptation: Transfer learning mitigates data scarcity by initialising networks with weights pre-trained on extensive datasets, thereafter fine-tuning them on smaller target datasets (Yosinski et al., 2014). In remote sensing, domain adaptation techniques address distributional discrepancies between pre-training and target data, enhancing efficacy (Tuia et al., 2016). Self-supervised pre-training on unlabelled remote sensing data yields an initialisation more aligned with domain characteristics (Caron et al., 2020).

2.4 Specialized GeoAI methods and emerging paradigms

Graph Neural Networks (GNNs) enhance deep learning for graph-structured data by learning representations that integrate network topology (Kipf & Welling, 2017). Applications encompass traffic forecasting on road networks, flood prediction in river systems, and spatial accessibility analysis (Jiang, 2021; Li et al., 2021).

Geospatial Foundation Models: Foundation models, which are extensive models pre-trained on varied datasets, signify a nascent paradigm for GeoAI (Bommasani et al., 2021). Prithvi, created by NASA and IBM, is trained on extensive datasets of satellite photography to acquire universal representations of Earth observation (Jakubik et al., 2024). The Segment Anything Model (SAM) offers zero-shot segmentation functionalities for geographical imagery (Kirillov et al., 2023). Foundation models democratise GeoAI by lowering data and knowledge barriers; nonetheless, concerns persist over its generalisation across many geographic contexts (Mai et al., 2025).

Physics-Informed Machine Learning: Physics-informed or theory-driven Machine learning incorporates domain knowledge—such as physical laws, geographic principles, and process comprehension—into model architectures or training methodologies (Karpatne et al., 2017; Reichstein et al., 2019). This hybrid methodology integrates data-driven learning with scientific comprehension, enhancing generalisation and physical plausibility.

Applications encompass the integration of mass balance constraints into hydrological models, the incorporation of ecosystem dynamics into biodiversity forecasts, and the application of thermodynamic principles to constrain climate models (Jiang & Luo, 2022; Daw et al., 2020).

2.5 Computational infrastructure

Hardware Acceleration: Graphics Processing Units (GPUs) are crucial for deep learning, enhancing training speed by 10-100 times relative to Central Processing Units (CPUs) (Raina et al., 2009). NVIDIA's CUDA platform prevails in scientific deep learning. Tensor Processing Units (TPUs), bespoke AI accelerators created by Google, provide superior performance for particular activities (Jouppi et al., 2017). High-Performance Computing (HPC) clusters offer scalable resources for extensive geographical analysis via distributed training over numerous GPUs.

Software Frameworks: Prominent deep learning frameworks encompass TensorFlow (extensive ecosystem, (Abadi et al., 2016), PyTorch (dynamic computation networks favoured in research, Paszke et al., 2019), and JAX (composable transformations for high-performance computing, Bradbury et al., 2018). Key geospatial libraries comprise GDAL/OGR (fundamental libraries for raster and vector formats), Rasterio (Pythonic access to raster data), GeoPandas (vector geospatial data handling), and Shapely (geometric operations). GeoAI-specific toolkits comprise the GeoAI Python Package (a unified framework, Wu, 2025), TorchGeo (a PyTorch domain library, Stewart et al., 2022), and Raster Vision (an end-to-end framework for satellite and aerial imagery).

Cloud Platforms: Google Earth Engine offers planetary-scale geospatial analysis with integrated machine learning capabilities, obviating the need for local data (Gorelick et al., 2017). Sentinel Hub provides access to multi-mission satellite data. Commercial cloud services (AWS SageMaker, Azure ML, Google Cloud Vertex AI) offer scalable computing, storage, and pre-trained model capabilities. ArcGIS amalgamates conventional GIS with machine learning and deep learning technologies, encompassing pre-trained models (Esri, 2024c).

2.6 Challenges and considerations

Data Requirements and Quality: The substantial demand for data in deep learning presents difficulties when labelled training data is limited. Active learning, semi-supervised learning, and few-shot learning methodologies substantially mitigate this issue; yet, essential trade-offs persist (Tuia et al., 2022). The quality of data—spatial precision, temporal relevance, and class label dependability—directly influences model efficacy. Spatial autocorrelation may obscure quality concerns during validation if inadequately addressed via spatial cross-validation (Meyer et al., 2018).

Computing Complexity: Cutting-edge models necessitate significant computing resources, requiring hours to weeks of GPU time for training. This restricts accessibility, however cloud services somewhat democratise access. Techniques such as model compression, quantisation, and knowledge distillation diminish deployment requirements (Hinton et al., 2015).

Interpretability and Explainability: Deep neural networks operate as "black boxes," rendering their decision-making processes opaque to human understanding (Rudin, 2019). Explainable AI (XAI) tools, such as saliency maps, attention visualisation, and attribution procedures, offer limited understanding (Selvaraju et al., 2017), although basic tensions between complexity/accuracy and interpretability remain.

Spatial Transferability and Generalisation: Models developed using data from a specific geographic area may exhibit suboptimal performance when utilised across locations with differing environmental attributes (Meyer & Pebesma, 2021). This requires meticulous validation with spatially independent test data and the application of domain adaptation strategies.

3. Application Domains of GeoAI

Geospatial Artificial Intelligence has moved beyond theoretical potential to become a practical reality in various application areas. GeoAI technologies are fundamentally transforming the utilisation of spatial intelligence in decision-making by optimising urban infrastructure, enhancing agricultural productivity, managing disaster responses, and monitoring environmental change (Mapular, n.d.; Sharma, 2023). According to VoPham et al. (2018), nearly any field characterised by geographic variability can leverage GeoAI's ability to discern patterns from geographical large data and produce actionable forecasts.

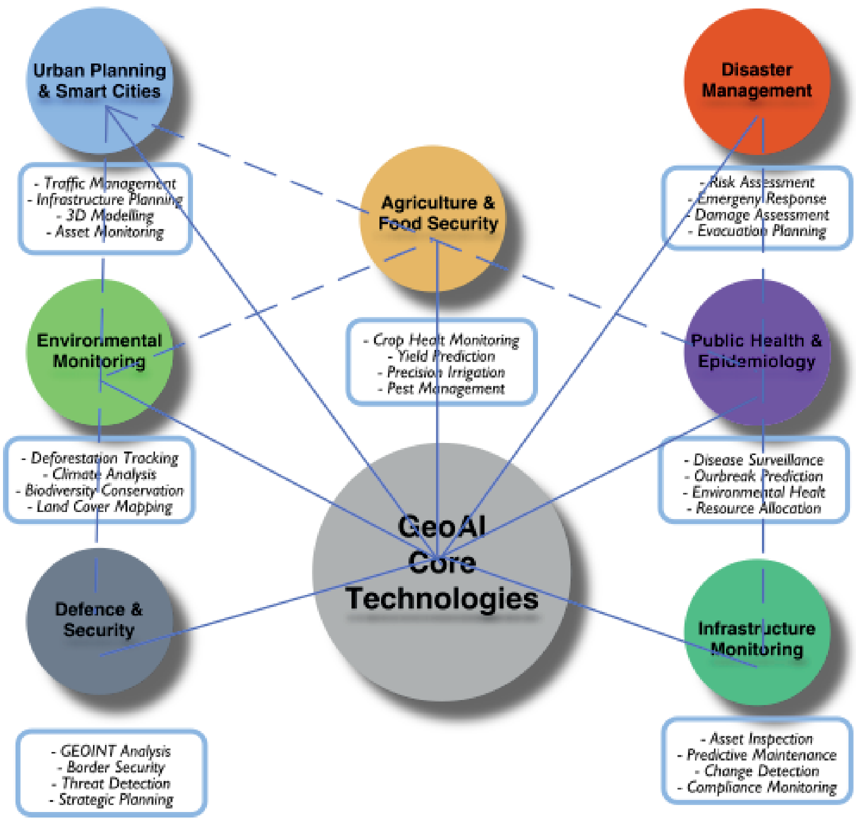

Figure 2. *Domains of GeoAI applications and their interrelations Overview of major application domains and principal use cases*

Table 2. *Comparative Analysis of GeoAI Application Domains, Technology Stack, Data Requirements, Performance Metrics, and Economic Impact*

Application Domain	Primary Use Cases	Key Technologies	Data Sources	Accuracy Range	Maturity Level	Economic Impact
Urban Planning & Smart Cities	• Traffic optimization • Infrastructure planning • 3D modeling • Asset monitoring	• Computer Vision • Predictive Analytics • IoT Integration • Digital Twins	• Satellite imagery • Drone surveys •Traffic sensors • Mobile data	85-95%	High	20-35% cost savings
Disaster Management	• Risk assessment • Early warning • Damage assessment • Resource allocation	• Deep Learning • Real-time Processing • Change Detection • Spatial Clustering	• Satellite imagery • Weather data • Social media • Ground sensors	80-92%	High	40-50% response improvement
Environmental Monitoring	• Deforestation tracking • Climate analysis • Land cover mapping • Conservation planning	• CNNs • Time-series Analysis • Multispectral Processing • Change Detection	• Sentinel-2/ Landsat • MODIS • LiDAR • Field data	88-96%	High	25-35% monitoring efficiency
Agriculture & Food Security	• Crop health monitoring • Yield prediction • Precision irrigation • Pest management	• Multispectral Analysis • ML Regression • Time-series DL • Spatial Interpolation	• Satellite imagery • Drone imagery • Weather stations • Soil sensors	82-94%	Medium-High	15-25% yield increase
Public Health & Epidemiology	• Disease surveillance • Outbreak prediction • Risk mapping • Resource planning	• Spatial Statistics • Predictive Modeling • Network Analysis • Clustering	• Health records • Mobility data • Environmental data • Demographics	75-88%	Medium	30-40% response efficiency
Infrastructure Monitoring	• Defect detection • Predictive maintenance • Change detection • Compliance monitoring	• Computer Vision • Object Detection • Anomaly Detection • ML Classification	• Aerial imagery • Drone surveys • LiDAR • Ground photos	90-98%	High	35-45% maintenance cost reduction
Defense & Security	• GEOINT analysis • Border monitoring • Threat detection • Strategic planning	• Deep Learning • Pattern Recognition • Real-time Analysis • Change Detection	• Satellite imagery • Radar data • Video feeds • Sensor networks	85-95%	High	Classified/ Strategic value

Notes: Accuracy ranges represent typical performance in operational deployments. Maturity levels reflect technological readiness and adoption rates. Economic impact varies by implementation scale and context.

3.1 Urban planning and smart cities

Smart cities exemplify the most extensive application of GeoAI technology, amalgamating various data sources to optimise urban operations and improve quality of life (Mortaheb & Jankowski, 2022). The smart city paradigm leverages synergies among Big Data, GIS, and Data Science to fulfil four policy objectives: augmenting urban service efficiency, promoting citizen quality of life, tackling societal difficulties, and generating geographical information regarding human-urban dynamics.

Traffic Management: Computer vision algorithms analyse video feeds from traffic cameras to track vehicle movements and enhance signal timing (Viso.ai, n.d.). Intelligent transport systems incorporate IoT sensors, GPS technology, and mobile applications to deliver adaptive route suggestions and enhance public transit timetables (Mapular, n.d.).

Infrastructure Monitoring: GeoAI facilitates continuous automated surveillance using drone-based aerial assessments and computer vision technologies that identify pavement fissures, bridge degradation, and illicit projects within hours instead of weeks (AeroMegh, 2025). Machine learning methods forecast likely problems prior to their occurrence, facilitating proactive maintenance that decreases costs by 35-45% (Chapter 3 data).

3D Urban Modelling: Sophisticated software generate digital replicas of entire cities, facilitating the visualisation of proposed developments, simulation of disaster scenarios, and evaluation of urban heat island effects (Viso.ai, n.d.; The GIS Journal, 2025). Natural language interfaces facilitate access, enabling non-expert planners to query spatial data via conversational prompts (Cooke, 2025).

3.2 Disaster management and emergency response

GeoAI improves disaster readiness via advanced risk modelling and delivers essential real-time intelligence during incidents (Mapular, n.d.; The GIS Journal, 2025).

Risk Assessment: Machine learning algorithms evaluate past catastrophe data, topographical characteristics, and climatic patterns to pinpoint susceptible regions. Deep learning models forecast flood-prone regions, wildfire hazards, and earthquake damage patterns, guiding zoning decisions and disaster preparedness (Li et al., 2023; Al Qundus et al., 2020).

Real-Time Response: Aerial footage processed via computer vision algorithms facilitates swift damage assessment post-disaster, accomplishing in hours what once necessitated weeks of physical surveys (AeroMegh, 2025). Machine learning models enhance the allocation of emergency resources by considering damage severity, population density, and accessibility (Alizadeh et al., 2022; Fan et al., 2021). GeoAI systems evaluate road networks instantaneously to provide ideal evacuation pathways.

Human-Centered Intelligence: The study of social media, mobile phone data, and crowdsourced reporting provide insights into population movements, needs, and feelings during crises, supplementing physical damage assessments (Imran et al., 2020; Sun et al., 2020).

3.3 Environmental monitoring and conservation

GeoAI transforms environmental monitoring by automated, extensive analysis of Earth observation data (The GIS Journal, 2025). Convolutional neural networks categorise land cover types—forests, grasslands, water bodies, urban areas—with precision comparable to or surpassing manual interpretation (Mapular, n.d.).

Applications: Change detection algorithms discern deforestation and facilitate prompt action against illegal logging (Viso.ai, n.d.). Deep learning techniques define wetland borders with multi-spectral satellite data (The GIS Journal, 2025). Machine learning models assess the effects of climate change by examining temperature patterns, precipitation trends, and vegetation health (Mapular, n.d.). Spatial models delineate essential ecosystems, ecological corridors, and conservation objectives for threatened species (Human-centered GeoAI, 2025).

3.4 Agriculture and food security

GeoAI facilitates precision agriculture techniques that enhance resource utilisation while maximising output (Arizton, 2025; The GIS Journal, 2025). Multi-spectral satellite imagery, analysed via deep learning, detects agricultural stress and disease outbreaks prior to the manifestation of observable signs, facilitating targeted interventions (Mapular, n.d.). Machine learning algorithms predict agricultural yields at field, regional, and national levels, guiding market planning and food security strategies (Arizton, 2025). GeoAI evaluates soil moisture data and meteorological predictions to propose accurate irrigation plans, minimising water usage while sustaining productivity (The GIS Journal, 2025). Predictive models anticipate pest outbreaks by analysing environmental factors, facilitating preventive strategies that minimise crop losses and pesticide application.

3.5 Public health and epidemiology

GeoAI revolutionises epidemiological surveillance by the integration of spatial data and health information (Mapular, n.d.; Human-centered GeoAI, 2025). Spatial clustering methods identify regional concentrations of disease cases, elucidating transmission pathways and risk variables (VoPham et al., 2018). Machine learning methods utilising historical outbreak data, climatic variables, and population movement forecast disease development and dissemination, facilitating proactive resource allocation (Mapular, n.d.). Throughout the COVID-19 pandemic, GeoAI detected hotspots, monitored transmission patterns, informed testing tactics, and enhanced vaccine delivery (Human-centered GeoAI, 2025). Other uses encompass air pollution exposure modelling, identification of climate-related health risks, mapping of disease vectors, and assessment of food deserts in urban environments.

3.6 Defense, security, and emerging applications

Geospatial Intelligence (GEOINT): GeoAI improves military operations by automating the study of satellite imagery and video streams. Machine learning algorithms identify anomalous behaviour, monitor vehicular movements, and oversee border regions, facilitating swifter threat detection compared to manual analysis (Arizton, 2025; Viso.ai, n.d.). Pattern recognition algorithms detect anomalous behaviours and enhance resource allocation for border security and counter-terrorism initiatives.

Emerging Applications: GeoAI offers critical functionalities for autonomous vehicle navigation, encompassing real-time object detection and route planning (Arizton, 2025). In real estate and location intelligence, property appraisal and site selection increasingly depend on GeoAI to analyse various spatial datasets (Mapular, n.d.). Remote sensing integrated with machine learning uncovers archaeological features obscured by plants, detects looting damage to cultural sites, and reconstructs historical landscapes (The GIS Journal, 2025).

4. Technical Infrastructure and Platforms

The disruptive applications of GeoAI depend on an advanced technical infrastructure that includes hardware, software, data, and cloud platforms. This chapter analyses the computing resources, tools, frameworks, and services that implement GeoAI, transitioning from research prototypes to commercial systems catering to billions of users. Comprehending this infrastructure is crucial for practitioners choosing suitable technologies and for researchers advancing next-generation GeoAI capabilities. The ecosystem is growing swiftly, with the emergence of new tools and platforms alongside the maturation of existing ones (Wu, 2025).

4.1 Hardware infrastructure

Computational Accelerators: Graphics Processing Units (GPUs) are essential for deep learning because of their parallel architecture, which is optimised for the matrix operations fundamental to neural network training and inference (Raina et al., 2009). NVIDIA GPUs lead in scientific computing, with CUDA offering extensive development tools. A contemporary GPU (NVIDIA A100, H100) can enhance training speed by 10 to 100 times relative to CPUs. Google's Tensor Processing Units (TPUs) provide superior performance for particular operations, especially beneficial for extensive training at scale (Jouppi et al., 2017). Cloud TPU accessibility democratises advanced AI hardware without substantial financial investment.

Edge Computing: For real-time GeoAI applications such as autonomous vehicles and drone-based monitoring, edge devices locally process data, eliminating cloud latency. The shift towards edge computing will intensify as applications require sub-second response times (Arizton, 2025; Viso.ai, n.d.).

High-Performance Computing (HPC): Extensive GeoAI applications—such as processing continental satellite archives and training foundational models—necessitate HPC clusters including hundreds or thousands of GPUs functioning concurrently. Distributed training frameworks facilitate model training that would be unfeasible on individual machines.

4.2 Software frameworks and libraries

Deep Learning Frameworks: TensorFlow (Abadi et al., 2016) offers a robust ecosystem from Google that facilitates research experimentation and production deployment, accompanied by substantial documentation and community support. PyTorch (Paszke et al., 2019) provides dynamic computation graphs and a clear API, enhancing its popularity in research and greatly improving production deployment capabilities. JAX (Bradbury et al., 2018) is an innovative framework that prioritises composable transformations and high-performance numerical computing, increasingly popular in scientific computing.

Geospatial Data Processing: Key libraries comprise GDAL/OGR (fundamental libraries facilitating the reading and writing of nearly all geospatial raster and vector formats), Rasterio (Pythonic interface to GDAL for raster data access), GeoPandas (enhances pandas dataframes with geospatial functionalities for vector data manipulation), and Shapely (performs geometric operations on vector geometries).

Integrated GeoAI Toolkits: Specialised frameworks connect artificial intelligence with geospatial fields. The GeoAI Python Package (Wu,

2025) offers a cohesive framework that merges artificial intelligence with geographical research via high-level APIs, which simplify intricate workflows while preserving adaptability. TorchGeo (Stewart et al., 2022) functions as a PyTorch domain library tailored for geographic data, encompassing datasets, transformations, and models. Raster Vision provides a comprehensive framework for deep learning with satellite and aerial photos.

4.3 Cloud platforms and services

Planetary-Scale Platforms: Google Earth Engine (Gorelick et al., 2017) transformed geospatial analysis by granting access to petabytes of Earth observation data alongside integrated cloud computing capabilities. It obviates the necessity for data download and storage, facilitating study at continental scales with uncomplicated scripts. Machine learning integration facilitates supervised classification, grouping, and regression. Sentinel Hub offers access to multi-mission satellite data together with cloud processing capabilities, facilitating custom workflows and API integration.

Commercial Cloud Services: Prominent vendors deliver extensive GeoAI functionalities. Amazon Web Services offers SageMaker for managed machine learning services, while S3 hosts the Public Dataset Program, which includes Sentinel-2, Landsat, and various Earth observation archives. Microsoft Azure provides Azure Machine Learning and Planetary Computer for cohesive machine learning and geographic data accessibility. Google Cloud Platform offers Vertex AI for machine learning workflows, integrated with Earth Engine for geospatial analysis.

GIS Platform Integration: ArcGIS (Esri, 2024a) offers an extensive GIS platform with profound AI/ML integration. ArcGIS Pro encompasses tools for picture categorisation, object detection, and geographical analysis. Pre-trained models and automated workflows diminish obstacles to GeoAI adoption, whereas ArcGIS Online facilitates cloud-based collaboration and analysis. QGIS is an open-source alternative with plugins that facilitate Python-based machine learning workflows, offering a cost-free solution for numerous applications.

Table 3. *Detailed Comparison of Software Frameworks and Libraries*

Framework	Organization	Primary Language	Key Features	Best For	GeoAI Integration
TensorFlow	Google	Python/ C++	- Production deplovment - TensorBoard visualization - TF Serving for APIs - Mobil/Edge support	Large-scale production systems, deployment at scale	Excellent: TF-GAN, TF Geo, Earth Engine integration
PyTorch	Meta/ Facebook	Python	- Dynamic computation - Intuitive debugguing - Strong research focus - TorchScript compilation	Research, rapid prototyping, academic use	Excellent: TF-GAN, TF Geo, Earth Engine integration
JAX	Google	Python	- Production deplovment - TensorBoard visualization - TF Serving for APIs - Mobil/Edge support	Large-scale production systems, deployment at scale	Excellent: TF-GAN, TF Geo, Earth Engine integration
Keras	Google (TF Team)	Python	- Production deplovment - TensorBoard visualization - TF Serving for APIs - Mobil/Edge support	Large-scale production systems, deployment at scale	Excellent: TF-GAN, TF Geo, Earth Engine integration
GDAL/ OGR	OSGeo	C/C+ +	- Production deplovment - TensorBoard visualization - TF Serving for APIs - Mobil/Edge support	Large-scale production systems, deployment at scale	Excellent: TF-GAN, TF Geo, Earth Engine integration
Rasterio	Mapbox/ Community	Python	- Production deplovment - TensorBoard visualization - TF Serving for APIs - Mobil/Edge support	Large-scale production systems, deployment at scale	Excellent: TF-GAN, TF Geo, Earth Engine integration
GeoPandas	Community	Python	- Production deplovment - TensorBoard visualization - TF Serving for APIs - Mobil/Edge support	Large-scale production systems, deployment at scale	Excellent: TF-GAN, TF Geo, Earth Engine integration
TorchGeo	Microsoft	Python	- Production deplovment - TensorBoard visualization - TF Serving for APIs - Mobil/Edge support	Large-scale production systems, deployment at scale	Excellent: TF-GAN, TF Geo, Earth Engine integration
GeAl Package	OpenGeo	Python	- Production deplovment - TensorBoard visualization - TF Serving for APIs - Mobil/Edge support	Large-scale production systems, deployment at scale	Excellent: TF-GAN, TF Geo, Earth Engine integration

4.4 Data infrastructure

Earth Observation Data: Various satellite missions offer a range of imagery appropriate for distinct uses. Landsat provides a continuous record spanning over 50 years, Sentinel offers high-frequency, high-resolution data, MODIS delivers daily worldwide coverage, and private entities (Planet, Maxar) furnish very high-resolution imagery. Publicly available, free data from governmental missions significantly enhances the accessibility of GeoAI, facilitating study and applications that were previously limited by data expenses.

Auxiliary Geospatial Data: Crucial supporting datasets including Digital Elevation Models (DEMs) for terrain analysis, OpenStreetMap for vector features (roads, buildings, land use), census and demographic data, climate and weather archives, and IoT sensor networks. This varied data ecology facilitates thorough spatial analysis.

Training Datasets and Benchmarks: Standardised datasets facilitate model comparison and provide reproducible research. Significant benchmarks comprise UC Merced, AID, and NWPU-RESISC45 for scene classification (with AID utilised in 41 studies and NWPU-RESISC45 in 40 studies as per Zhang et al., 2023), SpaceNet for building footprints, and other semantic segmentation benchmarks for land cover mapping.

4.5 Integration, interoperability, and challenges

Standards and Protocols: OGC standards (WMS, WFS, WCS) facilitate interoperability among platforms. GeoJSON and Cloud-Optimized GeoTIFF enable the sharing of geospatial data via the web. Workflow orchestration technologies like as Apache Airflow, Prefect, and MLflow facilitate the management of intricate GeoAI pipelines by coordinating data processing, model training, and deployment.

Cost and Accessibility: Although cloud platforms facilitate widespread access, large-scale GeoAI continues to be costly. Training sophisticated models can incur substantial expenses in computational time, and the inference costs for operational systems managing continuous data streams accumulate rapidly. Organisations must meticulously reconcile computational requirements with financial limitations.

Vendor Lock-In and Data Movement: Extensive integration with proprietary platforms engenders dependency risks. Open-source solutions offer adaptability but may necessitate greater knowledge. The volume of Earth observation data exerts pressure on network bandwidth and storage capacity. Cloud-optimized formats and on-the-fly processing address these problems; yet, data transportation continues to be a critical factor for large-scale applications.

References

Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., Isard, M., Kudlur, M., Levenberg, J., Monga, R., Moore, S., Murray, D. G., Steiner, B., Tucker, P., Vasudevan, V., Warden, P., ... Zheng, X. (2016). TensorFlow: A system for large-scale machine learning. In *Proceedings of the 12th USENIX Symposium on Operating Systems Design and Implementation* (pp. 265-283). USENIX Association.

AeroMegh. (2025, July 3). *GeoAI for urban infrastructure monitoring.* https://aeromegh.ai/white-paper/geoai-urban-infrastructure-monitoring/

Al Qundus, J., Dabbour, K., Gupta, S., Meisami, S., & Pelechrinis, K. (2020). Wireless sensor network for AI-based flood disaster detection. *Annals of Operations Research*, *319*, 697-719. https://doi.org/10.1007/s10479-020-03754-x

Alhichri, H., Alswayed, A. S., Bazi, Y., Ammour, N., & Alajlan, N. A. (2021). Classification of remote sensing images using EfficientNet-B3 CNN model with attention. *IEEE Access*, *9*, 14078-14094. https://doi.org/10.1109/ACCESS.2021.3051085

Alizadeh, M., Ngah, I., Hashim, M., Pradhan, B., & Pour, A. B. (2022). A hybrid analytic network process and artificial neural network (ANP-ANN) model for urban earthquake vulnerability assessment. *Remote Sensing*, *10*(6), 975. https://doi.org/10.3390/rs10060975

Analytics Vidhya. (2021, March 20). *Introducing machine learning for spatial data analysis*. https://www.analyticsvidhya.com/blog/2021/03/introducing-machine-learning-for-spatial-data-analysis/

Analytics Vidhya. (2021). *Machine learning for geospatial data*. https://www.analyticsvidhya.com

Arizton. (2025). *Top 5 geospatial AI trends to watch in 2025.* https://www.arizton.com/blog/top-5-geospatial-ai-trends-to-watch

Ball, J. E., Anderson, D. T., & Chan, C. S. (2017). Comprehensive survey of deep learning in remote sensing. *Journal of Applied Remote Sensing*, *11*(4), 042609.

Batty, M. (2018). Artificial intelligence and smart cities. *Environment and Planning B: Urban Analytics and City Science*, *45*(1), 3-6. https://doi.org/10.1177/2399808317751169

Bishop, C. M. (2006). *Pattern recognition and machine learning*. Springer.

Bommasani, R., Hudson, D. A., Adeli, E., Altman, R., Arora, S., von Arx, S., Bernstein, M. S., Bohg, J., Bosselut, A., Brunskill, E., Brynjolfsson, E., Buch, S., Card, D., Castellon, R., Chatterji, N., Chen, A., Creel, K., Davis, J. Q., Demszky, D., ... Liang, P. (2021). On the opportunities and risks of foundation models. *arXiv preprint arXiv:2108.07258*. https://arxiv.org/abs/2108.07258

Bradbury, J., Frostig, R., Hawkins, P., Johnson, M. J., Leary, C., Maclaurin, D., Necula, G., Paszke, A., VanderPlas, J., Wanderman-Milne, S., & Zhang, Q. (2018). *JAX: Composable transformations of Python+NumPy programs* (Version 0.3.13) [Computer software]. http://github.com/google/jax

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5-32.

Breiman, L., Friedman, J., Stone, C. J., & Olshen, R. A. (1984). *Classification and regression trees*. CRC Press.

Brenning, A. (2012). Spatial cross-validation and bootstrap for the assessment of prediction rules in remote sensing. *ISPRS Journal*, *65*, 593-603.

Brunsdon, C., Fotheringham, A. S., & Charlton, M. E. (1996). Geographically weighted regression. *Journal of the Royal Statistical Society D*, *47*(3), 431-443.

Caron, M., Misra, I., Mairal, J., Goyal, P., Bojanowski, P., & Joulin, A. (2020). Unsupervised learning of visual features by contrasting cluster assignments. In *Advances in Neural Information Processing Systems* (Vol. 33, pp. 9912-9924). Curran Associates.

Chavent, M., Kuentz-Simonet, V., Labenne, A., & Saracco, J. (2018). ClustGeo: An R package for hierarchical clustering with spatial constraints. *Computational Statistics*, *33*(4), 1799-1822. https://doi.org/10.1007/s00180-018-0791-1

Chege-Tierra, S. (2024, April 7). *Spatial intelligence: Why GIS practitioners should embrace machine learning - How to get started*. Towards AI. https://towardsai.net/p/l/spatial-intelligence-why-gis-practitioners-should-embrace-machine-learning-how-to-get-started

Chen, J., Li, K., Deng, Q., Li, K., & Philip, S. Y. (2020). Distributed deep learning model for intelligent video surveillance systems with edge computing. *IEEE Transactions on Industrial Informatics*, *17*(6), 3779-3789. https://doi.org/10.1109/TII.2020.3023928

Chen, L. C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2018). DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *40*(4), 834-848. https://doi.org/10.1109/TPAMI.2017.2699184

Choi, J. (2023). *Technical foundations of GeoAI*. GIS Professional Journal.

Choi, Y. (2023). GeoAI: Integration of artificial intelligence, machine learning, and deep learning with GIS. *Applied Sciences*, *13*(6), 3895. https://doi.org/10.3390/app13063895

Cooke, K. (2025, April 7). *The emergence of GeoAI in planning*. Esri. https://www.esri.com/en-us/industries/blog/articles/the-emergence-of-geoai-in-planning

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, *20*(3), 273-297. https://doi.org/10.1007/BF00994018

Daw, A., Thomas, R. Q., Carey, C. C., Read, J. S., Appling, A. P., & Karpatne, A. (2020). Physics-guided architecture (PGA) of neural networks for quantifying uncertainty in lake temperature modeling. In *Proceedings of the 2020 SIAM International Conference on Data Mining* (pp. 532-540). SIAM. https://doi.org/10.1137/1.9781611976236.60

Discover Computing. (2025, May 25). *An enhanced convolutional neural network architecture for semantic segmentation in high-resolution remote sensing images*. Springer. https://link.springer.com/article/10.1007/s10791-025-09610-5

Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S., Uszkoreit, J., & Houlsby, N. (2021). An image is worth 16x16 words: Transformers for image recognition at scale. In *International Conference on Learning Representations*. https://openreview.net/forum?id=YicbFdNTTy

Ermagun, A., & Levinson, D. (2018). Spatiotemporal traffic forecasting: Review and proposed directions. *Transport Reviews*, *38*(6), 786-814. https://doi.org/10.1080/01441647.2018.1442887

Esri Canada. (2024). *GeoAI series #2: The birth and evolution of GeoAI*. https://resources.esri.ca/education-and-research/geoai-series-2-the-birth-and-evolution-of-geoai

Esri Community. (2025, April 22). *Integrating GIS with AI and machine learning: The future of mapping science*. https://community.esri.com/t5/education-blog/integrating-gis-with-ai-and-machine-learning-the/ba-p/1580029

Esri. (2024a). *ArcGIS Pro: Overview*. https://www.esri.com/en-us/arcgis/products/arcgis-pro/overview

Esri. (2024b). *Esri and geospatial artificial intelligence (GeoAI)* [White paper]. https://downloads.regulations.gov/DOC-2024-0007-0022/attachment_1.pdf

Esri. (2024c). *Machine learning and AI: Use spatial algorithms for analysis*. https://www.esri.com/en-us/arcgis/products/spatial-analytics-data-science/capabilities/machine-learning-ai

Ester, M., Kriegel, H. P., Sander, J., & Xu, X. (1996). A density-based algorithm for discovering clusters in large spatial databases with noise. In *Proceedings of the 2nd International Conference on Knowledge Discovery and Data Mining* (pp. 226-231). AAAI Press.

Fan, C., Zhang, C., Yahja, A., & Mostafavi, A. (2021). Disaster City Digital Twin: A vision for integrating artificial and human intelligence for disaster management. *International Journal of Information Management*, *56*, 102049. https://doi.org/10.1016/j.ijinfomgt.2019.102049

Fotheringham, A. S., & Oshan, T. M. (2016). Geographically weighted regression and multicollinearity: Dispelling the myth. *Journal of Geographical Systems*, *18*(4), 303-329. https://doi.org/10.1007/s10109-016-0239-5

Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2002). *Geographically weighted regression*. Wiley.

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, 1189-1232.

Gao, S., Hu, Y., & Li, W. (2023). Introduction to the special issue on GeoAI for geographic knowledge discovery. *GeoInformatica*, *27*, 1-5. https://doi.org/10.1007/s10707-022-00479-7

Ghaffarian, S., Rezaie Farhadabad, A., & Kerle, N. (2023). Post-disaster recovery monitoring with Google Earth Engine. *Applied Geography*, *108*, 102552. https://doi.org/10.1016/j.apgeog.2023.102552

Glorot, X., Bordes, A., & Bengio, Y. (2011). Deep sparse rectifier neural networks. *AISTATS*, 315-323.

Goodchild, M. F. (2007). Citizens as sensors: The world of volunteered geography. *GeoJournal*, *69*(4), 211-221. https://doi.org/10.1007/s10708-007-9111-y

Goodchild, M. F. (2010). Twenty years of progress: GIScience in 2010. *Journal of Spatial Information Science*, *1*(1), 3-20. https://doi.org/10.5311/JOSIS.2010.1.2

Goodchild, M. F. (2011). Scale in GIS: An overview. *Geomorphology*, *130*(1-2), 5-9.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18-27. https://doi.org/10.1016/j.rse.2017.06.031

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 770-778). IEEE. https://doi.org/10.1109/CVPR.2016.90

Hengl, T., Nussbaum, M., Wright, M. N., Heuvelink, G. B., & Gräler, B. (2018). Random forest as a generic framework for predictive modeling of spatial and spatio-temporal variables. *PeerJ*, *6*, e5518. https://doi.org/10.7717/peerj.5518

Hinton, G., Vinyals, O., & Dean, J. (2015). Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*. https://arxiv.org/abs/1503.02531

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, *9*(8), 1735-1780. https://doi.org/10.1162/neco.1997.9.8.1735

Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 4700-4708). IEEE. https://doi.org/10.1109/CVPR.2017.243

Human-centered GeoAI. (2025, February 5). *Human-centered GeoAI foundation models: Where GeoAI meets human dynamics*. Urban Informatics. https://link.springer.com/article/10.1007/s44212-025-00067-x

Imran, M., Castillo, C., Diaz, F., & Vieweg, S. (2020). Processing social media messages in mass emergency: A survey. *ACM Computing Surveys*, *47*(4), 1-38. https://doi.org/10.1145/2771588

Ioffe, S., & Szegedy, C. (2015). Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *Proceedings of the 32nd International Conference on Machine Learning* (pp. 448-456). PMLR.

Jakubik, J., Roy, S., Phillips, C. E., Fraccaro, P., Godwin, D., Zadrozny, B., Szwarcman, D., Gomes, C., Nyirjesy, G., Edwards, B., Kimura, D., Simumba, N., Chu, L., Sankaran, K., Lu, S., Watson, C., Hamann, H. F., & Ramasubramanian, M. (2024). Foundation models for generalist geospatial artificial intelligence. *arXiv preprint arXiv:2310.18660*. https://arxiv.org/abs/2310.18660

Janowicz, K., Gao, S., McKenzie, G., Hu, Y., & Bhaduri, B. (2020). GeoAI: Spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. *International Journal of Geographical Information Science*, *34*(4), 625-636. https://doi.org/10.1080/13658816.2019.1684500

Jiang, W. (2021). Graph neural networks for geospatial data. *SIGSPATIAL Special*, *13*(1), 21-28.

Jolliffe, I. T. (2002). *Principal component analysis* (2nd ed.). Springer.

Jouppi, N. P., Young, C., Patil, N., Patterson, D., Agrawal, G., Bajwa, R., Bates, S., Bhatia, S., Boden, N., Borchers, A., Boyle, R., Cantin, P., Chao, C., Clark, C., Coriell, J., Daley, M., Dau, M., Dean, J., Gelb, B., ... Yoon, D. H. (2017). In-datacenter performance analysis of a tensor processing unit. In *Proceedings of the 44th Annual International Symposium on Computer Architecture* (pp. 1-12). ACM. https://doi.org/10.1145/3079856.3080246

Kamel Boulos, M. N., Peng, G., & VoPham, T. (2019). An overview of GeoAI applications in health and healthcare. *International Journal of Health Geographics*, *18*, Article 7. https://doi.org/10.1186/s12942-019-0171-2

Kamel Boulos, M. N., Shi, J., & Zhang, P. (2024). Generative AI in medicine and healthcare: Moving beyond the 'peak of inflated expectations'. *Future Internet*, *16*(12), 462. https://doi.org/10.3390/fi16120462

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, *147*, 70-90. https://doi.org/10.1016/j.compag.2018.02.016

Karpatne, A., Atluri, G., Faghmous, J. H., Steinbach, M., Banerjee, A., Ganguly, A., Shekhar, S., Samatova, N., & Kumar, V. (2017). Theory-guided data science: A new paradigm for scientific discovery from data. *IEEE Transactions on Knowledge and Data Engineering*, *29*(10), 2318-2331. https://doi.org/10.1109/TKDE.2017.2720168

Khan, S. D., & Jung, Y. S. (2024). IARU-Net: A hybrid CNN-attention approach for remote sensing. *Remote Sensing*, *16*(4), 712.

Kingma, D. P., & Ba, J. (2015). Adam: A method for stochastic optimization. In *International Conference on Learning Representations*. https://arxiv.org/abs/1412.6980

Kipf, T. N., & Welling, M. (2017). Semi-supervised classification with graph convolutional networks. In *International Conference on Learning Representations*. https://openreview.net/forum?id=SJU4ayYgl

Kirillov, A., Mintun, E., Ravi, N., Mao, H., Rolland, C., Gustafson, L., Xiao, T., Whitehead, S., Berg, A. C., Lo, W. Y., Dollár, P., & Girshick, R. (2023). Segment anything. In *Proceedings of the IEEE/CVF International Conference on Computer Vision* (pp. 4015-4026). IEEE. https://doi.org/10.1109/ICCV51070.2023.00371

Krivoruchko, K., & Gribov, A. (2019). Evaluation of empirical Bayesian kriging. *Spatial Statistics*, *32*, 100368. https://doi.org/10.1016/j.spasta.2019.100368

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems* (Vol. 25, pp. 1097-1105). Curran Associates.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436-444. https://doi.org/10.1038/nature14539

LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, *86*(11), 2278-2324. https://doi.org/10.1109/5.726791

Li, W., Arundel, S. T., Gao, S., Hsu, C. Y., & Wang, S. (2024). GeoAI for science: A comprehensive review and roadmap. *Journal of Spatial Information Science*, *29*, 1-17. https://doi.org/10.5311/JOSIS.2024.29.234

Li, W., Lee, H., Wang, S., Hsu, C. Y., & Arundel, S. T. (2023). Assessment of a new GeoAI foundation model for flood inundation mapping. In *Proceedings of the 6th ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery* (pp. 102-109). ACM. https://doi.org/10.1145/3615886.3627747

Li, Y., Zhang, H., Xue, X., Jiang, Y., & Shen, Q. (2021). Deep learning for remote sensing image classification: A survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *8*(6), e1264. https://doi.org/10.1002/widm.1264

Lin, T. Y., Goyal, P., Girshick, R., He, K., & Dollár, P. (2017). Focal loss for dense object detection. In *Proceedings of the IEEE International Conference on Computer Vision* (pp. 2980-2988). IEEE. https://doi.org/10.1109/ICCV.2017.324

LinkedIn. (2023, November 8). *How can you differentiate between supervised and unsupervised GIS machine learning?* https://www.linkedin.com/advice/1/how-can-you-differentiate-between-supervised-9zmfc

LinkedIn. (2023). *Supervised vs. unsupervised learning in GIS*. https://www.linkedin.com/pulse/

Liu, B., Wu, H., Wang, Y., & Liu, W. (2022). Few-shot learning for remote sensing scene classification. In *2022 IEEE International Geoscience and Remote Sensing Symposium* (pp. 6968-6971). IEEE. https://doi.org/10.1109/IGARSS46834.2022.9883975

Liu, S., Li, H., Gao, M., Wen, Q., Wang, T., Liu, C., & Li, X. (2025). *Efficient remote sensing image classification using the novel STConvNeXt convolutional network*. Scientific Reports. https://www.nature.com/articles/s41598-025-92629-x

Long, J., Shelhamer, E., & Darrell, T. (2015). Fully convolutional networks for semantic segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 3431-3440). IEEE. https://doi.org/10.1109/CVPR.2015.7298965

MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. In *Proceedings of the 5th Berkeley Symposium on Mathematical Statistics and Probability* (Vol. 1, No. 14, pp. 281-297). University of California Press.

Mai, G., Hu, Y., Gao, S., Cai, L., Janowicz, K., Yan, B., Zhu, R., & Liu, N. (2022). Symbolic and subsymbolic GeoAI: Geospatial knowledge graphs and spatially explicit machine learning. *Transactions in GIS*, *26*(8), 3118-3124. https://doi.org/10.1111/tgis.13012

Mai, G., Huang, W., Sun, J., Song, S., Mishra, D., Liu, N., Gao, S., Liu, T., Cong, G., Hu, Y., Cundy, C., Li, Z., Zhu, R., & Lao, N. (2025). Towards the next generation of geospatial artificial intelligence. *International Journal of Geographical Information Science*. Advance online publication. https://doi.org/10.1016/j.isprsjprs.2025.01.015

Manfreda, S., McCabe, M. F., Miller, P. E., Lucas, R., Madrigal, V. P., Mallinis, G., Dor, E. B., Helman, D., Estes, L., Ciraolo, G., Müllerová, J., Tauro, F., de Lima, M. I., de Lima, J. L., Maltese, A., Frances, F., Caylor, K., Kohv, M., Perks, M., ... Toth, B. (2018). On the use of unmanned aerial systems for environmental monitoring. *Remote Sensing*, *10*(4), 641. https://doi.org/10.3390/rs10040641

Mapular. (n.d.). *GeoAI: AI meets geospatial data for smarter insights*. https://www.mapular.com/geospatial-glossary/geoai-02

McInnes, L., Healy, J., & Melville, J. (2018). UMAP: Uniform manifold approximation and projection for dimension reduction. *arXiv preprint arXiv:1802.03426*. https://arxiv.org/abs/1802.03426

Meyer, H., & Pebesma, E. (2021). Predicting into unknown space? Estimating the area of applicability of spatial prediction models. *Methods in Ecology and Evolution*, *12*(9), 1620-1633. https://doi.org/10.1111/2041-210X.13650

Meyer, H., Katurji, M., Appelhans, T., Müller, M. U., Nauss, T., Roudier, P., & Zawar-Reza, P. (2018). Mapping daily air temperature for Antarctica based on MODIS LST. *Remote Sensing*, *8*(9), 732. https://doi.org/10.3390/rs8090732

Meyer, H., Reudenbach, C., Hengl, T., Katurji, M., & Nauss, T. (2018). Improving performance of spatio-temporal machine learning models using forward feature selection and target-oriented validation. *Environmental Modelling & Software*, *101*, 1-9.

Mortaheb, R., & Jankowski, P. (2022). Smart city re-imagined: City planning and GeoAI in the age of big data. *Journal of Urban Management*, *11*(3), 259-279. https://doi.org/10.1016/j.jum.2022.08.001

Mou, L., Ghamisi, P., & Zhu, X. X. (2017). Deep recurrent neural networks for hyperspectral image classification. *IEEE Transactions on Geoscience and Remote Sensing*, *55*(7), 3639-3655. https://doi.org/10.1109/TGRS.2016.2636241

Mountrakis, G., Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, *66*(3), 247-259. https://doi.org/10.1016/j.isprsjprs.2010.11.001

Nature. (2025). *Enhanced hybrid CNN and transformer network for remote sensing*. https://www.nature.com/articles/s41598-025-94544-7.pdf

NVIDIA. (2024, November 24). *Into the omniverse: How smart city AI agents transform urban operations*. NVIDIA Blog. https://blogs.nvidia.com/blog/smart-city-a-i-agents-urban-operations/

Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., Desmaison, A., Kopf, A., Yang, E., DeVito, Z., Raison, M., Tejani, A., Chilamkurthy, S., Steiner, B., Fang, L., ... Chintala, S. (2019). PyTorch: An imperative style, high-performance deep learning library. In *Advances in Neural Information Processing Systems 32 (NeurIPS 2019)* (pp. 8024-8035). Curran Associates, Inc.

Pettorelli, N., Laurance, W. F., O'Brien, T. G., Wegmann, M., Nagendra, H., & Turner, W. (2014). Satellite remote sensing for applied ecologists: Opportunities and challenges. *Journal of Applied Ecology*, *51*(4), 839-848. https://doi.org/10.1111/1365-2664.12261

Raina, R., Madhavan, A., & Ng, A. Y. (2009). Large-scale deep unsupervised learning using graphics processors. In *Proceedings of the 26th Annual International Conference on Machine Learning* (pp. 873-880). ACM. https://doi.org/10.1145/1553374.1553486

Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat. (2019). Deep learning and process understanding for data-driven Earth system science. *Nature*, *566*(7743), 195-204. https://doi.org/10.1038/s41586-019-0912-1

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. In *Medical Image Computing and Computer-Assisted Intervention* (pp. 234-241). Springer. https://doi.org/10.1007/978-3-319-24574-4_28

Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence*, *1*(5), 206-215. https://doi.org/10.1038/s42256-019-0048-x

Salehi, S. S. M., Erdogmus, D., & Gholipour, A. (2017). Tversky loss function for image segmentation using 3D fully convolutional deep networks. *Machine Learning in Medical Imaging*, 379-387.

Scientific Reports. (2025, March 11). *Efficient remote sensing image classification using the novel STConvNeXt convolutional network*. Nature. https://www.nature.com/articles/s41598-025-92629-x

Selvaraju, R. R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., & Batra, D. (2017). Grad-CAM: Visual explanations from deep networks via gradient-based localization. In *Proceedings of the IEEE International Conference on Computer Vision* (pp. 618-626). IEEE. https://doi.org/10.1109/ICCV.2017.74

Sharma, N. (2023, June 27). *What is GeoAI?* Medium. https://medium.com/@ns_geoai/what-is-geoai-90af81c6d17e

Simonyan, K., & Zisserman, A. (2015). Very deep convolutional networks for large-scale image recognition. In *International Conference on Learning Representations*. https://arxiv.org/abs/1409.1556

Smith, L. N. (2017). Cyclical learning rates for training neural networks. In *2017 IEEE Winter Conference on Applications of Computer Vision* (pp. 464-472). IEEE. https://doi.org/10.1109/WACV.2017.58

Spyrosoft. (2024, August 21). *GIS and artificial intelligence: What is GeoAI?* https://spyro-soft.com/blog/geospatial/gis-and-artificial-intelligence-what-is-geoai

Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: A simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research*, *15*(1), 1929-1958.

Stewart, A. J., Robinson, C., Corley, I. A., Ortiz, A., Lavista Ferres, J. M., & Banerjee, A. (2022). TorchGeo: Deep learning with geospatial data. In *Proceedings of the 30th International Conference on Advances in Geographic Information Systems (SIGSPATIAL '22)* (pp. 1-12). ACM. https://doi.org/10.1145/3557915.3560953

Sun, W., Bocchini, P., & Davison, B. D. (2020). Applications of artificial intelligence for disaster management. *Natural Hazards*, *103*, 2631-2689. https://doi.org/10.1007/s11069-020-04124-3

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., & Rabinovich, A. (2015). Going deeper with convolutions. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 1-9). IEEE. https://doi.org/10.1109/CVPR.2015.7298594

Tan, M., & Le, Q. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. In *Proceedings of the 36th International Conference on Machine Learning* (pp. 6105-6114). PMLR.

The GIS Journal. (2025, February 9). *Integrating deep learning with GIS: GeoAI [2025]*. https://thegisjournal.com/integrating-deep-learning-with-gis-geoai-2025/

Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography*, *46*(sup1), 234-240. https://doi.org/10.2307/143141

Tuia, D., Persello, C., & Bruzzone, L. (2016). Domain adaptation for the classification of remote sensing data: An overview of recent advances. *IEEE Geoscience and Remote Sensing Magazine*, *4*(2), 41-57. https://doi.org/10.1109/MGRS.2016.2548504

Tuia, D., Roscher, R., Wegner, J. D., Jacobs, N., Zhu, X., & Camps-Valls, G. (2022). Toward a collective agenda on AI for Earth science data analysis. *IEEE Geoscience and Remote Sensing Magazine*, *10*(2), 88-104. https://doi.org/10.1109/MGRS.2022.3145254

van der Maaten, L., & Hinton, G. (2008). Visualizing data using t-SNE. *Journal of Machine Learning Research*, *9*, 2579-2605.

Viso.ai. (n.d.). *AI geospatial intelligence: Smarter urban planning*. https://viso.ai/applications/geospatial-intelligence-and-computer-vision-in-urban-planning/

VoPham, T., Hart, J. E., Laden, F., & Chiang, Y. Y. (2018). Emerging trends in geospatial artificial intelligence (GeoAI): Potential applications for environmental epidemiology. *Environmental Health*, *17*, Article 40. https://doi.org/10.1186/s12940-018-0403-9

Woo, S., Park, J., Lee, J. Y., & Kweon, I. S. (2018). CBAM: Convolutional block attention module. In *Proceedings of the European Conference on Computer Vision* (pp. 3-19). Springer. https://doi.org/10.1007/978-3-030-01234-2_1

Wu, A. (2025, February 26). *What is GeoAI?* Medium. https://medium.com/towards-data-science/what-is-geoai-9h7k4j2x

Wu, Q. (2025). GeoAI: A Python package for integrating artificial intelligence with geospatial data analysis and visualization. *Journal of Open Source Software*. Under review. https://github.com/opengeos/geoai

Wulder, M. A., Loveland, T. R., Roy, D. P., Crawford, C. J., Masek, J. G., Woodcock, C. E., Allen, R. G., Anderson, M. C., Belward, A. S., Cohen, W. B., Dwyer, J., Erb, A., Gao, F., Griffiths, P., Helder, D., Hermosilla, T., Hipple, J. D., Hostert, P., Hughes, M. J., ... Zhu, Z. (2022). Current status of Landsat program, science, and applications. *Remote Sensing of Environment*, *225*, 127-147. https://doi.org/10.1016/j.rse.2019.02.015

Yosinski, J., Clune, J., Bengio, Y., & Lipson, H. (2014). How transferable are features in deep neural networks? In *Advances in Neural Information Processing Systems* (Vol. 27, pp. 3320-3328). Curran Associates.

Zhang, C., Sargent, I., Pan, X., Li, H., Gardiner, A., Hare, J., & Atkinson, P. M. (2023). Joint deep learning for land cover and land use classification. *Remote Sensing of Environment*, *221*, 173-187. https://doi.org/10.1016/j.rse.2018.11.014

Zhang, L., Zhang, L., & Du, B. (2024). Deep learning for remote sensing data: A technical tutorial on the state of the art. *IEEE Geoscience and Remote Sensing Magazine*, *4*(2), 22-40. https://doi.org/10.1109/MGRS.2016.2540798

Zhang, P., Shi, J., & Kamel Boulos, M. N. (2024). Generative AI in medicine and healthcare: Moving beyond the 'peak of inflated expectations'. *Future Internet*, *16*(12), 462. https://doi.org/10.3390/fi16120462

Zheng, X., Wang, B., Du, X., & Lu, X. (2022). Mutual attention inception network for remote sensing visual question answering. *IEEE Transactions on Geoscience and Remote Sensing*, *60*, 1-14. https://doi.org/10.1109/TGRS.2021.3079918

Chapter 7

AGRİCULTURAL WATER FOOTPRİNTS İN THE WORLD AND TURKEY

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1.Introduction

Water is one of the most fundamental resources for the survival of life. With a growing population, climate change, and globalization, the pressure on freshwater resources is increasing. In this context, the concept of the water footprint is a key indicator of where, how, and how much water is used (Turan, 2017). The water footprint consists of three components: blue (surface and groundwater), green (rainwater), and gray (pollution-diluting water). The agricultural sector accounts for approximately 70% of freshwater use globally and 77% in Turkey (Yıldıran & Aydın, 2025). Therefore, studies on agricultural water footprints are critical for sustainable water management.

Global warming, population growth, and industrialization continue to increase pressure on natural resources. Water, one of the essential components of life, is now at risk of depletion. Every product we consume contains a significant amount of hidden water. This invisible consumption is referred to as the water footprint (Hoekstra et al., 2011).The water footprint represents the total amount of freshwater used directly and indirectly by an individual, a society, or the production of a product. For example, although a cup of coffee contains only a small amount of water, approximately 140 liters of water are used in producing the coffee beans (Mekonnen & Hoekstra, 2010). This study aims to examine the concept of the water footprint, its calculation methods, sectoral effects, and strategies for reducing water use for a sustainable future. The rapidly growing global population, global climate change, and pressures on natural resources necessitate the adoption of sustainable practices in agricultural production. The agricultural sector is critically important for both its impact on natural resources and ecosystems. Establishing and expanding sustainable systems is crucial for the continued productivity of the agricultural sector and its critical role in global food security. The agricultural sector plays a significant role in maintaining a healthy and balanced human diet and food security (Doğan and Doğan, 2020). Therefore, agriculture, which can be defined as the production, storage, processing, and marketing of plant and animal products, is a sector of strategic importance for all countries, regardless of their level of development (Acıbuca et al., 2021).

Sustainable agriculture is an approach that aims to protect ecosystems and sustain agricultural production over the long term by using resources efficiently and minimizing environmental impacts (Gomiero et al., 2011). Examples of sustainable agricultural practices include crop rotation systems, organic farming, integrated pest management, and precision agriculture techniques (Pretty and Bharucha, 2014). These methods offer a model for achieving economic, social, and environmental balance in agricultural production. However, water availability is the primary component of agricultural production, and considering the world's dwindling water resources, more efficient use of water has become an increasingly important phenomenon. In this context, the concept of "water footprint" has emerged as an effective tool for understanding and managing the impact of agricultural activities on water resources.

The water footprint represents the total amount of water consumed during the production process of a product or service (Hoekstra and Chapagain, 2009). This concept is often divided into three main components: blue, green, and gray water. Blue water represents water consumed from surface and groundwater sources, green water represents rainwater stored in the soil, and gray water represents the amount of contaminated water that needs to be reused (Lovarelli et al., 2016).

Agricultural production, which accounts for a significant portion of these components, is a prominent sector in the global distribution of the water footprint. Water footprint analyses identify vulnerabilities in production processes and enable the development of water-saving strategies. This method also plays a critical role in agricultural activities' adaptation to climate change and sustainable food security (Deepa et al., 2021).

This review aims to clarify the assessment of the water footprint measurement and management in agricultural production and to understand its future position.

2.Global Agricultural Water Footprint

Agriculture is the largest user of freshwater resources worldwide. While agricultural water use is lower in developed countries thanks to modern irrigation techniques, it is significantly higher in developing countries. Global agricultural production is under significant pressure due to climate change and the unbalanced distribution of water resources. Dependence on blue water, particularly in arid regions, is increasing, leading to sustainability challenges (Turan, 2017).

The global decline in water resources has led countries to consider the amount of water consumed in the production of imported and exported goods. To explain this concept, Tony Allan coined the term "virtual water" in the early 1990s. Virtual water refers to the total amount of water consumed in the production of a good or service (Chapagain and Hoekstra, 2003). When a product is transferred from one country to another as an import or export item, the amount of water used in the process is considered, thus engaging in virtual water trade. This situation contributes to the conservation of water resources in water-scarce countries by importing products with high virtual water content from other countries instead of producing them. Conversely, countries with high water resources can transform their water resources into added value by producing and exporting agricultural products with high virtual water content, thereby enhancing their economies (Hoekstra and Hung, 2002)

3.The Water Footprint Concept And Types

The water footprint, developed by Prof. Arjen Hoekstra, quantifies the total freshwater used in the production and consumption of goods and services. It considers both direct and indirect water use throughout the supply chain (Hoekstra et al., 2011). Water footprint consists of three main components:

3.1. Blue Water Footprint

Freshwater withdrawn from surface and groundwater sources. Common in agricultural irrigation, industrial production, and domestic use. Industrial sectors (20% of global water use) consume water for cooling, cleaning, and processing. The textile sector, especially cotton-based products, has high water footprint values due to irrigation and dyeing processes (WWF, 2020).

3.2. Green Water Footprint

Rainwater stored in soil and absorbed by plants, particularly important in agriculture.

3.3. Grey Water Footprint

The amount of freshwater required to dilute pollutants to acceptable environmental standards (Mekonnen & Hoekstra, 2010). Energy production—particularly thermal power plants and biofuel crops—also contributes significantly to water consumption.

4. Water Footprint Calculation and Examples

A water footprint calculation is calculated by summing the amount of water used directly and indirectly by a product or activity throughout its life cycle. These calculations take into account different sectors and types of use, such as agriculture, industry, services, and individual consumption. The methodology developed by the Water Footprint Network (WFN) has standardized this measurement on a global scale (Hoekstra et al., 2011).

The calculation consists of three basic steps:

a. Life Cycle Analysis (LCA): Water use in all processes, from raw materials to consumption, is examined.

b. Differentiating Water Footprint Types: Water consumption at each stage is classified as blue, green, and gray water.

c. Determining Total Water Amount: The sum of all water types used gives the total water footprint of the product or process.

5. Examples from Daily Life

A Cup of Coffee: 140 Liters of Water

A cup of coffee contains an average of 7 grams of roasted coffee. Approximately 140 liters of water is used to produce this amount (Mekonnen & Hoekstra, 2010). The majority of this water is green water used during the cultivation of the coffee beans.

1 kg of Beef: 15,000 Liters of Water

The water footprint of meat products is quite high due to factors such as the production of the feed consumed by the animal throughout its life and its housing conditions. Approximately 99% of the water required for 1 kilogram of beef goes into agricultural feed production (Hoekstra, 2008).

One Pair of Jeans: 7,000–10,000 Liters of Water

Approximately 1 kilogram of cotton is required for one pair of jeans. Cotton production requires a significant amount of irrigation, resulting in a high water footprint. Furthermore, the production and dyeing processes also consume gray water (WWF, 2020).

One Slice of Bread: 40 Liters of Water

The stages from growing the wheat used for one slice of bread to baking it require a total of approximately 40 liters of water (FAO, 2017).

6. Personal Water Footprint

An individual’s daily water footprint is determined not so much by the water they drink as by the food they consume, the clothes they wear, and the energy they use. According to the global average, an individual’s total daily water footprint is approximately 3,800 liters, nearly enough to fill a small swimming pool (Hoekstra et al., 2011). This figure is much higher in developed countries.

7 .Efforts to Reduce the Water Footprint of Agricultural Production in the World and Türkiye

Turkey’s total water footprint is approximately 140 billion cubic meters per year. Green water accounts for 64% of this, blue water for 19%, and gray water for 17% (Turan, 2017). The agricultural sector accounts for the largest share of water consumption, at 89%. Turkey’s annual per capita water availability is estimated at 1,340 cubic meters, placing the country in the water-stressed category (Yıldıran & Aydın, 2025).

Agriculture is responsible for about 70% of global freshwater consumption (FAO, 2017). Crops such as rice, wheat, and corn require substantial green and blue water. Livestock production significantly increases water footprints due to feed cultivation.

When evaluated on a product-by-product basis, grains account for the largest share of Turkey's agricultural water footprint at 57%. This is followed by vegetables (15%), oilseed crops (9%), industrial crops (8%), and fruits (4%) (Yıldıran & Aydın, 2025). Strategic crops such as cotton, wheat, and hazelnuts are critical to Turkey's water footprint.Another critical issue arising from climate change is the depletion of water resources. Furthermore, one of the critical issues highlighted in the report is the concept of the water footprint. The use of traditional and modern techniques for the efficient use of water resources, particularly in arable farming, is crucial. In this regard, the establishment of rotation systems appropriate to the region's ecology (Yue et al., 2023), the development of conservation tillage methods (Chandra et al., 2023), good agricultural practices (Borsato et al., 2018), the use of efficient irrigation systems, and the use of modern technologies, including precision agriculture practices (Singh et al., 2022), stand out as prominent topics.

Shrestha et al. (2013) used local meteorological, agronomic, and irrigation data at high spatial resolution to perform a water footprint analysis for the production of nine crops (wheat, rice, maize, millet, potato, sugarcane, lentil, pulses, mustard seed, and vegetables) in Nepal, according to the global water footprint standard (Hoekstra et al., 2011). Similarly, Chapagain and Hoekstra (2011) measured freshwater use for rice production at the global level. For this purpose, the authors distinguished between two different sources: irrigation water abstracted from groundwater or surface water (blue water) and rainwater (green water), and also calculated the volume of water polluted by agricultural nitrogen use.

Mekonnen and Hoekstra (2010) and Hoekstra (2011) examined the water footprint of numerous crops and processes, assessing agriculture at a high spatial resolution. Their results indicated that maize had the lowest water footprint (1222 m^3/t), while wheat had the highest (1827 m^3/t). Rice's water footprint (1644 m^3/t) was close to the average. Sugar crops and vegetables had low water footprints of 200 and 300 m^3/t, respectively. Fruits reached 1000 m^3/t, and oil crops 2400 m^3/t. Pulses, spices, and nuts required higher volumes, ranging from 4000 to 9000 m^3/t, respectively. They calculated the water footprint of pasta production. The results showed that the most effective stages were durum wheat cultivation (average 1.644 dm^3/kg pasta) and cooking (10 dm^3/kg pasta). In particular, the water footprint of pasta produced in Italy and Türkiye ranged from 1,336 dm^3/kg and 2,847 dm^3/kg, respectively. The graywater footprint ranged from 72% of the total water footprint in the United States (balanced by high bluewater) to 91% in Türkiye (Lovarelli et al., 2016). Yue et al. (2023) compared six different rotation systems in a field study and reported that a regionally appropriate cropping pattern reduced the carbon footprint and water footprint. Chandra et al. (2022) examined the effects of different planting methods and fertilization practices and found that the practices resulted in positive results on soil carbon and health, as well as carbon and water footprints. Rahman et al. (2021) reported that reduced tillage increased carbon sequestration up to 10-fold compared to conventional methods, and that conservation tillage methods also allowed for water footprint reduction. Nasseri (2023) reported that conservation tillage increases crop productivity while reducing water footprint in wheat farming. Jin et al. (2023) conducted a field study in China between 2018 and 2020, focusing on different planting methods and rice-rapeseed rotations. They determined that planting on dry land contributed to reducing the water footprint. Barsato et al. (2018) examined the effects of tillage, rotation, and different fertilizer applications on the graywater footprint and demonstrated that soil pollution can be reduced through appropriate tillage methods without sacrificing yield. They also determined that precision agriculture practices reduce the graywater footprint.

8.Water use in the global and Turkish agricultural sectors.

When comparing water use in the global agricultural sector with Turkey's, it is seen that Turkey's agricultural water consumption is above the global average. The intensive use of blue water, especially in arid regions, increases pressure on freshwater resources in Turkey. Conversely, in some regions, the use of green water is more advantageous for production. This reveals differences in water footprints based on regional climate and crop patterns (Turan, 2017; Yıldıran & Aydın, 2025).

Water resources are not distributed equally across regions worldwide. Therefore, it is not possible to accurately calculate the average amount of water per capita and varies significantly by region. For Turkey, the average water potential is expressed as 183 billion m^3, and the target is to increase this to 190 billion m^3 by the end of the year (DSI, 2024). Meanwhile, the total amount of usable water provided by 25 basins in Turkey is calculated as 25 billion m3 (DSI, 2020). According to assessments conducted by the United Nations World Water Assessment Program (UNWWAP), 70% of global freshwater resources are consumed through agriculture, 20% through industry, and the remaining 10% through domestic use. These rates vary from developed to underdeveloped countries, and increased industrial activity in developed countries results in higher water consumption.

In many underdeveloped countries around the world, more than 90% of their total water consumption is used in agriculture (UNWWAP, 2014). According to DSI (2020) data, 44 billion m^3 (77%) of Turkey's 57 billion m^3 freshwater potential is allocated to agriculture, while the remaining 13 billion m^3 (23%) is allocated to industry and domestic use (Anonymous, 2013, 2021a, 2021b).

The concept of a water footprint sheds light on the amount of water consumed during the production process, providing detailed and in-depth information about each step. Furthermore, the concept of a water footprint is an indicator of the direct and indirect use of fresh water by consumers or producers (Hoekstra et al., 2009). While virtual water indicates the amount of water used in a product's production process, the concept of a water footprint reflects not only the amount but also the type of water used (blue, green, and gray) and when and where it is used. Therefore, the concept of a water footprint provides much more detailed information than the concept of virtual water (Şahin, 2018). A blue water footprint indicates the amount of groundwater and surface water used in a product's production process, while a green water footprint indicates the amount of rainwater used (Mekonnen and Hoekstra 2010).

The greywater footprint is an indicator that measures the indirect impact of a product, service, or human activity on water resources. Specifically, it refers to the amount of clean water required to dilute the pollutants used in a production process or activity. In other words, it calculates the amount of water required to recycle polluted water without harming the environment (Hoekstra et al., 2009).

9.Sustainability and Future Perspectives

Increasing water efficiency in agriculture is a priority for the sustainability of water resources in Turkey. Expanding modern irrigation techniques, planning crop patterns according to climate and water potential, and increasing practices such as rainwater harvesting are crucial. Furthermore, importing water-intensive products through virtual water trade can contribute to reducing pressure on water resources (Turan, 2017).

Sustainable agriculture, by definition, requires a continuous process of optimization. This concept has gained prominence alongside the concept of sustainable development since the publication of the Brundtland Report in 1987 (Tait and Morris, 2000). MacRae et al. (1989) defined sustainable agriculture as management procedures that work with natural processes to conserve all resources, minimize waste and environmental impacts, prevent problems, and promote agroecosystem resilience, self-regulation, evolution, and continuous production for the nourishment and fulfillment of all. Reganold et al. (1990) argued that for a farm to be sustainable, it must produce sufficient quantities of high-quality food, conserve its resources, and be both environmentally safe and profitable. They stated that a sustainable farm would rely as much as possible on beneficial natural processes and renewable resources derived from the farm itself, rather than relying on purchased materials such as fertilizer. However, similar definitions have not been definitively agreed upon (Velten et al., 2015).

The need for a sustainable agriculture concept stems from factors such as the depletion or toxicity of natural resources, alarming global food security, combating climate change, the need to protect ecosystems, and economic and social contributions (Khan et al., 2021). From this perspective, the primary goals of sustainable agricultural systems can be listed as follows:

Reducing the use of chemical fertilizers and pesticides,

Preserving and increasing biodiversity,

Supporting local production and consumption,

Improving the socioeconomic levels of producers,

Adapting to climate change and encouraging the development of modern production techniques,

Achieving food security by preventing food waste,

Increasing the use of renewable energy sources

While each of these primary objectives is of critical importance, water is the primary material of agriculture, just as it is the source of life. The most important factor determining the cropping patterns, productivity, and contribution to the food supply in a region is the region's water availability and the success of its irrigation systems (Pimentel et al., 1997; Marothia, 2003; Sauer et al., 2010; Pereira, 2017). Therefore, the use and proper management of water resource conservation systems are of critical importance. For the effective use and proper management of water resources, it is necessary to calculate the amount of water used in all processes, from the production of any agricultural product to its transportation, thus meticulously identifying areas within the system where savings are needed. The primary reason for the acceleration of research on the water footprint in agricultural production is precisely because it contributes to the proper management of this process.

10. Conclusion And Recommendations

Water is essential for all living organisms. Ensuring the sustainability of water resources is one of the major global challenges of the 21st century. Population growth, climate change, pollution, and overuse threaten water security.

Water footprint studies are a critical indicator of water management in Turkey and globally. Turkey's limited water resources necessitate sustainable water use in agricultural production. Therefore, developing policies to reduce the water footprint is crucial for ensuring a safe water supply for future generations. The essential elements for the continuity of sustainable agriculture include protecting water resources, expanding renewable energy sources, reducing carbon emissions, and preserving soil health and biodiversity. Water resources, which form the foundation of agriculture and life, are increasingly vital. Therefore, considering the water footprint concept, which allows for the calculation of water consumption at each stage of agricultural production and the development of appropriate strategies, forms the basis of proper water and land management.

By 2050, the global population will reach 9.4 billion, and nearly 3.76 billion people will face severe water-related problems. Water scarcity affects food security, energy, biodiversity, and climate resilience. In the coming years, planning will become essential to determine which regions offer the most advantageous water footprints for producing a given crop. Research reveals that despite equal yields, there are still differences in water resources used. Clearly identifying crop patterns based on the water potential of different regions, enabling more efficient use of water resources, will enable the preservation of underground resources and increased income for regional producers. Strategies and innovative approaches supporting sustainable agriculture will be a cornerstone of future agricultural policies. In this context, the water footprint concept will serve as an indispensable guide for both agricultural producers and decision-makers.

References

Acıbuca, V., Doğan, S., Doğan, Y. (2021). Midyat/Mardin ilçesinde tarımsal faaliyetlerin SWOT analizi. Bahri Dağdaş Bitkisel Araştırma Dergisi,11 (2): 173-179, 2022.

Anonim. (2013). Devlet Su İşleri 2012 Faaliyet Raporu. Erişim tarihi 2025,erişim adresi https://www.dsi.gov.tr/Sayfa/Detay/759

Anonim. (2021a). Devlet Su İşleri 2020 Faaliyet Raporu. Erişim tarihi 2025,erişim adresi https://www.dsi.gov.tr/Sayfa/Detay/759

Anonim. (2021b). Su ve Atıksu İstatistikleri. Türkiye İstatistik Kurumu.Erişim tarihi 2025, erişim adresi https://data.tuik.gov.tr/Bulten/Index?p=Su-ve-Atiksu-Istatistikleri- 2020-37197.

Borsato, E., Galindo, A., Tarolli, P., Sartori, L. & Marinello, F. (2018). Evaluation of the greywater footprint comparing the ındirect effects of different agricultural practices. Sustainability, 10: 3992.

Chandra, M. S., Naresh, R. K., Bhatt, R., Manisha, Gourkhede, P. H., Kumar,R., Kadam, P. V. & Gawdiya, S. (2023). Impact of tillage cum cropestablishment methods and nutrient management strategies on wetrice (*Oryza sativa* L): crop productivity, water footprint, soil healthand profitability in typic Ustochrept soils under semiarid subtropical environment. Paddy and Water Environment, 21: 165-179.

Chapagain, A. K. & Hoekstra, A. Y. (2003). Virtual water flows between nations in relation to trade in livestock and livestock products (Vol. 13). Delft, The Netherlands.

Doğan, Y. & Doğan, S. (2020). Koronavirüs Pandemisi ve Türkiye'de Bitkisel Üretime Etkisi, Artuklu Kaime Uluslararası İktisadi ve İdari Araştırmalar Dergisi, 3(1), 56-78.

Deepa, R., Anandhi, A. & Alhashim, R. (2021). Volumetric and impactoriented water footprint of agricultural crops: A review. Ecological Indicators, 130: 108093.

FAO (2017). Water for Sustainable Food and Agriculture. Food and Agriculture Organization of the United Nations.

Gomiero, T., Pimentel, D. & Paoletti, M. G. (2011). Is there a need for a more sustainable agriculture? Critical reviews in plant sciences, 30(1-2): 6- 23.

Hoekstra, A. Y. (2011). The water footprint assessment manual: Setting the global standard. Routledge.

Hoekstra, A. Y., Chapagain, A., Martinez-Aldaya, M. & Mekonnen, M. (2009). Water footprint manual: State of the art.

Hoekstra, A. Y. & Hung, P. Q. (2002). Virtual water trade: A quantification of virtual water flows between nations in relation to international crop trade. Research Report Series No. 11, Da Delft, Netherlands.

Jin, Z., Liao, W., Mu, Y., Li, Y. & Nie, L. (2023). Integrated assessment of water footprint and energy production efficiency in different rice-rape rotation systems. Energy, 266: 126535.

Khan, N., Ray, R. L., Sargani, G. R., Ihtisham, M., Khayyam, M. & Ismail, S. (2021). Current progress and future prospects of agriculture technology: Gateway to sustainable agriculture. Sustainability, 13(9): 4883.

Lovarelli, D., Bacenetti, J. & Fiala, M. (2016). Water Footprint of crop productions: A review. Science of the total environment, 548: 236- 251.

MacRae, R. J., Hill, S. B., Henning, J. & Mehuys, G. R. (1989). Agricultural science and sustainable agriculture: a review of the existing scientific barriers to sustainable food production and potential solutions. Biol. Agric. Hortic., 6: 173-219.

Marothia, D. K. (2003). Enhancing sustainable management of water resource in agriculture sector: the role of institutions. Indian Journal of Agricultural Economics, 58(3): 406-426.

Mekonnen, M. M. & Hoekstra, A. Y. (2010). A global and high-resolution assessment of the green, blue and grey water footprint of wheat. Hydrology and earth system sciences, 14(7): 1259-1276.

Mekonnen, M. M. & Hoekstra, A. Y. (2011). The green, blue and grey water footprint of crops and derived crop products. Hydrology and earth system sciences, 15(5): 1577-1600.

Nasseri, A. (2023). Water footprint in wheat production under conservation tillage. Archives of Agronomy and Soil Science, 69(14): 3362-3374.

Pereira, L. S. (2017). Water, agriculture and food: challenges and issues. Water Resources Management, 31(10): 2985-2999.

Pimentel, D., Houser, J., Preiss, E., White, O., Fang, H., Mesnick, L., Barsky, T., Tariche, S., Schreck, J. & Alpert, S. (1997). Water resources: agriculture, the environment, and society. BioScience, 47(2): 97-106.

Pretty, J. & Bharucha, Z. P. (2014). Sustainable intensification in agricultural systems. Annals of botany, 114(8): 1571-1596.

Rahman, M., Aravindakshan, S., Hoque, M. A., Rahman, M. A., Gulandaz, A., Rahman, J. & Islam, T. (2021). Conservation tillage (CT) for climate-smart sustainable intensification: Assessing the impact of CT on soil organic carbon accumulation, greenhouse gas emission and water footprint of wheat cultivation in Bangladesh. Environmental and Sustainability Indicators 10: 100106.

Reganold, J. P., Papendick, R. I. & Parr, J. F. (1990). Sustainable Agriculture. Sci. Am., 262: 112-120.

Sauer, T., Havlík, P., Schneider, U. A., Schmid, E., Kindermann, G. & Obersteiner, M. (2010). Agriculture and resource availability in a changing world: The role of irrigation. Water Resources Research, 46: W06503.

Shrestha, S., Pandey, V. P., Chanamai, C., & Ghosh, D. K. (2013). Green,blue and grey water footprints of primary crops production in Nepal. Water resources management, 27, 5223-5243

Singh, V. K., Rajanna, G. A., Paramesha, V. & Upadhyay, P. K. (2022).Agricultural water footprint and precision management. In: P. Kumar, A.K. Pandey, S.K. Singh, S.S., Sighn, V.K. Sighn (eds.) Sustainable Agriculture Systems and Technologies, John Wiley & Sons Ltd.

Şahin, H. (2018). Su ayak izi kavramının sürdürülebilir su yönetimi çalışmalarında kullanılması. Yüksek lisans tezi, Akdeniz Üniversitesi, Fen Bilimleri Enstitüsü, Antalya.

Tait, J. & Morris, D. (2000). Sustainable development of agricultural systems: Competing objectives and critical limits. Futures, 32: 247-260.

Turan, E. S. (2017). Türkiye'nin su ayak izi değerlendirmesi. Turk Hij Den Biyol Derg, 74(EK-1),55-62.https://doi.org/10.5505/TurkHijyen.2017.29592.

Velten, S., Leventon, J., Jager, N. & Newig, J. (2015). What is sustainable agriculture ? Systematic Review. Sustainability, 7(6): 7833-7865 Yue, Q., Sheng, J., Cheng, K., Zhang, Y., Guo, Z. & Sun, G. (2023).

WWF (2020). The Hidden Cost of Cotton. World Wide Fund for Nature.

Yıldıran, R., & Aydın, Y. (2025). Agricultural Water Footprint Status of Türkiye. Agro-Science Journal of Iğdır University, 3(1), 38-48. https://dergipark.org.tr/tr/pub/iutbd.

Yue, Q., Sheng, J., Cheng, K., Zhang, Y., Guo, Z. & Sun, G. (2023).Sustainability assessment on paddy-upland crop rotations by carbon, nitrogen and water footprint integrated analysis: A field scale investigation. Journal of Environmental Management, 339: 117879.

Chapter 8

APPROACHES FOR MANAGING WATER STRESS IN GREENHOUSE VEGETABLE CULTIVATION

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INTRODUCTION

Greenhouses are a controlled environment that protects plants from negative weather conditions and harmful pests. It also makes it possible to grow crops outside of the usual growing season. While this production system offers significant advantages for sustainable and high-yield vegetable cultivation throughout the year, it requires careful management of environmental conditions. Vegetable species, especially, are susceptible to physiological stress due to their short development periods, high metabolic activities, and sensitivity to environmental conditions. Stress factors such as heat, light, water, salinity, and nutrient deficiencies reduce photosynthetic efficiency, result in losses in flowering and fruit set, and significantly limit final yield. These loss can be prevented with proper and applicable stress management. In greenhouse vegetable cultivation, rather than eliminating stress factors entirely, managing these stresses correctly and effectively is a more realistic and important approach (Li et al. 2022).

In conventional greenhouse cultivation, physiological stresses are mostly reduced through reactive methods that can be implemented immediately after a problem arises, such as shading, ventilation, or standard irrigation regimes. However, extreme and sudden temperature/humidity changes, salinity problems, and similar environmental pressures associated with climate change can cause permanent damage to plant metabolism (Nahar et al., 2013). Under these conditions, reactive intervention methods alone are often insufficient (Kittas and Bartzanas 2007). When plants face increasing stress, the symptoms are mild at first. However, if timely measures are not taken, these damages can worsen and become permanent (Moustaka and Moustakas 2023).

Changing production conditions clearly demonstrate that immediate interventions alone are insufficient today. Therefore, it is emphasized that stress management should be approached as an integrated and sustainable strategy encompassing the entire production process, from seed planting to harvest (Fahad et al. 2017). Completely eliminating stress in modern production methods is generally not possible. However, it has been proven that yield losses can be significantly reduced with an effective management strategy (Kumari et al. 2022).

With this in mind, water stress, one of the most common and economically critical abiotic stress factors in greenhouse vegetable cultivation, will be discussed in detail in this section. In addition, applicable modern approaches to water stress management and their scientific basis will be evaluated.

1. PHYSIOLOGICAL BASES OF WATER STRESS IN GREENHOUSE VEGETABLE CULTIVATION

Water is the most important compound involved in fundamental processes such as photosynthesis and respiration in plants. It is also essential for the occurrence of intracellular physiological activities, the maintenance of intracellular turgor, and the uptake and transport of nutrients. Greenhouse vegetable production is usually carried out in regions with sufficient water resources to prevent water from becoming a stress factor. However, errors in the amount and timing of irrigation, as well as the characteristics of the soil and/or growing medium, can cause stress conditions in plants in the form of both water deficiency (drought) and water excess. Water deficiency or overwatering can cause a disruption in the physiological balance of plants and result in plant losses. In this context, water stress is generally examined under two headings: "drought stress" and "excess water and oxygen deficiency."

1.1. Drought Stress in Greenhouse Vegetables

Drought stress in plants begins when the volumetric water content in the soil falls to between the 10-20% level, depending on the soil texture (Fu et al. 2008). Due to water deficiency in the soil, water and water-soluble nutrients cannot penetrate the plant through the absorbent hairs in the root hairs (Farooq et al. 2008). Since there is not enough water entering the cells, turgor cannot be maintained (Anjum et al. 2011). Consequently, cellular events such as cell expansion, cell division, organelle movement, and the transfer of nutrients within In photosynthesis, H^+ from water is required for energy and nutrient production (Barber 2017) (Figure 1). In respiration, water is necessary for the formation of H^+ bonds in the structure of ATP (Prieß et al. 2018). Under water stress conditions caused by water deficiency, these two most important processes in plants (photosynthesis and respiration) slow down and their efficiency decreases (Qiao et al. 2024). As a result of the inability to carry out these two processes and produce sufficient nutrients, events such as leaf area reduction, failure to form shoots, small fruit formation, flower drop, and shortened plant height are observed in plants, especially in greenhouse vegetables (Farooq et al. 2008) (Figure 1).

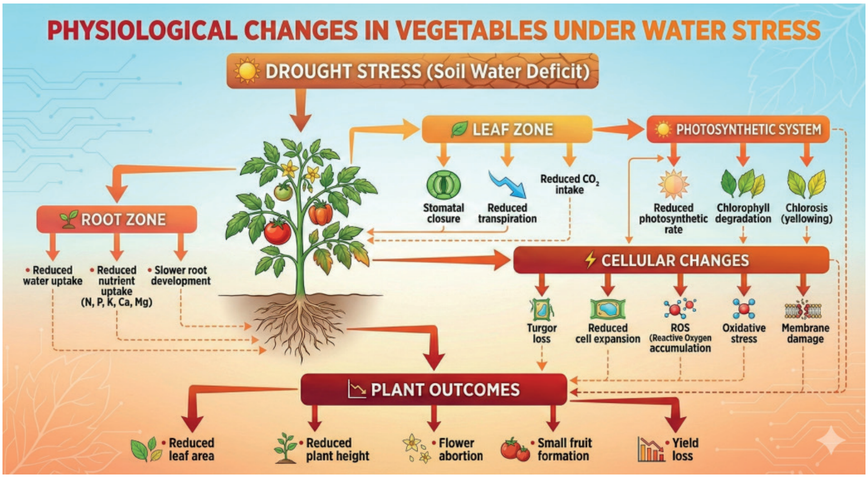

Figure 1: *Physiological changes in vegetables under drought stress . This schematic representation has been prepared as an illustrative example based on previously published studies (Anjum et al. 2011, Barber 2017, Qiao et al. 2024, Farooq et al. 2008, Razi and Muneer 2021)*

Stomata close partially or completely in response to drought stress to reduce water loss through transpiration (Gupta et al. 2020) (Figure 2). This closure restricts CO_2 entry, leading to a decrease in photosynthesis rate (Qiao et al. 2024, Farooq et al. 2008) (Figure 1) (Figure 2). During prolonged drought periods, oxidative stress occurs due to damage to photosynthetic pigments and the accumulation of reactive oxygen species (ROS). These conditions can lead to irreversible damage in leaves, such as chlorosis (yellowing) and necrosis (tissue death) (Qiao et al. 2024, Razi and Muneer 2021).

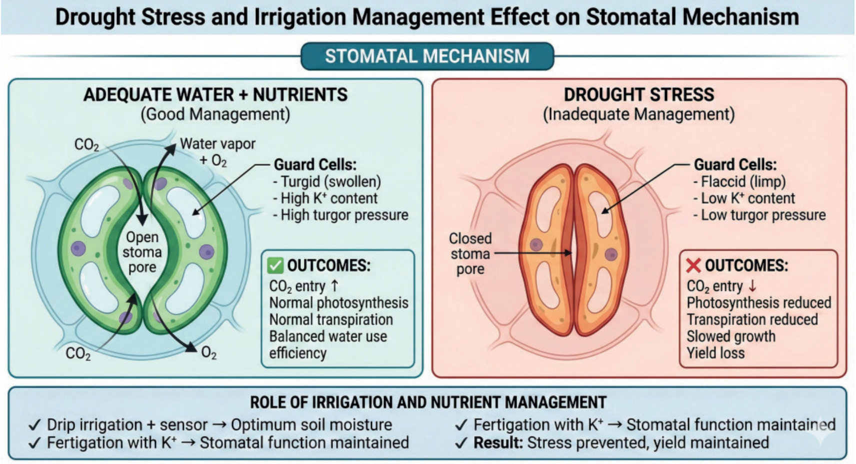

Figure 2: *Drought stress and irrigation management effect on stomatal mechanism. This schematic representation has been prepared as an illustrative example based on previously published studies (Gupta et al. 2020, Mubashir et al. 2023, Qiao et al. 2024, Farooq et al. 2008)*

When there is a lack of water in the soil and, as a result, nutrients cannot be transferred to the plant, nutrient deficiencies occur in plants. For example, studies have reported that water stress in tomatoes reduces the uptake of essential nutrients, particularly nitrogen and potassium, leading to chlorosis in leaves and stunted growth (Mubashir et al. 2023, Lyu et al. 2025). Another study found that drought applied during the flowering and fruit development stages in greenhouse tomato cultivation reduced yield by 13% and 26%, respectively (Cui et al. 2020). Furthermore, under low irrigation conditions in tomatoes, plant height decreased by 20%, leaf area by 50%, fresh shoot weight by 43%, and chlorophyll content by 17% (Turan et al. 2023, Yıldız and Aki 2025). On the other hand, in eggplant, it has been observed that it reduces cell membrane stability and leaf water content and triggers deficiencies in micronutrients such as zinc, and these deficiencies negatively affect photosynthetic efficiency and fruit yield (Semida et al. 2021). Similarly, in peppers and cucumbers, water deficiency has been reported to cause a decrease in macro- and micronutrients (e.g., calcium, magnesium) in plant tissues and lead to physiological disorders (Schwarz et al. 2010). Consequently, nutrient deficiencies associated with water scarcity cause significant losses in both growth and product quality in these vegetables (Kim et al. 2022, Mubashir et al. 2023).

1.2. Overwatering and Oxygen Deficiency in Greenhouse Vegetables

Plants may experience a variety of problems in greenhouse cultivation due to insufficient drainage, heavy soils, and incorrect irrigation methods. The soil moisture content should generally be between 40-60% by volume, although this varies depending on the soil type (Libohova et al. 2018). Under these conditions, there is insufficient air in the soil. Thus, oxygen deficiency or anaerobic conditions occur in plant roots. Since the roots cannot perform aerobic respiration adequately, energy production decreases. This inhibits plant cell division and restricts root development. Under oxygen-free conditions, cells begin anaerobic respiration and start using lactic and ethanolic substances instead of oxygen. At the same time, toxic substances begin to accumulate within the cells. This causes cell breakdown and necrosis in the roots (Zhang et al. 2025).

Due to the root structure being damaged, nutrient uptake slows down and nutrient deficiencies appear in the plant. Some symptoms similar to drought stress can appear in the upper part of the plant. Particularly, a reduction in the uptake of elements such as nitrate, calcium, and iron shows itself in the form of chlorosis in the leaves, tip burn in young leaves, and general growth failure. A previous study on overwatering reported that while soil oxygen decreased by 4% in tomato plants, shoot length decreased by 25%, and fresh weight and total leaf area decreased by 60-70% after 2 weeks. Furthermore, a 32% decrease in leaf nitrogen content and a significant increase in ethylene production were observed (Fiebig and Dodd 2016). Similarly, Yin et al. (2023) reported up to 60% reductions in plant height, 59% reductions in single fruit weight, and 80% reductions in fruit yield in six tomato genotypes under excessive water application. In a study examining the effects of excessive watering on tomato seedlings, it was noted that there was deterioration in the root morphology of the seedlings, a decrease in root length and root surface area, a reduction in leaf area, and a shortening of plant height (Liu et al. 2023). In peppers, over-watering has been reported to promote the development of pathogens (especially *Pythium spp*. and *Phytophthora capsici*) in the soil, causing diseases such as root rot, stem necrosis, leaf drop, and wilting (Díaz-Pérez and Hook 2017). Another study on cucumbers found that plants subjected to overwatering for 10 days showed a decrease in plant height, number of leaves, and leaf area, with declines of up to 40% in fresh and dry biomass (Barickman et al. 2019). However, in another study, it was reported that the total soluble salt content in cucumber greenhouses subjected to excessive irrigation decreased from 8.65 g/kg to 0.597 g/kg (Deng et al. 2022).

In a molecular-level study on eggplant, it was noted that extreme water stress causes differences in genes and miRNAs associated with chlorophyll and lignin metabolism. Specifically, the study reported that adaptation genes were activated (Jiang et al. 2023). In another study, eggplant plant height, SPAD (chlorophyll) value, and fruit yield decreased by 30-40%, respectively. Furthermore, yield loss under flooding conditions was found to be higher than under drought conditions. There were differences between different eggplant varieties in response to excessive irrigation, and some varieties (e.g., Purple King) were reported to have higher yields and chlorophyll values (Zohura et al. 2024).

In summary, both insufficient and excessive water in protected vegetable cultivation can lead to irreversible physiological disorders at the root and shoot levels, disruptions in nutrient uptake, and significant yield losses. Under drought stress, restricted water and nutrient uptake, loss of turgor, and decreased photosynthetic capacity are the main problems. Conversely, under excessive water conditions, oxygen deficiency, necrosis in root tissues, pathogen development, and hormonal imbalances emerge as fundamental problems. Therefore, in greenhouse vegetable production, it is important to develop integrated management strategies that limit the emergence of these stress factors, reduce their severity, and increase plant tolerance. In the following section, modern and practical approaches that can be used in the management of temperature and water stress will be discussed in detail in the context of protected vegetable cultivation.

2. WATER STRESS MANAGEMENT PRACTICES IN GREENHOUSES VEGETABLE CULTIVATION

Previous sections have focused on the physiological basis of water stress in greenhouse vegetable cultivation. The negative effects of water stress on growth and yield in crops such as tomatoes, peppers, eggplants, and cucumbers have also been examined. This section, however, explores how water stress can be managed during the production process. While traditionally stresses have mostly been mitigated using reactive methods, increasing environmental risks associated with climate change require planned and monitoring-based integrated approaches. Greenhouse climate control, precision watering and drainage systems, the use of biostimulants, and sensor-supported digital decision systems are some of the prominent modern applications in this scope. These methods are evaluated below in terms of greenhouse vegetable cultivation.

2.1. Irrigation and Nutrient Strategies in Drought Stress Management

As stated earlier, in greenhouse vegetable cultivation, stress factors caused by over or lack of water negatively affect turgor pressure, photosynthesis mechanisms, and nutrient uptake in plants. In order to decrease these problems and prevent yield loss in plants, this stress must be reduced using correct and effective methods. This stress can be effectively managed through sensitive watering techniques that allow for effective water use and correct plant feeding practices that increase drought tolerance.

In modern greenhouse agriculture systems, the goal is to accurately determine the plant's water requirements and meet these needs with appropriate irrigation systems. Drip irrigation systems and fertigation systems deliver the necessary water to the root zone, minimizing water loss and ensuring that nutrients are supplied according to the plant's needs (Yang et al. 2023). Moisture sensors (tensiometers, TDR/FDR probes) and simple automation units integrated into these irrigation systems are used. In this way, the timing and amount of irrigation can be adjusted according to the actual water needs of the plant. These sensors analyze soil or air moisture to generate real-time data and prepare irrigation programs according to the actual water needs of the plant. In addition, based on the plant, devices that measure water flow in the leaves, leaf moisture, and stem diameter are being tested (Marino et al. 2021).

During flowering and fruit development periods, applying water at the right time and in the right amount is of great importance in greenhouse vegetable cultivation. In this period, ethylene and abscisic acid hormone levels increase in plants that encounter drought stress, and flower and fruit drop occurs. Cui et al. (2020) reported that water restrictions during these periods led to yield reductions of 13–26%. While Muñoz-Carpena et al. (2005) showed that sensor-controlled drip irrigation saves water with similar yields in tomatoes, Vázquez et al. (2011) stated that the same system increases yield and water use efficiency in processing tomatoes. Besides the right watering system, correct plant nutrition also plays an important role in increasing plant resistance to drought stress. Providing essential elements such as potassium and nitrogen in appropriate amounts improves intracellular osmotic balance and water use efficiency. Potassium also plays an important role in maintaining the turgor balance necessary for the functioning of the stomatal mechanism (Mubashir et al. 2023) (Figure 2). The application of macronutrients in vegetable production via drip irrigation (fertigation) increases fertilizer use efficiency and productivity (Singh et al. 2023). While foliar applications for micronutrients provide immediate corrective effects, particularly under stress conditions such as drought (Semida et al. 2021). In conclusion, the combined use of drip irrigation, sensor-based irrigation management, and fertigation in greenhouse vegetable cultivation increases water and nutrient use efficiency. Furthermore, these practices offer a powerful tool for minimizing drought-related yield losses.

2.2. Management of Waterlogging and Oxygen Deficiency

Soils with high clay content, agricultural areas lacking adequate drainage, and improper irrigation techniques can cause root asphyxiation in plants. This condition can lead to stunted growth and death. Furthermore, soil-borne pathogens can proliferate in soils with low oxygen levels, limiting plant nutrient uptake (Zhang et al. 2025). Therefore, the primary target in managing excess water is to maintain the air-water balance in the soil, providing a viable environment for plant roots (Ben-Noah and Friedman 2018).

The first step toward improvement is establishing an effective drainage system in the greenhouse substructure. Drainage channels and pipes are the most common methods used to remove excess water from the soil surface (Wu et al. 2022). In addition, the use of soilless farming systems is an effective solution in greenhouses with unfavorable soil that is not actively used (Mielcarek et al. 2023). In such production systems, growing media with high air porosity and balanced water-holding capacity (peat, cocopeat, perlite mixtures) are preferred for use in place of soil or in combination with soil in raised pads or troughs. In this way, both the risk of root suffocation due to excess water is reduced and the controlled delivery of water is facilitated (Mielcarek et al. 2023).

The irrigation program should be adjusted in terms of frequency and quantity to prevent the risk of excess water, especially under low evapotranspiration conditions (closed, low light, and cool days). Soil moisture sensors allow for early intervention in cases of over-irrigation. In addition, the quality and salinity level of the irrigation water are also very significant criteria. Irrigation carried out to eliminate soil salinity problems that may arise due to excessive fertilization can cause problems in terms of oxygen deficiency in the roots in cases of inadequate drainage.

In cases of excess water, it is important to regularly check the roots and root collars and to clear any obstructions in the irrigation lines. This integrated approach, supported by appropriate cultural measures such as rotation and solarization when necessary, can significantly reduce the negative effects of excess water in protected vegetable cultivation.

2.3 Biostimulants and Antistress Applications Against Water Stress

In greenhouse vegetable cultivation, water stress cannot always be fully controlled through irrigation management alone. In these situations, complementary biostimulants and stress-preventing applications are used to increase plant resistance. Biostimulants are defined as products containing seaweed extracts, protein hydrolysates, humic and fulvic acids, free amino acids, arbuscular mycorrhizal fungi, microalgae extracts, phytohormones (e.g., salicylic acid, melatonin), certain microorganisms, and specific mineral elements. They are defined as products that regulate processes such as nutrient uptake, root development, antioxidant defense, and stress tolerance in plants (Di Sario et al. 2025). Under greenhouse conditions, these applications are typically applied several times, depending on the plant's growth stage, either to the root zone via drip irrigation or to the leaves via foliar spraying.

Studies have reported that seaweed-derived biostimulants (e.g., extracts of *Laminaria digitata* and *Ascophyllum nodosum*) can reduce water stress-induced biomass loss in plants such as tomatoes and lettuce from 45% to 25% and maintain photosynthetic activity (Velasco-Clares et al. 2025; Campobenedetto et al. 2021). According to a study conducted on peppers, protein hydrolysates and amino acid-based biostimulants increase the resistance of plants to water loss (Agliassa et al. 2021). Similar results were reported in another study conducted on 'Chery' tomatoes; protein hydrolysates and amino acid-based biostimulants were shown to increase antioxidant enzyme activities and mitigate the adverse effects of water stress (Gil-Ortiz et al. 2023). Application of humic substance-based biostimulants to lettuce roots or leaves contributed to the preservation of photosynthetic capacity under water stress conditions and reduced the oxidative damage caused by water stress (Atero-Calvo et al. 2025). It was reported that applying a biostimulant derived from *Ascophyllum nodosum* + *Laminaria digitata* three times to tomato plants against drought stress primed the plants against stress and reduced stress symptoms by regulating reactive oxygen species (ROS) responses under water stress (Cerruti et al. 2024).

Minerals such as silicon (Si), calcium (Ca), and potassium (K), as well as signaling molecules like salicylic acid (SA) and jasmonate (JA), are used at appropriate doses in greenhouses vegetable cultivation to increase plant resistance to abiotic stresses such as temperature and water stress. These compounds are reported to support osmotic balance by strengthening cell wall and membrane integrity, positively affecting defense mechanisms and antioxidant enzyme activities (El-Mogy et al. 2025, Song et al. 2023). In cucumbers under water stress, the foliar application of Ca, K, and Si nanoparticles increased antioxidant enzyme activities (SOD, CAT), chlorophyll content, water use efficiency, and yield, while reducing MDA and ABA levels (El-Mogy et al. 2025). Similarly, it has been reported that SiO_2 application in lettuce plants increased chlorophyll and anthocyanin content and enhanced stress tolerance under heat and drought stress conditions (Simko et al. 2025).

These results show that biostimulants and antistress applications are effective tools that complement traditional irrigation and fertilization strategies in water stress management. However, the performance of these products varies depending on plant type, application rate and timing, and environmental conditions. Therefore, the use of biostimulants in greenhouse vegetable production should be approached in an integrated manner with greenhouse climate and irrigation management, adapted to local conditions.

2.4 Monitoring Water Stress and Digital Decision Support Systems

Sustainable agricultural practices are becoming increasingly effective through the continuous monitoring of soil moisture and greenhouse climate parameters using sensors in greenhouse vegetable cultivation. Furthermore, integrating this data into digital decision support systems is also gaining importance (Dirlik et al. 2025, Incrocci et al. 2020) (Figure 3). As stated earlier, continuously measuring soil or growing medium moisture with devices such as tensiometers, TDR/FDR, and capacitive sensors greatly benefits agricultural activities. Additionally, processing data on parameters such as air temperature, relative humidity, and light in a digital system provides fast and accurate results. With this method, the amount of water required for the roots can be increased by 30-50% by reducing unnecessary watering (Dirlik et al. 2025, Palumbo et al. 2021, Abdelmoneim et al. 2025) (Figure 3). Sensor-based irrigation has resulted in yield increases of up to 47% and water savings of 36-47% in vegetables such as tomatoes and green beans (Dirlik et al. 2025, Palumbo et al. 2021). In recent years, applications have been developed for these systems that alert producers when critical levels are exceeded (Cayuela et al. 2022, Conde et al. 2024). With these systems, yield and quality losses due to water stress are prevented with real-time data.

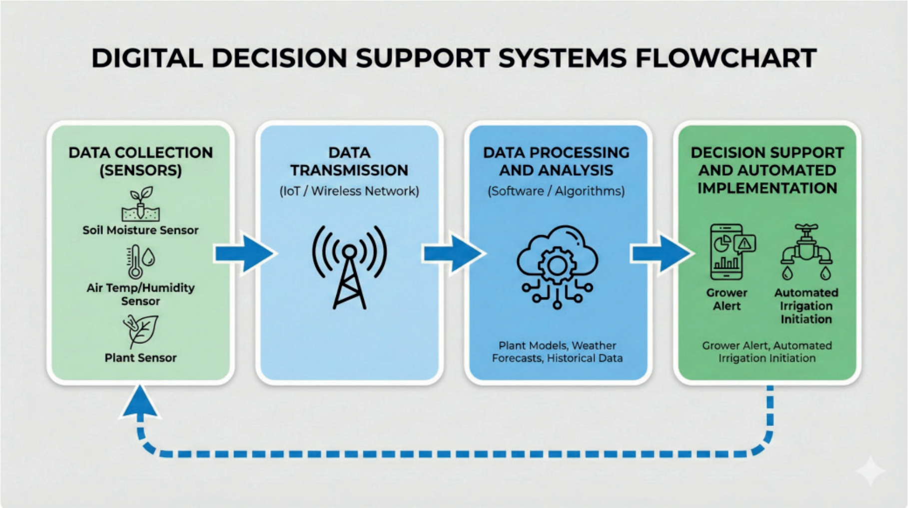

Figure 3: *Digital desicion support system flowchart. This schematic representation has been prepared as an illustrative example based on previously published study (Dirlik et al. 2025, Incrocci et al. 2020, Palumbo et al. 2021, Abdelmoneim et al. 2025), Cayuela et al. 2022, Conde et al. 2024)*

The main reason for the uncommon use of sensors is the inability to afford the costs and calibration requirements. However, low-cost and easier-to-calibrate IoT-based systems can reduce these barriers (Abdelmoneim et al. 2025, Okasha et al. 2021).

As a result, sensor-based monitoring and digital decision support systems offer effective and evidence-based solutions for preventing water stress and increasing water use efficiency in greenhouse vegetable cultivation.

3. CONCLUSION AND RECOMMENDATIONS

Water stress is one of the most significant abiotic stress factors limiting greenhouse vegetable cultivation. This stress can cause serious physiological damage to plant roots and shoots, inhibit the uptake of nutrients, and consequently lead to significant yield losses. In this chapter, we have tried to demonstrate that some practices have been highly successful in combating water stress. The integrated use of sensor-supported irrigation technology, precision irrigation techniques, proper fertigation, appropriate variety selection, etc., can be a solution against drought stress. In cases of excessive water stress, solutions can be achieved through methods such as selecting appropriate growing environments, implementing effective drainage systems, and correctly adjusting greenhouse slopes. Additionally, adjusting irrigation programs according to soil evaporation rates significantly contributes to this process. Besides technical applications, plant resistance supported by biostimulants and antistress applications further reduces the effects of water stress.

In particular, the use of seaweed extracts and protein hydrolysates has greatly increased stress resistance in tomato, pepper, and lettuce cultivation. In addition, it has been observed that mineral elements such as silicon (Si), calcium (Ca), and potassium (K) support plant cell walls and membranes, reducing the effects of ROS caused by water stress.

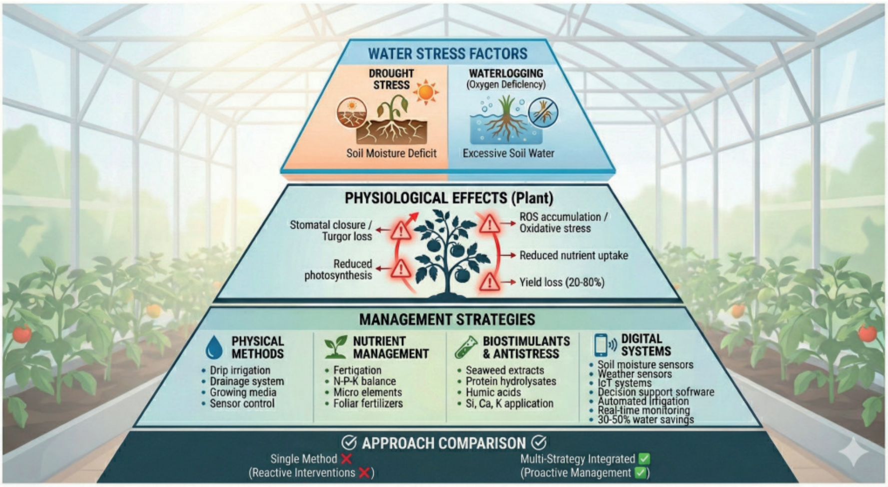

Figure 3: *Proactive and holistic approach model in water stress management instead of reactive interventions. The figure highlights the importance of integrating sensor-based digital systems, biostimulant applications, and technical cultural measures in combating the negative effects of water stress (drought and excessive water) on crop yield.*

The integrated use of sensor-based monitoring and digital decision support systems enables effective irrigation with real-time data without considering water as a stress factor in greenhouse production. Despite the increasing use of integrated automation systems in recent years, high costs have limited producers. However, according to recent developments, low-cost IoT-based sensors enable more precise, sustainable, and economical water stress management.

Consequently, water stress management in protected vegetable cultivation should be approached holistically rather than only intervening when problems arise. In this process, the combined use of variety selection, drainage, appropriate irrigation, nutrient management, biostimulant use, and digital monitoring systems will yield the highest success (Figure 3).

REFERENCES

Abdelmoneim, A. A., Al Kalaany, C. M., Dragonetti, G., Derardja, B., & Khadra, R. (2025). Comparative analysis of soil moisture-and weather-based irrigation scheduling for drip-irrigated lettuce using low-cost Internet of Things capacitive sensors. *Sensors*, *25*(5), 1568.

Agliassa, C., Mannino, G., Molino, D., Cavalletto, S., Contartese, V., Bertea, C., & Secchi, F. (2021). A new protein hydrolysate-based biostimulant applied by fertigation promotes relief from drought stress in *Capsicum annuum* L.. *Plant physiology and biochemistry* : PPB, 166, 1076-1086 . https://doi.org/10.1016/j.plaphy.2021.07.015.

Anjum, S. A., Xie, X., Wang, L. C., Saleem, M. F., Man, C., & Lei, W. (2011). Morphological, physiological and biochemical responses of plants to drought stress. *African journal of agricultural research*, 6(9), 2026-2032.

Atero-Calvo, S., Magro, F., Masetti, G., Navarro-León, E., Blasco, B., & Ruiz, J. M. (2025). Potential for Drought Stress Alleviation in Lettuce (*Lactuca sativa* L.) with Humic Substance-Based Biostimulant Applications. *Plants*, *14*(15), 2386.

Barber, J. (2017). A mechanism for water splitting and oxygen production in photosynthesis. *Nature plants*, *3*(4), 1-5.

Barickman, T. C., Simpson, C. R., & Sams, C. E. (2019). Waterlogging causes early modification in the physiological performance, carotenoids, chlorophylls, proline, and soluble sugars of cucumber plants. *Plants*, 8(6), 160.

Ben-Noah, I., & Friedman, S. P. (2018). Review and evaluation of root respiration and of natural and agricultural processes of soil aeration. *Vadose Zone Journal*, 17(1), 1-47.

Campobenedetto, C., Agliassa, C., Mannino, G., Vigliante, I., Contartese, V., Secchi, F., & Bertea, C. M. (2021). A biostimulant based on seaweed (*Ascophyllum nodosum* and *Laminaria digitata*) and yeast extracts mitigates water stress effects on tomato (*Solanum lycopersicum* L.). *Agriculture*, 11(6), 557.

Cayuela, C. M. F., Perea, R. G., Poyato, E. C., & Montesinos, P. (2022). An ICT-based decision support system for precision irrigation management in outdoor orange and greenhouse tomato crops. *Agricultural Water Management*, *269*, 107686.

Cerruti, P., Campobenedetto, C., Montrucchio, E., Agliassa, C., Contartese, V., Acquadro, A., & Bertea, C. M. (2024). Antioxidant activity and comparative RNA-seq analysis support mitigating effects of an algae-based biostimulant on drought stress in tomato plants. *Physiologia Plantarum*, *176*(6), e70007.

Conde, G., Guzmán, S. M., & Athelly, A. (2024). Adaptive and predictive decision support system for irrigation scheduling: An approach integrating humans in the control loop. *Computers and Electronics in Agriculture*, *217*, 108640.

Cui, J., Shao, G., Lu, J., Keabetswe, L., & Hoogenboom, G. (2019). Yield, quality and drought sensitivity of tomato to water deficit during different growth stages. *Scientia agrícola*, *77*, e20180390.

Deng, L., Fu, L., Zhang, K., Shen, Y., Feng, G., Zhang, L., ... & Liu, C. (2022). Effects of fertilizer and waterlogging on the diversity and functioning of the microbial community in greenhouse cultivation soil. *Chemical and Biological Technologies in Agriculture*, *9*(1), 31.

Di Sario, L., Boeri, P., Matus, J. T., & Pizzio, G. A. (2025). Plant biostimulants to enhance abiotic stress resilience in crops. *International Journal of Molecular Sciences*, *26*(3), 1129.

Díaz-Pérez, J., & Hook, J. (2017). Plastic-mulched Bell Pepper (*Capsicum annuum* L.) Plant Growth and Fruit Yield and Quality as Influenced by Irrigation Rate and Calcium Fertilization. *Hortscience*, 52, 774-781. https://doi.org/10.21273/hortsci11830-17.

Dirlik, I., Uğurlar, F., & Kaya, C. (2025). Sensor-Guided Smart Irrigation for Tomato Production: Comparing Low and Optimum Soil Moisture in Greenhouse Environments. *Food and Energy Security*, *14*(2), e70082.

Mohamed, E. M., ABDELDAYM, E. A., ABDELAZIZ, S. M., ISMAIL, A. M., EL-BELTAGI, H. S., RAMADAN, K. M., ... & MOTTALEB, S. A. (2025). Foliar application of calcium, silicon, and potassium nanoparticles improves growth, and fruit quality of drought-stressed cucumber plants through modulation of osmolytes, antioxidant enzymes, photosynthesis efficiency, and phytohormones. *Notulae Botanicae Horti Agrobotanici Cluj-Napoca*, *53*(2), 14470-14470.

Fahad, S., Bajwa, A. A., Nazir, U., Anjum, S. A., Farooq, A., Zohaib, A., ... & Huang, J. (2017). Crop production under drought and heat stress: plant responses and management options. *Frontiers in plant science*, *8*, 1147.

Farooq, M., Wahid, A., Kobayashi, N. S. M. A., Fujita, D. B. S. M. A., & Basra, S. M. (2009). Plant drought stress: effects, mechanisms and management. In *Sustainable agriculture* (pp. 153-188). Dordrecht: Springer Netherlands.

Fiebig, A., & Dodd, I. (2016). Inhibition of tomato shoot growth by over-irrigation is linked to nitrogen deficiency and ethylene.. *Physiologia plantarum*, 156 1, 70-83 . https://doi.org/10.1111/ppl.12343.

Fu, Z., Ciais, P., Wigneron, J. P., Gentine, P., Feldman, A. F., Makowski, D., ... & Smith, W. K. (2024). Global critical soil moisture thresholds of plant water stress. *Nature Communications*, *15*(1), 4826.

Gil-Ortiz, R., Naranjo, M. Á., Atares, S., & Vicente, O. (2023). Antioxidant responses of water-stressed cherry tomato plants to natural biostimulants. *Agronomy*, *13*(9), 2314.

Gupta, A., Rico-Medina, A., & Caño-Delgado, A. (2020). The physiology of plant responses to drought. *Science*, 368, 266 - 269.

Incrocci, L., Thompson, R., Fernández-Fernández, M., Pascale, S., Pardossi, A., Stanghellini, C., Rouphael, Y., & Gallardo, M. (2020). Irrigation management of European greenhouse vegetable crops. *Agricultural Water Management*, 242, 106393.

Jiang, Z., Xia, X., Liu, Y., He, J., & Yang, X. (2023). Integrated miRNA and mRNA transcriptome analysis reveals eggplant's (*Solanum melongena* L.) responses to waterlogging stress. *Agronomy*, *13*(9), 2215.

Kim, Y. X., Son, S. Y., Lee, S., Lee, Y., Sung, J., & Lee, C. H. (2022). Effects of limited water supply on metabolite composition in tomato fruits (*Solanum lycopersicum* L.) in two soils with different nutrient conditions. *Frontiers in Plant Science*, *13*, 983725.

Kittas, C., & Bartzanas, T. (2007). Greenhouse microclimate and dehumidification effectiveness under different ventilator configurations. *Building and Environment*, 42(10), 3774-3784.

Kumari, V. V., Banerjee, P., Verma, V. C., Sukumaran, S., Chandran, M. A. S., Gopinath, K. A., ... & Awasthi, N. K. (2022). Plant nutrition: An effective way to alleviate abiotic stress in agricultural crops. *International Journal of Molecular Sciences*, *23*(15), 8519.

Li, X., Hu, X., Song, S., & Sun, D. (2022). Greenhouse management for better vegetable quality, higher nutrient use efficiency, and healthier soil. *Horticulturae,* 8(12), 1192.

Libohova, Z., Seybold, C., Wysocki, D., Wills, S., Schoeneberger, P., Williams, C., ... & Owens, P. R. (2018). Reevaluating the effects of soil organic matter and other properties on available water-holding capacity using the National Cooperative Soil Survey Characterization Database. *Journal of soil and water conservation*, *73*(4), 411-421.

Liu, C., Lan, C., Li, C., Li, C., & Huang, J. (2023). Exogenous spermidine and calcium alleviate waterlogging stress in cherry tomato at the seedling stage. *Scientia Horticulturae*, *307*, 111504.

Lyu, X., Hassan, H. M., Zan, Y., & Tan, J. (2025). Interactive effects of irrigation and fertilization on the growth and physiological characteristics of greenhouse tomatoes*, Solanum lycopersicum* L. *Scientific Reports*, *15*(1), 6007.

Marino, G., Scalisi, A., Guzmán-Delgado, P., Caruso, T., Marra, F. P., & Lo Bianco, R. (2021). Detecting mild water stress in olive with multiple plant-based continuous sensors. *Plants*, *10*(1), 131.

Mielcarek, A., Kłobukowska, K., Rodziewicz, J., Janczukowicz, W., & Bryszewski, K. Ł. (2024). Water nutrient management in soilless plant cultivation versus sustainability. *Sustainability*, *16*(1), 152.

Moustaka, J., & Moustakas, M. (2023). Early-stage detection of biotic and abiotic stress on plants by chlorophyll fluorescence imaging analysis. *Biosensors*, 13(8), 796.

Mubashir, A., Nisa, Z. U., Shah, A. A., Kiran, M., Hussain, I., Ali, N., ... & AbdElgawad, H. (2023). Effect of foliar application of nano-nutrients solution on growth and biochemical attributes of tomato (Solanum lycopersicum) under drought stress. *Frontiers in Plant Science*, *13*, 1066790.

Muñoz-Carpena, R., & Dukes, M. D. (2005). Automatic irrigation based on soil moisture for vegetable crops: Abe356/ae354, 6/2005. *EDIS*, *2005*(8).

Nahar, K., Hasanuzzaman, M., Ahamed, K. U., Hakeem, K. R., Ozturk, M., & Fujita, M. (2015). Plant responses and tolerance to high temperature stress: role of exogenous phytoprotectants. In *Crop production and global environmental issues* (pp. 385-435). Cham: Springer International Publishing.

Okasha, A. M., Ibrahim, H. G., Elmetwalli, A. H., Khedher, K. M., Yaseen, Z. M., & Elsayed, S. (2021). Designing low-cost capacitive-based soil moisture sensor and smart monitoring unit operated by solar cells for greenhouse irrigation management. *Sensors*, *21*(16), 5387.

Palumbo, M., D'Imperio, M., Tucci, V., Cefola, M., Pace, B., Santamaria, P., ... & Montesano, F. F. (2021). Sensor-based irrigation reduces water consumption without compromising yield and postharvest quality of soilless green bean. *Agronomy*, *11*(12), 2485.

Prieß, M., Göddeke, H., Groenhof, G., & Schäfer, L. V. (2018). Molecular mechanism of ATP hydrolysis in an ABC transporter. *ACS central science*, *4*(10), 1334-1343.

Qiao, M., Hong, C., Jiao, Y., Hou, S., & Gao, H. (2024). Impacts of drought on photosynthesis in major food crops and the related mechanisms of plant responses to drought. *Plants*, *13*(13), 1808.

Razi, K., & Muneer, S. (2021). Drought stress-induced physiological mechanisms, signaling pathways and molecular response of chloroplasts in common vegetable crops. *Critical Reviews in Biotechnology*, 41, 669 - 691.

Schwarz, D., Rouphael, Y., Colla, G., & Venema, J. (2010). Grafting as a tool to improve tolerance of vegetables to abiotic stresses: Thermal stress, water stress and organic pollutants. *Scientia Horticulturae*, 127, 162-171.

Semida, W. M., Abdelkhalik, A., Mohamed, G. F., Abd El-Mageed, T. A., Abd El-Mageed, S. A., Rady, M. M., & Ali, E. F. (2021). Foliar application of zinc oxide nanoparticles promotes drought stress tolerance in eggplant (*Solanum melongena* L.). *Plants*, *10*(2), 421.

Simko, I., Zhao, R., & Peng, H. (2025). Differential Impact of SiO2 Foliar Application on Lettuce Response to Temperature, Salinity, and Drought Stress. *Plants*, *14*(12), 1845.

Singh, J., Sandal, S. K., Yousuf, A., & Sandhu, P. S. (2023). Effect of drip irrigation and fertigation on soil water dynamics and productivity of greenhouse tomatoes. *Water*, *15*(11), 2086.

Song, W., Shao, H., Zheng, A., Zhao, L., & Xu, Y. (2023). Advances in roles of salicylic acid in plant tolerance responses to biotic and abiotic stresses. *Plants*, *12*(19), 3475.

Turan, M., Ekinci, M., Argin, S., Brinza, M., & Yildirim, E. (2023). Drought stress amelioration in tomato (*Solanum lycopersicum* L.) seedlings by biostimulant as regenerative agent. *Frontiers in Plant Science*, *14*, 1211210.

Vázquez, N., Huete, J., Pardo, A., Suso, M. L., & Tobar, V. (2010, August). Use of soil moisture sensors for automatic high frequency drip irrigation in processing tomato. In *XXVIII International Horticultural Congress on Science and Horticulture for People (IHC2010): International Symposium on 922* (pp. 229-235).

Velasco-Clares, D., Navarro-León, E., Izquierdo-Ramos, M. J., Blasco, B., & Ruiz, J. M. (2025). Enhancing drought tolerance in lettuce: The efficacy of the seaweed-derived biostimulant cytolan® stress applied at different growth stages. *Horticulturae*, *11*(2), 157.

Wu, Q., He, Y., Qi, Z., & Jiang, Q. (2022). Drainage in paddy systems maintains rice yield and reduces total greenhouse gas emissions on the global scale. *Journal of Cleaner Production*, *370*, 133515.

Yang, P., Wu, L., Cheng, M., Fan, J., Li, S., Wang, H., & Qian, L. (2023). Review on drip irrigation: impact on crop yield, quality, and water productivity in China. *Water*, 15(9), 1733.

Yang, X., Lu, M., Wang, Y., Wang, Y., Liu, Z., & Chen, S. (2021). Response mechanism of plants to drought stress. *Horticulturae*, *7*(3), 50.

Teker Yıldız, M., & Akı, C. (2025). Evaluation of Physiological and Biochemical Responses of Four Tomato (*Solanum lycopersicum* L.) Cultivars at Different Drought Stress Levels. *Agronomy*, *15*(3), 653.

Yin, J., Niu, L., Li, Y., Song, X., Ottosen, C. O., Wu, Z., ... & Zhou, R. (2023). The effects of waterlogging stress on plant morphology, leaf physiology and fruit yield in six tomato genotypes at anthesis stage. *Vegetable Research*, *3*(1).

Zhang, Y., Chen, X., Geng, S., & Zhang, X. (2025). A review of soil waterlogging impacts, mechanisms, and adaptive strategies. *Frontiers in Plant Science*, *16*, 1545912.

Zohura, F. T., Naher, N., Sultana, T., & Rao, T. V. V. L. N. (2024). Study on the effect of drought and waterlogging conditions on yield and growth of three local varieties of eggplant (*Solanum melongena* L.). *Archives of Agriculture and Environmental Science*, *9*(4), 661-666.

Chapter 9

EPIGENETIC DEFENSE CODES: NEXT-GENERATION REGULATORS OF SECONDARY METABOLITE-MEDIATED PLANT PROTECTION

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INTRODUCTION

1. The New Face of Plant Immunity with Epigenetic Codes

Because plants are stationary life forms, instead of fleeing from environmental threats, they recognize these threats and develop internal defense mechanisms. These defense systems have become complex and multi-layered throughout the evolutionary process. Physical barriers (epidermis, lignin), receptor-based pathogen recognition systems (PRRs), reactive oxygen species (ROS), and, most importantly, secondary metabolites are the basic components of these defense systems (Cui et al., 2025; Joshi et al., 2025). Secondary metabolites (SMs) are biologically active compounds that are not essential in the plant life cycle but are vital under environmental stress conditions. Classified as flavonoids, alkaloids, terpenoids, phenolics and glucosinolates, these compounds protect the plant in a multifaceted way thanks to their antimicrobial, antioxidant, antifungal, and antigenic properties (Mahanta et al., 2025). Classical genetic approaches assume that the biosynthesis of these metabolites is controlled by genetic pathways (enzyme genes, transcription factors). However, advanced molecular studies in the last decade have revealed that these regulatory systems are not limited to the genetic code, and that epigenetic mechanisms additionally play a profound role in this process (Ben Ammar, 2025; Choi et al., 2025). The response of plants to environmental stimuli largely depends on the synthesis and distribution of SMs. Take for instance, glucosinolates in Brassica species, tropane alkaloids in Solanaceae species and isoflavonoids in Fabaceae species rapidly accumulate, especially during pathogen attacks, forming a defensive wall (Martins et al., 2020; Tong et al., 2025). The production of these compounds is not static; it changes dynamically according to the intensity and duration of environmental stress, the age of the plant, and even previous stress experiences. At this point, epigenetic memory comes into play. By "remembering" previous stressors, plants can respond more quickly and effectively to similar threats in the future. This phenomenon is called priming, and it has been shown to be epigenetically based in many SM genes (Nair et al., 2022; Abdulraheem et al., 2024). Epigenetic regulation encompasses mechanisms that permanently or temporarily alters gene expression without changing the DNA sequence. In plants, there are three main mechanisms of this regulation: DNA methylation: Genes can be silenced by adding methyl groups to gene promoter regions. Histone modifications: The chromatin structure is loosened or tightened by acetylation/methylation of histone proteins surrounding the DNA. RNA-based silencing (RNAi): Small RNA molecules inhibit protein synthesis by degrading the target mRNA. These mechanisms can directly affect structural and regulatory genes involved in secondary metabolite biosynthesis pathways. Take for instance, in Nicotiana attenuata, genes responsible for nicotine biosynthesis have been shown to be rapidly activated following unwinding of DNA methylation after stress (Tong et al., 2025). Similarly, in Arabidopsis thaliana, glucosinolate biosynthesis genes have been found to carry both H3K27me3 repressive and H3K4me3 activating histone modifications, indicating that they can be switched on and off in an environmentally sensitive manner (Choi et al., 2025). This regulation creates a plastic defense system, allowing plants to adjust both their local and systemic immunity to environmental conditions. One of the most striking findings is that some epigenetic changes create not only individual responses but also hereditary defense strategies that can be passed down to subsequent generations (Ben Ammar, 2025). This phenomenon is particularly observed in perennial plants and perennial species. Take for instance, parental plants exposed to a pathogen show a lower infection rate and higher levels of microbial malformations (SM) compared to their offspring (Huang et al., 2025). This epigenetic inheritance is thought to be advantageous in terms of natural selection and to increase the ecological resilience of these species. The integration of epigenetic information into plant biotechnology means the permanent restructuring of defense systems without the need for external chemical applications. Take for instance: Epigenetic repression of specific metabolite genes can be removed using DNA methyltransferase inhibitors. Negative regulators controlling SM production can be silenced with RNAi-based small RNAs. Epigenetic markers can be targeted with genome editing (e.g., CRISPR-dCas9) (Mahanta et al., 2025). These strategies are particularly important for sustainable agriculture, environmentally friendly disease control, and reduced pesticide use.

2. Molecular Foundations of Epigenetic Mechanisms

When plants face environmental threats, they can survive by reprogramming their defense systems. The flexibility and sensitivity of these defense systems are shaped not only by genetic information but additionally by epigenetic regulation. Epigenetic mechanisms are systems that control gene expression without altering the DNA sequence, can be heritable, and can be modulated in response to environmental stimuli (Cui et al., 2025). The role of epigenetic markers in plant defense systems, particularly in the production of secondary metabolites, has been extensively researched in recent years. These compounds perform vital functions such as protection against pathogens, insect defense, and stress tolerance. That's why, epigenetic control of genes encoding or regulating these compounds plays a fundamental role in plant defense biology (Ben Ammar, 2025). Three basic epigenetic mechanisms will be detailed below: DNA methylation, Histone modifications, RNA-based silencing (RNA interference, RNAi). DNA methylation occurs through the modification of cytosine bases, usually in the CG (CpG) regions, with methyl groups. In plants, this mechanism is often associated with gene silencing. However, in recent years, it has been shown that methylation can change dynamically depending on the environment and has a direct effect on secondary metabolite production (Cimmino et al., 2025; Ibragić et al., 2025; Jangpangi et al., 2025). Take for instance, in Arabidopsis thaliana, decreased DNA methylation increased flavonoid synthesis, while in Nicotiana attenuata, demethylation in nicotine biosynthesis pathways led to a significant increase in alkaloid levels (Tong et al., 2025). DNA methyltransferase (MET1, DRM2) and demethylase (ROS1) enzymes are key players in this regulation. Moreover, DNA methylation also functions as part of the epigenetic priming mechanism. During the first encounter with a pathogen, demethylation of defense genes can occur, allowing for a faster defense response upon repeated exposure to the same pathogen (Mencia et al., 2025). This mechanism forms the basis of the concept of epigenetic memory. Histones are proteins that wrap around DNA within the nucleus. Chemical modifications of these proteins (e.g., methylation, acetylation, ubiquitination) determine the readability of DNA. Activator markers (H3K4me3, H3K9ac) increase gene expression, while repressor markers (H3K9me2, H3K27me3) cause gene silencing (Choi et al., 2025). The role of histone modifications in plant defense is clearly documented. Take for instance, in Brassica napus, a significant increase in the expression levels of genes associated with glucosinolate production was detected upon removal of the H3K27me3 repressor marker (Fan & Feng, 2025; Moon et al., 2025; Wu et al., 2025). This demonstrates the strong control of histone markers over secondary metabolite production. On the other hand, bivalent histone modifications can be found in some gene regions. This means that the same region carries both active (e.g., H3K4me3) and repressive (e.g., H3K27me3) markers. In this way, gene expression can be rapidly activated or repressed in response to environmental stimuli. This has been demonstrated in defense genes in Arabidopsis (Choi et al., 2025). Histone modifications also serve a transcriptional memory function. Especially under repeated stress conditions, specific histone markers become persistent, creating a state of ready metabolite production in response to the next attack (Bashir & Setyawati, 2025; Ibragić et al., 2025). RNA interference (RNAi) is the process of repressing gene expression through small RNA molecules. Specifically, molecules such as miRNA and siRNA indirectly control the production of defense compounds by targeting regulatory genes involved in secondary metabolite biosynthesis (Grewal & Roy, 2025; Upadhyay et al., 2025). Take for instance, miR858 limits phenylpropanoid production by repressing MYB transcription factors, which play a critical role in flavonoid synthesis. However, in the case of pathogen attack, miR858 expression decreases, MYB activity increases, and flavonoid production accelerates (Yang et al., 2025). Moreover, RNAi systems can also influence epigenetic processes at the DNA level, such as RdDM (RNA-directed DNA methylation). siRNAs can perform transcriptional silencing by guiding methylation sites on DNA (Cui et al., 2025). In terms of application, RNAi technology is used to increase secondary metabolites in both model plants and agricultural plants. Kumar et al. (2025) managed to manipulate plant immunity by temporarily suppressing alkaloid synthesis using an RNAi-based silencing method (Shah et al., 2025). Epigenetic mechanisms are not isolated; rather, they function as complementary and interacting structures. DNA methylation can direct histone modifications; small RNAs can perform gene silencing at both the transcriptional and post-transcriptional levels. Take for instance, in the study by Fan & Feng (2025), an increase in H3K9me2 histone markers was observed along with an increase in DNA methylation in flavonoid gene clusters. The accumulation of siRNAs in the same region indicates that a coordinated silencing mechanism is at work. These integrated systems allow defense responses to operate with precise timing. The plant first recognizes the threat, then, through epigenetic pathways, activates or deactivates only the necessary genes. This saves energy while simultaneously creating an effective defense (Choi et al., 2025). Controlling epigenetic regulation allows for the development of more resistant and productive plant varieties in modern agriculture. Epigenetic priming has the potential to reduce pesticide use. Take for instance: Defense genes can be activated with DNA demethylase-inducing chemicals. Specific gene regions can be modified with CRISPR/dCas9-fused epigenetic regulators. With RNAi-based applications, metabolite profiles can be temporarily altered (Kumar et al., 2025). Thanks to these techniques, environmentally friendly and sustainable plant protection strategies can be developed without the need for genetic modification.

3. Epigenetic Interaction Pathways of Secondary Metabolite Production

Plants produce secondary metabolites for defense under biotic and abiotic stress conditions. These compounds, in addition to their direct toxic effects, play a role in cellular defense signaling and interplant communication (Khan et al., 2025). However, the production of these compounds is tightly controlled because it is energy intensive. Recent research shows that this control occurs not only at the transcriptional level but additionally at the epigenetic level. In particular, the production of major metabolite groups such as flavonoids, alkaloids, and terpenoids is regulated by epigenetic modifications according to environmental conditions (Açıkgöz, 2025; Açıkgöz et al., 2025). This is detailed below with examples for each group. Flavonoids are a class of metabolites derived from the phenylpropanoid pathway that have functions such as UV protection, pathogen resistance, and antioxidant defense. Anti-microbial flavonols and antiviral flavonones play a critical role in defense (Kırgeç et al., 2023). Flavonoid biosynthesis is generally controlled by the transcription factors MYB, bHLH, and WD40. The expression of these genes is regulated by epigenetic mechanisms (Chen et al., 2025; Rani & Chaudhary, 2026). DNA methylation: In Arabidopsis, methylation in the MYB111 promoter region suppresses flavonol synthesis. After stress, this region becomes demethylated, and an increase in flavonoids is observed (Wang et al., 2025). Histone modifications: Active markers such as H3K4me3 and H3K9ac are concentrated in flavonoid biosynthesis genes. miRNAs: miR858 limits flavonoid production by suppressing MYB factors; this suppression disappears under pathogen stress (Kumar et al., 2025). Zhang et al. (2025) analyzed post-stress anthocyanin accumulation in cotton and found that this accumulation was associated with the suppression of H3K27me3. The same study showed that some flavonoid gene promoters undergo remethylation via the RdDM pathway. Alkaloids are generally neurotoxic or bitter-tasting compounds and are effective against threats such as insects, fungi, and bacteria. Examples include compounds such as nicotine, morphine, capsaicin, and sanguinarine. A study on Nicotiana attenuata showed that DNA demethylation in the gene cluster region controlling nicotine production activated transcription (Tong et al., 2025). When MET1 expression decreased, nicotine levels increased. Hussain et al. (2025) temporarily silenced an acetyltransferase gene involved in alkaloid biosynthesis using the VIGS method, altering the metabolite content in the plant (Jose et al., 2025). This demonstrated the feasibility of RNA-based silencing. The fact that alkaloid-encoding genes are often clustered makes it possible to control these regions epigenetically as blocks. Masuda et al. (2025) showed that gene expression decreased in regions where H3K9me2 increased in these clusters. Terpenoids encompass a wide variety of secondary metabolites, including volatile compounds. Examples used in defense include limonene, geraniol, taxol, and gibberellic acid. They are effective in both antimicrobial and signal transduction. DNA methylation plays a role, particularly in silencing TPS (terpenoid synthase) genes. Fan & Feng (2025) showed increased production in these genes under stress, along with demethylation. Histone acetylation was found to be associated with active gene expression, particularly in TPS promoter regions. siRNAs target the transcripts of some TPS genes, applying post-transcriptional silencing. Sometimes defense compounds are activated co-activated. Choi et al. (2025) showed that in Arabidopsis, both flavonoid and terpenoid genes have similar histone markers under stress, and that this synergy is coordinated at genetic and epigenetic levels. Accumulation of epigenetic markers has been observed in regions where genes encoding defense components converge. A region repressed by DNA methylation can fully activate a gene cluster upon demethylation. When H3K27me3 repression is removed, multiple defense genes can be activated simultaneously. sRNA clusters can simultaneously carry out both promoter methylation and transcript degradation. This holistic structure, especially when combined with the concept of epigenetic memory, allows the plant to develop a more effective secondary response to the same threat. With recent developments, applications targeting epigenetic mechanisms have begun to be tested in the field: CRISPR-dCas9 systems, combined with proteins that methylate or remove DNA, enable epigenetic modification of the target gene. Flavonoid biosynthesis can be activated at the desired time and region with RNAi-based spray applications. Defense genes can be activated before stress with epigenetic priming agents (such as azacytidine). These strategies hold great promises for reducing pesticide use and developing biologically based plant protection systems (Bashir & Setyawati, 2025).

4. Epigenetic Inheritance and the Transmission of Defense Memory

Although plants, unlike animals, do not possess circulating immune cells, they have the capacity to "remember" their responses to environmental threats at the epigenetic level. This phenomenon is called "epigenetic memory," and in some cases, this memory can be passed down through generations (Feng & Xia, 2025). This defense memory is particularly evident in gene clusters involved in the biosynthesis of secondary metabolites (Yang & Lu, 2025). Epigenetic memory allows the plant to "remember" a stress it has previously encountered, enabling it to produce a faster and stronger response when exposed to the same threat. These responses can be recorded as DNA methylation patterns, histone modifications, and small RNA profiles (Choi et al., 2025). Plants can alter their DNA methylation profiles under stress. While some of these changes are temporary, others become permanent and can be transmitted via mitotic or meiotic pathways. Take for instance, the RdDM (RNA-directed DNA methylation) mechanism silences defense genes by targeting methylation. However, demethylation removal after stress leads to faster activation of the same defense genes (Feng & Xia, 2025). As an example, demethylation in the promoter region of the AT5G24010 gene in Arabidopsis thaliana made the plant more susceptible to bacterial attack; the same gene was activated earlier in the next generation (Deleris et al., 2016). Some histone markers (particularly H3K4me3, H3K27me3) can become persistent, leaving an epigenetic tag on defense genes. Choi et al. (2025) showed that these markers can be transmitted through mitotic divisions and passed on to seeds. Biosynthetic gene clusters associated with secondary metabolites, when activated following environmental stresses, traces of this activation can be detected in histone profiles. Small RNAs, such as siRNA and tasiRNA, provide post-transcriptional silencing by interacting with defense genes following a stress response. These molecules can, in some cases, be transferred to seeds. Take for instance, in Nicotiana tabacum, siRNAs suppress nicotine biosynthesis genes, and this silencing can persist for generations (Tong et al., 2025).

Flavonoid production varies according to environmental stimuli. Flavonoid biosynthesis genes activated by epigenetic markers after stress show faster expression in subsequent stresses. This mechanism has been documented, particularly in intergenerational transmission after UV stress (Zhang et al., 2024). Alkaloid biosynthesis is generally associated with cluster structures. Epigenetic markers acquired on these clusters (e.g., H3K9me2) can be persistent, allowing for rapid activation of the same gene set in subsequent generations (Yu et al., 2018; Wagh et al., 2025). Some terpenoid genes, such as TPS21 (Terpene Synthase 21), are activated by demethylation after pathogen attack. The expression level of these genes is higher in the second generation when the same stress is repeated (Fan & Feng, 2025). Transgenerational epigenetic inheritance is possible through the transmission of an epigenetic state to germ cells. This is limited but proven in plants. Similar defense profiles have been observed in the offspring of plants particularly exposed to drought, salinity, and pathogen pressure (Bashir et al., 2026). Another example is shown in Brassica napus, where water stress increased glucosinolate production in descendant individuals, and this increase was correlated with histone acetylation in the promoters of the relevant genes (Ben Ammar, 2025). These findings demonstrate that plants can "remember" their stress history and pass on an epigenetic immunity strategy to future generations. Next-generation agricultural biotechnology aims to artificially trigger these epigenetic inheritance mechanisms. Take for instance: Epimutagens (DNA methylation inhibitors such as azacytidine) enable early activation of defense genes. The methylation status of specific gene regions can be altered with CRISPR/dCas9-TET or dCas9-MQ1 systems. Defense metabolites can be artificially modulated with RNAi sprays (Basso et al., 2025). Thanks to these applications, the defense memory of plants can be programmed without the need for genetic modification. This has great potential, especially in terms of reducing pesticide use and adapting to the climate crisis (Zidan et al., 2025).

5. Agricultural Applications and the Future of Epigenetic Regulation

Today, agriculture still relies heavily on chemical use to combat biotic stressors (pathogens, pests). However, these methods pose serious risks to environmental health, soil microbiota, and human health. In this context, ways to increase plant resistance without genetic modification have gained significant importance. Epigenetic regulation is a new generation strategy that can offer biological and sustainable solutions to this need (Karalija et al., 2025). By epigenetically activating defense genes, both chemical inputs can be reduced and the production of metabolite-based biopesticides can be encouraged. Epi mutagenesis aims to direct gene expression by altering DNA methylation. Since these changes do not involve genetic mutations, they are more acceptable in terms of regulation. Chemicals that inhibit DNA methylation (e.g., 5-azacytidine, zebularin) remove methylation in the promoter regions of some defense genes. This, in turn, increases the production of defense metabolites (Kouighat et al., 2025). Take for instance, in Arabidopsis, 5-azacytidine application resulted in increased expression of defense genes such as PR1 and PDF1.2, leading to an increase in secondary metabolite levels. Although limited to this extent, attempts have been made to activate defense genes with superficial epi mutagenic sprays. Especially when applied before stress, "priming" effects can trigger sustained defense responses (Fan & Feng, 2025). While the classical use of CRISPR technology is in gene editing, in recent years it has become possible to regulate epigenetic markers without genetic modification using dCas9 (catalytically inactive Cas9) systems. dCas9-DNMT3A: Provides gene silencing by adding a methyl group to the target gene region. dCas9-TET1: Performs gene activation by providing demethylation. dCas9-p300: Opens promoter regions with histone acetyltransferase, increasing gene expression. CRISPR-based epigenetic modifications are particularly preferable in gene regions where defense metabolites cluster. Thus, the entire gene family or biosynthetic pathway can be activated together (Feng & Xia, 2025). Epigenetic priming is an approach that aims to acquire epigenetic marks by applying mild stress to the plant and obtain a faster and stronger response to subsequent attacks. This priming can sometimes be passed down through generations. Ibragić et al. (2025) showed that low-dose UV application in cotton increased the H3K4me3 mark in the promoters of flavonoid genes and that higher expression was achieved upon repeated UV exposure. Epigenetic memory development was observed in plants when they were exposed to low salt stress, mild heat shock, and small amounts of biotic agents under controlled conditions. This strategy specifically targets the activation of defense metabolites during the seedling stage (Choi et al., 2025). Many secondary metabolites additionally have the potential to act as biological pesticides. Epigenetically increasing these metabolites could produce alternatives to conventional pesticides. Flavonols (quercetin, kaempferol) have inhibitory effects against many bacteria and fungi. The production of these compounds can be increased by lowering the miR858 level. Volatile terpenoids (limonene, pinene) function as interplant alarm signals. Their production increases when H3K9ac histone acetylation is added to gene promoters (Fan & Feng, 2025). In Brassica species, removing the H3K27me3 repressor mark increases glucosinolate production and provides resistance to insects (Ben Ammar, 2025). Even without genetic modification, most epigenetic engineering applications still face regulatory uncertainty. It is not yet clear how long epigenetic changes persist and how they can be reversed depending on environmental conditions. With new generation epigenomic, metabolomic, and transcriptomic tools, targeted and rapid analysis is becoming possible. In the future, epigenetic information could be integrated into agricultural artificial intelligence systems and become part of decision support mechanisms (Bashir & Setyawati, 2025).

6. Conclusion

The defense strategies developed by plants against environmental stress conditions are not only based on genetic potential but additionally vary depending on epigenetic regulations shaped by interaction with the environment. This study details how secondary metabolite production is controlled by epigenetic mechanisms, how these processes function in the context of plant protection, and their potential future applications. The impact of epigenetic processes such as DNA methylation, histone modifications, and RNA-based silencing on plant defense genes and secondary metabolite biosynthesis pathways is supported by a growing number of studies. These regulations are not limited to short-term responses but can also be transmitted to future generations through epigenetic memory and even transgenerational heritage. These epigenetic networks have been shown to play important roles, particularly in the synthesis of major metabolite groups such as flavonoids, alkaloids, and terpenoids. In this context, epigenetic regulatory mechanisms enable the development of biologically based and environmentally friendly protection systems as alternatives to conventional pesticide use. Epigenetic modification using CRISPR/dCas9 systems, controlled use of epi mutagens, targeted gene silencing techniques via small RNAs, and epigenetic priming strategies will be among the fundamental components of future agricultural technologies. However, there are some critical issues that need to be resolved before these technologies can be widely adopted. The permanence of epigenetic changes, their reversibility depending on environmental conditions, regulatory deficiencies, and difficulties in field application remain high on the research agenda. To wrap things up, epigenetic regulation mechanisms bridge the gap between plant defense and secondary metabolite production, offering a new paradigm in agricultural biotechnology. This approach represents both a major shift in fundamental science and an important breakthrough for the future of sustainable agriculture. In the coming years, epigenetic engineering is expected to play a decisive role in many areas, such as plant breeding, biopesticide production, and environmentally friendly protection applications.

References

Abdulraheem, M. I., Xiong, Y., Moshood, A. Y., Cadenas-Pliego, G., Zhang, H., & Hu, J. (2024). Mechanisms of plant epigenetic regulation in response to plant stress: recent discoveries and implications. Plants, 13(2), 163.

Akif Açıkgöz, M. (2025). Salicylic acid and chitosan elicitors: Pre-harvest foliar applications improve antioxidant activity by increasing phenolic compounds in *Achillea gypsicola* Hub-Mor. Chemistry & Biodiversity, e202402716.

Açıkgöz, M. A., Ay, E. B., & Kocaman, B. (2025). Secondary metabolites and biological activities from *Achillea gypsicola* Hub-Mor. under foliar applications of chitosan and salicylic acid. Food Science & Nutrition, 13(5), e70225.

Bashir, H., & Setyawati, A. (2025). Decoding the mechanisms of plant epigenetic adaptations to stress. Reviews in Agricultural Science, 13(2), 1–19.

Bashir, S., Zargar, S. M., & Husaini, A. M. (2026). Epigenetic-modifications induced by plant-microbial interactions modulate plant immunity, defense-response and mutualistic associations. Molecular Biology Reports, 53(1), 86.

Basso, M. F., Vásquez, D. D. N., Campos-Pinto, E. R., Pinheiro, D. H., Cruz, B., Maktura, G. C., … & Grossi-de-Sa, M. F. (2025). Progress and opportunities of in planta and topical RNAi for the biotechnological control of agricultural pests. Agronomy, 15(4), 859.

Ben Ammar, H. (2025). Epigenetic regulation of glucosinolate biosynthesis: Mechanistic insights and breeding prospects in Brassicaceae. DNA, 5(4), 51.

Chen, L., Cheng, Y., & Hong, G. (2025). Molecular insights into the regulation of flavonoid biosynthesis in fruits. Horticulture Research, uhaf306.

Choi, D., Lee, S. W., & Kim, D. H. (2025). Bivalent histone modifications orchestrate temporal regulation of glucosinolate biosynthesis during wound-induced stress responses in Arabidopsis. Plant, Cell & Environment.

Cimmino, L., Staiti, A., Carputo, D., Docimo, T., D'Amelia, V., & Aversano, R. (2025). Adaptable alchemy: Exploring the flexibility of specialized metabolites to environmental perturbations through post-translational modifications (PTMs). Plants, 14(3), 489.

Cui, Q., Hu, S., Chu, R., Chen, Y., Taheri, A., Yang, F., … & Yang, D. (2025). How DNA methylation regulates plant natural product biosynthesis: From epigenetics to secondary metabolism. Plant, Cell & Environment.

Deleris, A., Halter, T., & Navarro, L. D. N. A. (2016). DNA methylation and demethylation in plant immunity. Annual Review of Phytopathology, 54(1), 579–603.

Fan, P., & Feng, X. (2025). Regulation of secondary metabolism in vegetable crops. In Growth Regulation and Quality Improvement of Vegetable Crops (pp. 145–181). Springer Nature Singapore.

Grewal, R. K., & Roy, A. (2025). Insight into the regulation of plant secondary metabolism by microRNAs. In Plant Secondary Metabolites (pp. 341–363). CRC Press.

Huang, C. Y., Gebiola, M., Wei, Y., Mauck, K. E., & Jin, H. (2025). A multifunctional citrus-derived antimicrobial peptide controls vascular bacterial pathogen. Journal of Integrative Plant Biology.

Ibragić, S., Dahija, S., & Karalija, E. (2025). The good, the bad, and the epigenetic: Stress-induced metabolite regulation and transgenerational effects. Epigenomes, 9(2), 10.

Jangpangi, D., Patni, B., Chandola, V., & Chandra, S. (2025). Medicinal plants in a changing climate: understanding the links between environmental stress and secondary metabolite synthesis. Frontiers in Plant Science, 16, 1587337.

Jose, S., Rahman, M., Keloth, M. R. A., Mohapatra, S., Rithesh, L., Kumar, S., … & Bouket, A. C. (2025). Omics-based strategies to unravel the role of melatonin in biotic and abiotic stress amelioration. In Melatonin: Signal Transduction Mechanisms and Defense Networks in Plants (pp. 41–82). Springer Nature Singapore.

Joshi, M., Samadhiya, P., Jajoo, A., & Verma, S. (2025). From stress to success: Mechanisms of elicitor-induced secondary metabolism. In Elicitation Methods for Improvement in Plant Secondary Metabolites (pp. 3–36). Springer Nature Singapore.

Karalija, E., Ibragić, S., Dahija, S., & Šamec, D. (2025). Transgenerational memory of phenotypic traits in plants: Epigenetic regulation of growth, hormonal balance, and stress adaptation. Current Issues in Molecular Biology, 47(6), 404.

Khan, A., Kanwal, F., Ullah, S., Fahad, M., Tariq, L., Altaf, M. T., … & Zhang, G. (2025). Plant secondary metabolites Central regulators against abiotic and biotic stresses. Metabolites, 15(4), 276.

Kouighat, M., Farhaoui, A., Assouguem, A., Taoussi, M., Belabess, Z., & Lahlali, R. (2025). Epigenetics for combating plant pathogens: Updated methods and current achievements. In Epigenetics for Climate-Smart and Sustainable Agriculture (pp. 309–325). CABI.

Kumar, R., Tiwari, R. K., Lal, M. K., Singh, A., Jha, J., Madival, V. A., … & Singh, G. (2025). Omics-based approaches in deciphering molecular mechanisms of tomato leaf curl New Delhi virus infection. In ToLCNDV: Insights into Virome Dynamics and Management (pp. 27–47). Springer Nature Singapore.

Kırgeç, Y., Batı-Ay, E., & Açıkgöz, M. A. (2023). The effects of foliar salicylic acid and zinc treatments on proline, carotenoid, chlorophyll content and antioxidant enzyme activity in Galanthus elwesii Hook. Horticulturae, 9(9), 1041.

Mahanta, D. K., Komal, J., Samal, I., Bhoi, T. K., Kumar, P. D., Mohapatra, S., … & Mastinu, A. (2025). Plant defense responses to insect herbivores through molecular signaling, secondary metabolites, and associated epigenetic regulation. Plant-Environment Interactions, 6(1), e70035.

Martins, D., Araujo, S. D. S., Rubiales, D., & Vaz Patto, M. C. (2020). Legume crops and biotrophic pathogen interactions: A continuous crosstalk of a multilayered array of defense mechanisms. Plants, 9(11), 1460.

Masuda, S., Komatsu, T., Atia, S., Suzuki, T., Hayashi, M., Toyoda, A., … & Inagaki, T. (2025). Iron-dependent JMJD1A-mediated demethylation of H3K9me2 regulates gene expression during adipogenesis. Genes to Cells, 30(3), e70023.

Mencia, R., Arce, A. L., Houriet, C., Xian, W., Contreras, A., Shirsekar, G., … & Manavella, P. A. (2025). Transposon-triggered epigenetic chromatin dynamics modulate EFR-related pathogen response. Nature Structural & Molecular Biology, 32(1), 199–211.

Moon, H., Kim, H., & Kim, D. H. (2025). A histone methyltransferase, early flowering in short days (EFS), is required for reproductive organ development in Brassica rapa. Horticulture, Environment, and Biotechnology, 1–14.

Nair, A. U., Bhukya, D. P. N., Sunkar, R., Chavali, S., & Allu, A. D. (2022). Molecular basis of priming-induced acquired tolerance to multiple abiotic stresses in plants. Journal of Experimental Botany, 73(11), 3355–3371.

Rani, S., & Chaudhary, S. (2026). Epigenetic regulation of plant flavonoid metabolism. In Flavonoids for Plant Development and Stress Tolerance (pp. 39–56). Academic Press.

Shah, M. A., Tramboo, H. A., & Rehman, S. A. (2025). Role of vector management strategies in mitigating tomato leaf curl New Delhi virus infection. In ToLCNDV: Insights into Virome Dynamics and Management (pp. 141–167). Springer Nature Singapore.

Tong, A., Wang, B., & Wu, J. (2025). DNA methylation valley as a distinguishing feature in root-specific nicotine-related genes in Nicotiana attenuata. Frontiers in Plant Science, 16, 1647622.

Upadhyay, R., Saini, R., Shukla, P. K., & Tiwari, K. N. (2025). Role of secondary metabolites in plant defense mechanisms: Molecular and biotechnological insights. Phytochemistry Reviews, 24(1), 953–983.

Wagh, S. G., Patil, A. M., Patil, G. B., Mankar, S. P., Rastogi, K., & Nishiguchi, M. (2025). Small RNA and epigenetic control of plant immunity. DNA, 5(4), 47.

Wang, Y., Chen, J., He, G., Yin, L., & Liao, Y. (2025). Unlocking the potential of flavonoid biosynthesis through integrated metabolic engineering. Frontiers in Plant Science, 16, 1597007.

Wu, X., Tian, Y., Li, W., An, J., Wu, Z., Huang, L., … Wu, Q. (2025). The transcription factor BoMYC2 negatively regulates seed size in broccoli. Theoretical and Applied Genetics, 138(9), 236.

Yang, J., Lu, X., Hu, S., Yang, X., & Cao, X. (2025). microRNA858 represses SbMYB47 and regulates flavonoid biosynthesis in Scutellaria baicalensis. Plant Physiology, 197(1), kiae607.

Yang, L., & Lu, Q. (2025). Beyond cutting: CRISPR-driven synthetic biology toolkit for next-generation microalgal metabolic engineering. International Journal of Molecular Sciences, 26(15), 7470.

Yu, R., Wang, X., & Moazed, D. (2018). Epigenetic inheritance mediated by coupling of RNAi and histone H3K9 methylation. Nature, 558(7711), 615–619.

Zhang, L., Wang, X., Zu, Y., He, Y., Li, Z., & Li, Y. (2024). Effects of UV-B radiation exposure on transgenerational plasticity in rice. International Journal of Molecular Sciences, 25(9), 4766.

Zhang, Z., Long, Y., Liu, Y., Huo, W., Li, J., Ren, Z., … & Li, W. (2025). H3K27me3 modulates fiber cell initiation in upland cotton. Industrial Crops and Products, 226, 120751.

Zidan, N. E. H. A., Abdel-Halim, K. Y., & Eissa, F. (2025). Climate change impacts on pesticide use and fate in the environment. In Climate Change Impacts on Toxins and Health Effects (pp. 149–170).

Chapter 10

AGRICULTURAL COOPERATIVE MOVEMENT IN SUGAR BEET PRODUCTION: A VIEW FROM THE TURKISH PERSPECTIVE

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1. Introduction

The agricultural sector has historically held a significant place in the economic and social structures of countries; it has been considered a strategic area in terms of ensuring food security, creating employment, and supporting rural development. Products directly related to agriculture-based industries necessitate addressing the agricultural sector not only in terms of production but also in terms of industry, trade, and employment. In this context, sugar beet stands out as one of the most prominent examples of the strong link between agriculture and industry, both globally and in Türkiye (Kadıoğlu, 2009; Yücel, 2023).

Sugar beet production differs from many other agricultural products due to its high input use, the need for planned production, and the necessity of processing it shortly after harvest. These characteristics have made sugar beet more dependent on organized and planned production models rather than individual production. In particular, the continuity of raw material supply, quality standardization, and marketing security are critically important for the healthy functioning of the sugar industry (Çalışkan et al., 2020). Therefore, sugar beet production in Türkiye, as in most countries, is carried out within the framework of contract farming and organized production structures (Taşpınar, 2019).

In Türkiye, sugar beet production has been central to agricultural policies since the early years of the Republic (Fedai, 2016). The sugar industry was systematically developed to encourage domestic sugar production, reduce dependence on foreign sources, and support rural development (Eştürk, 2018). During this process, sugar beet farming became a regular source of income for thousands of grower families; and sugar factories played a significant role in shaping the economic and social life of their regions. However, the sustainability of this structure depended more on growers acting within an organized framework rather than on individual efforts (Paksoy, 2023).

Cooperativism in agricultural production is an important organizational model that enables growers to become more resilient against market conditions by combining their economic power (Özüdoğru, 2010). Cooperatives aim to solve the problems faced by small and medium-sized growers in areas such as production, financing, marketing, and access to information within a collective structure (Yıldız, 2020). In countries like Türkiye, where agricultural enterprises largely consist of small family farms, cooperativism is considered one of the fundamental tools for agricultural sustainability (Engindeniz Yücel and Yercan, 2024).

In the context of sugar beet production, cooperative organization holds a privileged position in Turkish agriculture. Sugar Beet Growers' Cooperatives are not only structures that support growers in the production process; they are also institutional carriers of agricultural-industrial integration. Through these cooperatives, growers have gained a stronger position in input supply, credit access, production planning, and marketing processes. Furthermore, the cooperatives' participation in sugar factories or their direct industrial investments have enabled growers to share in the added value (Özer Topaloğlu, 2021).

The quota system and contract farming model applied in sugar beet production in Türkiye further enhance the importance of cooperatives. Growers are included in production planning through cooperatives; marketing risks are significantly reduced thanks to purchase and price guarantees (Koç et al., 2018). This has made sugar beet production a more stable source of income compared to many other agricultural products. At the same time, cooperatives play an intermediary role between growers and state and industrial organizations, effectively influencing the implementation of agricultural policies in the field (Timurkaynak, 2017).

However, factors such as globalization, climate change, increasing input costs, and structural transformation in agriculture are presenting sugar beet production and growers with new challenges (Koç and Yıldırım, 1997; Kadakoğlu et al., 2023). Changes in sugar policies, debates surrounding starch-based sugar production, and international competition are making the role of cooperatives even more important. Under these conditions, evaluating the current functions of cooperativism and revealing its potential for the future is of great importance.

The main objective of this study is to examine the role and strategic importance of cooperatives in the sustainability of sugar beet production in Türkiye, from both economic and institutional perspectives. The study investigates the functions of Sugar Beet Growers' Cooperatives in the production process, their contributions to growers, and their place in agricultural-industrial integration, addressing the problems encountered and offering future assessments. The study utilizes data from previous studies on the subject and from FAO, the Turkish Statistical Institute (TURKSTAT), the Ministry of Agriculture and Forestry (MAF), Türkiye Sugar Factories Inc. (Türkşeker), and the Union of Sugar Beet Growers Cooperatives (Pankobirlik). The obtained data are presented in graphs and tables using percentage and index calculations.

2. Global Sugar Beet and Sugar Production

Sugar beet is one of the most important agricultural products in global sugar production. Sugar production comes from two main sources: sugarcane and sugar beet. Sugarcane is mostly grown in tropical and subtropical regions, while sugar beet is widely produced in temperate climates. Therefore, sugar beet is a primary raw material for sugar, especially in Europe, North America, and parts of Asia.

Approximately one-third of global sugar production comes from sugar beet. Sugar beet is preferred in many developed and developing countries due to its high sugar content, suitability for advanced agricultural techniques, and amenity to mechanization. Furthermore, sugar beet farming strengthens agricultural-industrial integration and makes significant contributions to employment and rural development.

World sugar beet production increased during the 2015/16-2023/24 period. In 2023/24, sugar beet production reached 281.19 million tons. However, the increase in world sugar production during the same period was lower. 181.38 million tons of sugar were produced in 2023/24 (Table 1).

Table 1. *Developments in Sugar Beet and Sugar Production Worldwide*

Years	Production area (ha)	Sugar beet Production (ton)	Index (2015/16=100	Yield (Kg/ha)	Sugar production (ton)	Index (2015/16=100
2015/16	4,208,371	240,319,765	100	57,105	174,676,732	100
2016/17	4,587,746	278,811,858	116	60,773	178,479,499	102
2017/18	4,984,014	313,971,150	131	62,996	178,525,085	102
2018/19	4,788,192	273,423,200	114	57,104	182,135,160	104
2019/20	4,650,037	280,724,641	117	60,370	176,791,086	101
2020/21	4,335,966	250,420,967	104	57,754	173,089,040	99
2021/22	4,427,127	269,000,527	112	60,762	175,357,422	100
2022/23	4,298,648	260,004,206	108	60,485	187,626,279	107
2023/24	4,520,200	281,194,639	117	62,208	181,384,000	104

Kaynak: FAOSTAT, 2025.

Sugar beet production in the world is concentrated in certain countries. European Union countries have a significant share in world sugar beet production. France, Germany, and Poland, in particular, stand out in terms of both production quantity and efficiency. Modern agricultural techniques, high-yield seeds, and advanced irrigation systems are widely used in these countries. The Russian Federation and Ukraine hold significant positions in world sugar beet production due to their vast agricultural areas. The United States, on the other hand, intensively produces sugar beets, particularly in the Midwestern states (such as Minnesota, North Dakota, and Michigan). In Asia, China stands out among the countries in sugar beet production. Although sugar production in China is largely based on sugarcane, sugar beet production is increasing in the northern regions. In addition, Türkiye, Iran, and Kazakhstan are among the countries contributing to world sugar beet production (Figure 1).

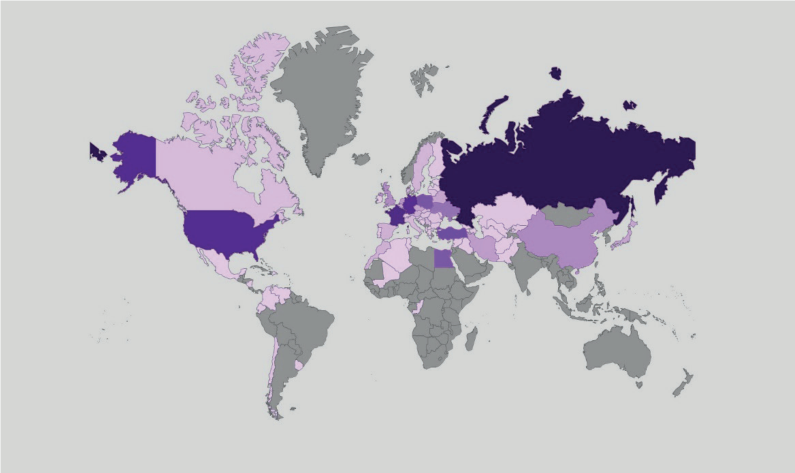

Figure 1. *Major Sugar Beet Producing Countries*
Source: FAOSTAT, 2025.

Sugar beet is a plant that prefers cool and temperate climates. Long daylight hours, sufficient rainfall or irrigation, and fertile soil are essential for high yields. Therefore, sugar beet production is generally common in mid-latitude countries. Extreme temperatures and drought negatively affect the plant's development and can reduce its sugar content.

Globally, climate change is also affecting sugar beet production. Drought, dwindling water resources, and extreme weather events are making production planning difficult and can lead to yield losses. Therefore, many countries are turning to developing more resilient beet varieties and adopting water-saving methods.

Worldwide sugar beet production is significantly influenced by government policies and international trade regulations. In the European Union, in particular, sugar production has been regulated for many years through quotas and subsidy policies. These policies aim to protect growers while simultaneously ensuring market stability. However, with the spread of globalization and free trade, competition in the sugar market has increased. The lower cost of sugarcane production has led to a decline in sugar beet production in some countries. Nevertheless, many countries continue to support sugar beet production for reasons such as food security, protection of domestic production, and rural development.

Worldwide, sugar beet production faces various challenges such as increasing production costs, environmental problems, and changing consumption habits. Criticism of sugar consumption from a health perspective has led to a decrease in sugar demand in some countries. On the other hand, biofuel production and alternative uses offer new opportunities for sugar beet.

In the future, the importance of sustainable agricultural practices in sugar beet production will increase. Production models that consume less water, are environmentally friendly, and have high yields will come to the forefront. In addition, digital farming applications and precision farming techniques will increase productivity and enhance the competitiveness of growers.

Sugar beet has an important place in world agriculture and the sugar industry. Widely produced in temperate climate regions, this product has both economic and strategic value for many countries. Despite the environmental and economic changes experienced on a global scale, it is predicted that sugar beet production will maintain its importance worldwide with appropriate policies and modern agricultural methods.

In the 2023/24 period, world sugar production was 181.38 million tons, consumption was 179.97 million tons, surplus was 1.41 million tons, import demand was 69.12 million tons, export availability was 69.63 million tons, closing stocks were 97.81 million tons, and the stock/consumption ratio was 54.35% (FAOSTAT, 2025). World sugar production is expected to decrease by 3.32% in the 2024/25 period, reaching 175.54 million tons. 78% of this will be sugar derived from sugar beets. Adverse climatic conditions, diseases, and low sucrose content are cited as potential causes of this decrease (Şekertürk, 2025). In addition to sugar obtained from sugar beet processing, by-products such as molasses and beet pulp are also used in livestock farming and industry. This makes sugar beet a high-value agricultural product.

3. Sugar Beet and Sugar Production in Türkiye

Sugar beet is a strategic agricultural product of great economic and social importance in Turkish agriculture. As the basic raw material for the sugar industry, sugar beet also supports rural employment, enables the development of agriculture-based industries, and contributes to livestock farming through its many by-products. Türkiye is among the countries suitable for sugar beet production in terms of climate and soil conditions and holds an important position in world sugar beet production (Demirdöğen, 2022).

Sugar beet is a cool-climate crop, usually sown in spring and harvested in autumn. It prefers deep, organically rich, and well-drained soils. Irrigation, fertilization, and disease control are crucial for achieving high yields. Since sugar beet production is labor-intensive, it requires both mechanization and human labor (Çiçek et al., 2022).

In 2024/25, sugar beet production by organizations producing sugar from sugar beets (Türkşeker, cooperatives, and the private sector) involved 93,293 growers planting sugar beets on 3.28 million decares of land, resulting in a production of 22.41 million tons. Basic data on sugar beet production for the last 10 years is given in Table 2. As can be seen, significant increases in production and yield have been recorded.

Table 2. *Sugar Beet Production Area and Production Quantity in Türkiye*

Years	Number of growers	Production area (da)	Production (ton)	Index (2015/16=100)	Yield (kg/da)
2015/16	103,400	2,739,912	16,022,783	100	5,848
2016/17	105,460	3,219,533	19,592,731	122	6,086
2017/18	110,131	3,388,829	21,149,020	132	6,241
2018/19	106,237	2,906,976	17,436,100	109	5,998
2019/20	88,279	3,100,807	18,054,320	113	5,822
2020/21	93,812	3,363,483	23,025,738	144	6,846
2021/22	86,097	3,023,486	17,767,086	111	5,876
2022/23	77,065	2,954,052	19,253,962	120	6,518
2023/24	99,714	3,628,146	25,250,213	158	6,960
2024/25	93,293	3,281,033	22,413,958	140	6,831

Source: TURKSTAT, 2025; Türkşeker, 2025.

Sugar beet production in Türkiye is mainly concentrated in the Central Anatolia, Aegean, Black Sea, and Eastern Anatolia regions. Konya, Eskişehir, Yozgat, Aksaray, Kayseri, Ankara, Afyonkarahisar, and Tokat are among the leading producing provinces (Figure 2). The Central Anatolia Region, in particular, accounts for a large portion of Türkiye's sugar beet production thanks to its vast agricultural areas and favorable climatic conditions.

Figure 2. *Important Provinces in Sugar Beet Production in Türkiye*

Source: TURKSTAT, 2025.

Sugar beet production has generally developed in regions where sugar factories are located. The main reason for this is the need to process the beets quickly after harvesting. This situation has led to a strong link between agriculture and industry, and sugar factories have been at the center of economic life in many cities (Karabulut and Topak, 2007).

In Türkiye, sugar beet production has been supported and planned by the state for many years. A quota system is implemented to balance supply and demand in sugar production. Under this system, growers are informed in advance how much sugar beet they can plant, and production is planned accordingly. The quota system aims to prevent overproduction while simultaneously securing growers' incomes. However, quota systems are sometimes criticized by growers. In particular, reductions in quota amounts can lead to income loss for growers. Despite this, sugar beet remains a reliable source of income for many growers (Erdinç, 2017).

In Türkiye's sugar industry, a total of 20 companies operate: 15 beet sugar producers and 5 starch-based sugar producers (Table 3). Additionally, there are 5 starch-based sugar producers that do not have quota rights and produce solely for export. Türkşeker owns 15 factories. However, the immovable properties and structures of the Çarşamba Sugar Factory were transferred to Machinery and Chemical Industry Inc. by Presidential Decrees No. 9315 and 9316 dated December 25, 2024.

Table 3. *Number of Sugar Producing Companies and Factories in Türkiye*

Structure	Number of companies	Number of factories
Sugar produced from beets	15	33
- Türkşeker	1	15
- Cooperative	3	6
- Private sector	11	12
Sugar produced starch-based	5	5

Source: Türkşeker, 2025.

Currently, Türkiye has a total sugar production capacity of 4.39 million tons annually, comprising 3.30 million tons of beet sugar and 1.09 million tons of starch-based sugar. Table 4 shows the total A quota sugar production amounts, calculated by Türkşeker, cooperatives, and private factories, based on the allocated quota for beet sugar production.

Table 4. *Quota - Production Relationship (Beet Sugar - A Quota)*

Years	Quota (ton)	Production (ton)	Production/ Quota (%)	Production/Quota (%)	
				Türkşeker	Cooperative + private sector
2015/16	2,250,000	1,890,957	84	79	90
2016/17	2,385,000	2,383,480	100	100	100
2017/18	2,536,500	2,525,244	100	99	100
2018/19	2,565,000	2,205,505	86	76	92
2019/20	2,632,500	2,457,568	93	96	92
2020/21	2,632,500	2,632,363	100	100	100
2021/22	2,632,500	2,469,299	94	92	95
2022/23	2,681,250	2,450,308	91	81	98
2023/24	2,837,250	2,837,474	100	100	100
2024/25	2,837,250	2,422,219	85	61	99

Source: Türkşeker, 2025.

In the 2024/25 marketing year, a Presidential Decree allocated 2.84 million tons of A quota and 141,863 tons of B quota to companies producing sugar from sugar beets. In the 2024/2025 marketing year, 35.72% of the total A quota sugar amount in the country was allocated to Türkşeker, 35.34% to cooperatives, and 29.94% to the private sector. As a result of the campaign lasting 83-191 days nationwide, 21.56 million tons of sugar beet were processed from a production of 22.41 million tons, and a total of 2.75 million tons of sugar (A quota + C sugar) was produced (Table 5).

Table 5. *Developments in Beet Sugar Production in Türkiye*

Years	Campaign Duration (days)	Processed beet (ton)	Sugar production (ton)
2015/16	82	15,418,923	1,976,124
2016/17	118	18,715,614	2,559,122
2017/18	105	20,467,586	2,769,588
2018/19	95	17,049,102	2,273,263
2019/20	99	17,751,820	2,535,602
2020/21	70-177	22,291,911	3,069,306
2021/22	43-132	17,423,766	2,519,549
2022/23	54-149	18,858,051	2,652,190
2023/24	82-182	24,251,403	3,335,353
2024/25	83-191	21,556,496	2,749,706

Source: Türkşeker, 2025

Sugar beet production is not limited to sugar production alone. By-products such as beet pulp, molasses, and leaves are used as animal feed, which increases the added value of the production. Furthermore, sugar factories provide direct and indirect employment to thousands of people in their regions (Yılmaz et al., 2023). For growers living in rural areas, sugar beet is an important product that provides a regular income. The guaranteed purchase price reduces the growers' production risk. In this respect, sugar beet is considered one of the fundamental agricultural products contributing to rural development.

Sugar beet production in Türkiye also faces some problems. Rising input costs (diesel fuel, fertilizer, seeds, and irrigation) can cause growers to abandon production. Furthermore, environmental factors such as climate change, dwindling water resources, and drought negatively impact production (Ünsal, 2024). In addition, starch-based sugar (SBS) production and import policies are also subjects of debate for sugar beet growers. This situation highlights the need to protect domestic sugar beet production.

Sugar beet is a strategically important product for Turkish agriculture and economy. Its structure, which brings together agriculture, industry, and livestock sectors, makes a multifaceted contribution. Supporting growers, disseminating modern agricultural techniques, and using water resources efficiently are crucial for ensuring the sustainability of production. With the right policies, sugar beet production in Türkiye will continue to contribute to both the national economy and rural development in the long term.

Türkşeker was included in the privatization scope by the High Council of Privatization's decision dated 20/12/2000 and numbered 2000/92, and in the public share privatization program by its decision dated 02/08/2008 and numbered 2008/50 (Aygen and Duman, 2021). In the privatizations carried out in 2018, 10 sugar factories belonging to Türkşeker were privatized. Currently, Türkşeker is one of the leading industrial enterprises in our country for 99 years, with 15 sugar factories, as well as 3 machinery factories, 1 electromechanical equipment factory, 1 alcohol factory, and 1 sugar institute. Türkşeker was removed from the privatization scope and program by Presidential Decree dated 29/4/2021 and numbered 3923, and its entire capital was transferred to the Türkiye Wealth Fund. It was assigned to the Ministry of Agriculture and Forestry by Presidential Decree No. 4083 dated 12/11/2021 (Türkşeker, 2025).

4. Sugar Beet and Sugar Marketing in Türkiye and Prices

Sugar beet is a strategically important industrial crop in Turkish agriculture, forming the basic raw material for the sugar industry. Both the production and marketing processes of sugar beet are crucial for the success of agricultural activities. In Türkiye, unlike many other agricultural products, sugar beet marketing is carried out within a planned and contractual framework rather than under free market conditions. This ensures both income security for growers and a regular supply of raw materials for the sugar industry (Kanat, 2023).

In Türkiye, sugar beet marketing is largely based on contract farming. Before the planting season begins, growers sign contracts with sugar factories or Sugar Beet growers' Cooperatives, and the amount of beets they will produce is determined in advance. This system reduces uncertainty in production and eliminates marketing risk (Tuğcu, 2009).

The most important actors in the marketing of sugar beet are sugar factories, Sugar Beet Growers' Cooperatives, and Pankobirlik. Growers do not offer their beets directly to the free market; they deliver them to the factory with which they have a contract. In this respect, sugar beet is considered one of the agricultural products with the fewest marketing problems.

One of the most important factors shaping sugar beet marketing in Türkiye is the quota system. Implemented to balance supply and demand in sugar production, this system determines the amount of beets to be produced each year. Under the quota system, growers are granted planting permits, and all of the beets produced are purchased at a predetermined price.

While the quota system provides price and purchase guarantees for growers, it is also considered a factor that limits marketing flexibility. Growers may experience difficulties in marketing the sugar beets they produce outside the quota. Nevertheless, the system ensures that sugar beet marketing in Türkiye is carried out in a regular and stable manner.

Sugar beet prices are determined annually by the government, sugar factories, and relevant stakeholders before the start of the production season. Pricing takes into account production costs, inflation, input prices, and market conditions. The announced purchase price applies to all growers and eliminates price uncertainty in the market. Table 6 shows the changes in the base purchase prices for quota A.

Table 6. *Sugar Beet Prices Received by Growers*

Years	Base purchase price (A Quota) (TL/ton)	Türkşeker base purchase price (A Quota) (TL/ton)	Average grower price (TL/ton) (*)
2015/16	191	190	190
2016/17	194	190	190
2017/18	210	210	210
2018/19	235	235	240
2019/20	300	300	320
2020/21	336	336	360
2021/22	420	420	410
2022/23	1,400	1,400	1,500
2023/24	1,750	1,750	1,910
2024/25	2,375	2,262	2,310

(*) TURKSTAT data

Source: TÜRKSTAT, 2025; Türkşeker, 2025.

In addition to the price of sugar beets, growers may also receive quota premiums, early delivery premiums, and other support payments. These payments aim to increase growers' income and maintain the attractiveness of sugar beet production. Timely payments during the marketing process are crucial for grower satisfaction.

Sugar Beet Growers' Cooperatives are one of the most important organizational elements in sugar beet marketing in Türkiye. These cooperatives act as intermediaries between growers and sugar factories, managing contract processes, organizing beet delivery, and protecting growers' rights (Çiçek, 2021).

Cooperatives also play an active role in logistics activities such as the transportation, storage, and shipment of sugar beets to the factory. This makes the marketing process more organized and cost-effective. In regions where cooperatives are strong, growers experience minimal marketing problems (Oğuz and Mete, 2017).

Sugar beet is a product that needs to be processed quickly after harvesting. Therefore, the marketing process must be well-planned from a logistical perspective. Growers deliver their beets to sugar factories on the specified dates and at the designated delivery points. During delivery, the quality criteria of the beets (sugar content, soil content, etc.) are taken into account and evaluated accordingly.

While sugar beet marketing in Türkiye generally has a stable structure, some problems exist. Rising transportation costs, delays in delivery processes, and quality degradation can negatively impact growers. Furthermore, the tightening of quotas is limiting the marketing opportunities of some growers. In addition, starch-based sugar production and sugar imports are among the factors affecting the market share of beet sugar. This situation indirectly impacts the marketing power of sugar beet growers and cooperatives.

According to the Sugar Law No. 4634, production planning is carried out in Türkiye to meet the demand for sugar, and the amount of sugar to be marketed within the country is determined by quotas allocated by the President (Çiçek, 2022). It is programmed that 95% of Türkiye's annual sugar needs will be met by beet sugar and 5% by starch-based sugars. With Law No. 7103, starting from the 2019/2020 marketing year, the quota for starch-based sugars has been determined annually by presidential decree as 2.5% of the total national A quota. The beet sugar and starch-based sugar quotas for each year are given in Table 7.

Table 7. *Beet Sugar and Starch-Based Sugar Quotas (1,000 ton)*

Years	Beet sugar quota (A)	Starch-based sugar quota (A)	Total quota (A)
2015/16	2,363	250	2,613
2016/17	2,504	255	2,769
2017/18	2,523	267	2,790
2018/19	2,565	135	2,700
2019/20	2,633	67.5	2,700
2020/21	2,633	67.5	2,700
2021/22	2,633	67.5	2,700
2022/23	2,681	68.75	2,750
2023/24	2,837	72.75	2,910
2024/25	2,837	72.75	2,910

Source: Pankobirlik, 2025.

In Türkiye, sugar beet marketing has a planned structure based on contract farming, a quota system, and cooperatives. This system largely eliminates marketing risk by offering growers purchase and price guarantees. However, factors such as increasing costs, policy changes, and global competition necessitate the continuous improvement of the marketing process. Strengthening cooperatives, improving logistics infrastructure, and continuing grower-friendly policies are crucial for maintaining an effective marketing structure.

Türkşeker is committed to keeping sugar sales prices at a minimum level to reduce food inflation and regulate the market, ensuring that our citizens can consume sugar at affordable prices. The ex-factory sales prices (excluding VAT) determined for beet sugar, representing the weighted average for Türkiye, and the general average for starch-based sugar are given in Table 8.

Table 8. *Sugar Prices in Türkiye*

Years	Beet sugar price (TL/kg)	Change (%)	Starch-based sugar price (TL/kg)	Change (%)
2015/16	2.70	7.14	1.87	7.00
2016/17	2.66	-1.48	1.92	2.67
2017/18	2.87	7.89	2.11	9.90
2018/19	3.13	9.06	2.70	27.96
2019/20	3.54	13.10	3.30	22.22
2020/21	3.66	3.39	3.66	10.91
2021/22	8.16	122.95	6.74	84.15
2022/23	19.37	137.38	18.57	175.52
2023/24	25.04	29.27	29.80	60.47

Source: Türkşeker, 2025.

In Türkiye, as with other products, protectionist measures for sugar are determined and implemented in accordance with the World Trade Organization

Agreement on Agriculture, "Commitments to Market Access". A 10% reduction was committed from the 150% import protection rate, which was committed as a ceiling, until 2004. From 2004 onwards, the customs duty was reduced to 135% and remains at the same rate. Since no specific protectionist measures are foreseen, the current import protection rate may occasionally be insufficient depending on world sugar prices and exchange rate fluctuations. The fact that world market prices are below domestic prices necessitates that the sustainability of the sector be secured with high protection rates. In the 2024/25 period, Türkiye imported 200,000 tons of crystal sugar and 20,700 tons of starch-based sugar, while exporting 345,100 tons of starch-based sugar (Türkşeker, 2025). Developments regarding production, use, foreign trade, and self-sufficiency levels in sugar beet and sugar in Türkiye are given in Table 9.

Table 9. *Sugar Beet and Sugar Balance in Türkiye*

Sugar Beet								
Years	Supply = usage (ton)	Usable production (ton)	Import (ton)	Domestic use (ton)	Processed (ton)	Losses (ton)	Export (ton)	Sufficiency level (%)
2015/16	16,022,783	16,022,783	-	16,022,783	15,418,923	603,860	-	100
2016/17	19,592,731	19,592,731	-	19,592,731	18,715,614	877,117	-	100
2017/18	21,149,020	21,149,020	-	21,149,020	20,467,586	681,434	-	100
2018/19	17,436,100	17,436,100	-	17,436,100	17,049,102	386,998	-	100
2019/20	18,054,320	18,054,320	-	18,054,320	17,751,820	302,500	-	100
2020/21	23,025,739	23,025,738	1	23,025,733	22,291,911	733,822	6	100
2021/22	17,767,101	17,767,085	16	17,767,077	17,423,766	343,311	24	100
2022/23	19,253,962	19,253,962	-	19,253,948	18,858,051	395,897	14	100
2023/24	25,250,213	25,250,213	-	25,250,119	24,251,403	998,716	94	100
Sugar								
Years	Supply = usage (ton)	Usable production (ton)	Import (ton)	Domestic use (ton)	Human consumption (ton)	Losses (ton)	Export (ton)	Sufficiency level (%)
2015/16	2,303,757	1,976,124	327,633	2,093,365	2,061, 965	31,400	251,833	94
2016/17	2,869,730	2,559,122	310,608	2,485,379	2,448,098	37,281	268,649	103
2017/18	3,060,680	2,769,588	291,092	2,384,887	2,349,114	35,773	251,319	116
2018/19	2,515,474	2,273,263	242,211	2,543,151	2,505,004	38,147	377,717	89
2019/20	2,819,264	2,535,602	283,662	2,562,852	2,524,409	38,443	244,712	99
2020/21	3,286,742	3,069,306	217,436	2,558,663	2,520,283	38,380	592,629	120
2021/22	2,924,248	2,519,549	404,699	2,641,249	2,601,630	39,619	463,178	95
2022/23	3,325,124	2,652,189	672,935	2,910,450	2,866,793	43,657	409,558	91
2023/24	3,588,689	3,335,540	253,149	2,494,566	2,457,148	37,418	515,222	134

Source: TURKSTAT, 2025.

5. Agricultural Cooperatives in Türkiye

Agricultural cooperatives are a form of organization formed by growers operating in the agricultural sector who voluntarily come together to protect and improve their economic, social, and cultural interests. In countries like Türkiye, where agriculture plays a significant role in terms of employment and production, agricultural cooperatives play an important role in both increasing growers' income levels and ensuring rural development. In Türkiye, agricultural cooperatives are an important subject that deserves examination in terms of their historical development, organizational structure, and the problems they face.

Cooperative activities in Türkiye date back to the Ottoman Empire. The National Funds established in 1863 under the leadership of Mithat Pasha, are considered the first examples of agricultural cooperatives. These funds aimed to meet the credit needs of growers and later formed the basis of the Agricultural Bank.

After the proclamation of the Republic, agricultural cooperatives were supported by the state and given a legal framework. The Cooperatives Law, enacted in 1935, regulated cooperative activities and encouraged the proliferation of cooperatives in the agricultural sector. Especially after the 1960s, Agricultural Development Cooperatives, Agricultural Credit Cooperatives, and Agricultural Sales Cooperatives increased rapidly.

The primary goal of agricultural cooperatives is to enable growers to meet their needs more easily and at a lower cost by acting collectively, needs that they would find difficult to meet individually. In this context, cooperatives operate in many areas, including input supply, product marketing, credit provision, storage, processing, and consulting services.

Thanks to cooperatives, growers can obtain agricultural inputs such as fertilizers, seeds, pesticides, and feed at more affordable prices; and they have the opportunity to market their products at better prices. In addition, cooperatives contribute to the quality and standardization of agricultural production, thus increasing the competitiveness of growers.

Agricultural cooperatives in Türkiye are organized into different types according to their areas of activity. Agricultural Credit Cooperatives are one of the most common types of cooperatives, providing growers with financing and inputs. These cooperatives contribute to the sustainability of agricultural production by facilitating growers' access to credit.

Agricultural Sales Cooperatives are established to help growers evaluate and market their products. Operating in products such as hazelnuts, cotton, olives, grapes, and sunflowers, these cooperatives help growers be less affected by market fluctuations. Furthermore, Agricultural Development Cooperatives operate with the aim of creating employment in rural areas, developing livestock farming, and supporting local development.

Agricultural cooperatives are an important tool in achieving rural development. Cooperatives contribute to a more balanced income distribution by enabling small-scale growers to have a voice in the market. They also help develop organizational awareness and strengthen social solidarity in rural areas.

Cooperatives also have the potential to increase the participation of women and young people in agricultural production. Women's cooperatives, in particular, play a significant role in promoting local products and supporting entrepreneurship. In this respect, agricultural cooperatives are considered not only an economic but also a social development tool.

In Türkiye; agricultural cooperatives constitute 18% of the total number of cooperatives and 57% of the number of cooperative members. Information on the number of agricultural cooperatives operating in Türkiye and the number of members is presented in Table 10. As can be seen, the cooperatives with the largest number are Agricultural Development Cooperatives (6,597). Agricultural Development Cooperatives constitute 56% of agricultural cooperatives (11,709). These cooperatives are affiliated to Village-Cooperative, Agriculture, Animal Husbandry, Forestry and Tea Regional Unions according to their fields of activity. When examined in terms of the number of members, it is seen that the cooperatives with the largest number of members are Sugar Beet Growers Cooperatives (1,399,339). Sugar Beet Growers Cooperatives constitute 38% of the total number of members of agricultural cooperatives (3,672,010) (Table). Sugar Beet Growers Cooperatives take the necessary measures regarding soil preparation, planting, growing and protecting sugar beets and other agricultural products, and increasing their yield per decare, and help their partners obtain useful information (Yücel Engindeniz and Yercan, 2024).

Agricultural cooperatives in Türkiye face various problems. These include management deficiencies, financing issues, insufficient awareness of cooperatives among members, and a lack of professional management. Furthermore, the political influence of some cooperatives hinders their effective and efficient operation. The inadequacy of cooperatives in marketing and branding is also a significant problem. This leads to low added value of cooperative products and prevents growers from achieving their expected income.

Table 10. *Agricultural Cooperatives Operating in Türkiye (2024)*

Law	Unit cooperatives			Cooperative regional unions				Cooperative central unions (**)			
	Cooperative type	Number of cooperative	Number of partners	Cooperative type	Number of partner unions	Number of partner cooperatives	Number of partners	Number of central unions	Number of partner unions	Number of partner cooperatives	Number of partners
1163	Agricultural Development	6,597	731,195	Village-cooperatives	16	1,423	166,444	1	19	1,277	146,332
				Agriculture	12	543	62,250	1	21	952	109,005
				Animal Husbandry	34	1,734	179,301	1	34	1,806	194,000
				Forestry	17	828	100,124	1	29	2,440	303,029
				Tea	5	35	65,752	1	5	35	65,752
1163	Irrigation	2,484	319,761	Irrigation	14	673	93,228	1	17	617	88,930
1163	Fishery	594	31,029	Fishery	17	232	14,304	1	17	199	11,403
1163	Sugar Beet Growers	31	1,399,339	Sugar Beet Growers	1	31	1,399,339	-	-	-	-
	Sub-total	**9,706**	**2,481,324**	**Sub-total**	**116**	**5,499**	**2,080,742**	**7**	**142**	**7,326**	**918,451**
1581	Agricultural Credit	1,618	853,869	Agricultural Credit	17	1,618	853,869	1	17	1,618	853,869
	Sub-total	**11,324**	**3,335,193**	**Sub-total**	**133**	**7,117**	**2,934,611**	**8**	**159**	**8,944**	**1,772,320**
4572	Agricultural Sales (*)	338	332,925	Agricultural Sales	13	281	308,346	-	-	-	-
1196	Tobacco Agriculture Sales (*)	18	939	Tobacco Agriculture Sales	1	9	124	-	-	-	-
1163	Fresh Fruit and Vegetable Marketing (*)	29	2,953	Fresh Fruit and Vegetable Marketing	-	-	-	-	-	-	-
Total	**General**	**11,709**	**3,672,010**	**Total**	**147**	**7,407**	**3,243,081**	**8**	**159**	**8,944**	**1,772,320**

(*) It is under the responsibility of the Ministry of Trade. (**) These are cooperative unions within the Agricultural Purpose Cooperative Central Unions.

Source: MAF, 2025.

Agricultural cooperatives are an indispensable element for the development of Turkish agriculture and rural development. To increase the effectiveness of cooperatives, it is necessary to strengthen their institutional structures, expand training and consultancy services, and make effective use of government support. Strong and sustainable agricultural cooperatives will increase the competitiveness of the agricultural sector in Türkiye, making significant contributions to both growers and the national economy.

6. Purposes and Activities of Sugar Beet Growers' Cooperatives in Türkiye

Sugar beet is one of the strategically important products in Turkish agriculture, holding a significant economic and social position thanks to its strong connection with both agricultural production and industry. The sustainability of sugar beet production has been made possible by growers operating within organized structures. In this context, Sugar Beet Growers' Cooperatives stand out as one of the most successful examples of agricultural-industrial integration in Türkiye. Sugar Beet Growers' Cooperatives are well-established organizations that protect the rights of growers, support production, and contribute to the development of the sugar industry (Çiçek and Acar, 2019).

The emergence of Sugar Beet Growers' Cooperatives in Türkiye is closely linked to the establishment of the sugar industry in the early years of the Republic. The Republican government placed great importance on developing domestic industry to ensure economic independence. In line with this, with the establishment of the Alpullu and Uşak Sugar Factories in 1926, sugar beet cultivation began to be systematically expanded.

Since sugar beet production necessitates a regular and continuous supply of raw materials, the organization of farmers became inevitable. In response to this need, sugar beet growers were encouraged to form cooperatives. The first Sugar Beet Growers' Cooperatives began to be established from the 1950s onwards and gradually spread throughout Türkiye. These cooperatives served as a bridge between sugar factories and growers (Ertan, 1997).

The 1970s marked a significant turning point for Sugar Beet Growers' Cooperatives. During this period, cooperatives began to be active not only in the production phase but also in the industrial sector, and the process of becoming shareholders in sugar factories accelerated. Thus, growers moved beyond simply being growers growing sugar beets and gained an industrialist identity as well.

In Türkiye, Sugar Beet Growers' Cooperatives are organized according to regional principles. Each cooperative encompasses growers in the sugar beet growing area of a specific sugar factory. The highest-level organization of these cooperatives is the Union of Sugar Beet Growers' Cooperatives (Pankobirlik). Pankobirlik ensures coordination among the cooperatives, develops common policies, and undertakes the representation of growers at the national level.

Pankobirlik has over 1 million members engaged in sugar beet production in 13,750 settlements across 64 provinces of Türkiye (Figure 3), 328 branches of 31 Sugar Beet Cooperatives, 6 Cooperative Sugar Factories (Amasya, Kayseri, Boğazlıyan, Konya, Çumra, Turhal), and over 50 agricultural subsidiaries (Pankobirlik, 2025).

Figure 3. *Distribution of Sugar Beet Grower Cooperatives in Türkiye*
Source: Pankobirlik, 2025.

Amasya Sugar Factory Inc., Kayseri Sugar Factory Inc., and Konya Sugar Factory Inc. are private companies within the Pankobirlik organization. Pankobirlik is a higher-level union established through joint ventures between local Sugar Beet Growers' Cooperatives and Türkşeker, with the aim of developing sugar beet farming and protecting the rights of local cooperatives by addressing their economic and technical shortcomings.

The Amasya, Kayseri, and Konya Sugar Factories, which were under the umbrella of Pankobirlik and had special status, were managed and managed by Türkiye Sugar Factories Inc. from their establishment until the early 1990s, through decisions of their Boards of Directors. In 1991, the Amasya Sugar Factory, and in 1992, the Kayseri and Konya Sugar Factories, relinquished their management authority to Türkiye Sugar Factories Inc. and became part of Pankobirlik.

The management structure of the cooperatives is based on democratic principles. Growers elect their managers through the general assembly and participate directly in cooperative activities. This structure ensures that growers have a say in decision-making processes, thus aligning with the fundamental principles of cooperativism.

The activities of Sugar Beet Growers' Cooperatives cover a very wide range. Foremost among these activities is the supply of inputs to growers. Cooperatives provide growers with inputs used in production, such as seeds, fertilizers, pesticides, fuel, and agricultural equipment, under favorable conditions. This reduces costs for growers and increases productivity. Another important activity of cooperatives is financing and credit services. Sugar Beet Growers' Cooperatives provide financial support to growers throughout the process from planting to harvesting by providing in-kind and cash loans. This support is of great importance, especially for small and medium-sized growers.

Production planning and contract farming practices are also among the core activities of cooperatives. Since sugar beet production is managed through a quota system, cooperatives plan production on behalf of growers and sign contracts with sugar factories. This eliminates the risk of growers being unable to sell their products and ensures income stability.

Over time, Sugar Beet Growers' Cooperatives have expanded beyond agricultural production and made significant investments in the industrial sector. Cooperatives have become shareholders in sugar factories or have begun operating them directly. This development has enabled growers to receive a greater share of the added value.

In addition to sugar production, the production of ethanol, feed, molasses, and starch-based by-products has also become part of the cooperatives' activities. By-products such as beet pulp and molasses make significant contributions to the livestock sector and increase the economic value of production.

Sugar Beet Growers' Cooperatives make significant contributions to the development of economic and social life in their regions. Cooperatives and affiliated organizations create employment in rural areas and have a mitigating effect on migration. They also contribute to the development of solidarity and organizational awareness among growers.

Cooperatives increase the knowledge level of growers through training and consultancy activities, and support the spread of modern agricultural techniques. This contributes to both increased productivity and the development of an environmentally conscious production approach.

Pankobirlik, with over 50 subsidiaries, continues to serve its members and contribute to the economy without interruption. Its place and contribution within the national economy, as expressed in the 2020 figures, is as follows:

It has a capital of 349 million USD, total assets of 2.596 billion USD, a turnover of 2.272 billion USD, has provided 63 million USD in in-kind and cash support to its members, and paid 65 million USD in taxes to the treasury (Pankobirlik, 2025).

Sugar Beet Growers' Cooperatives also face some structural and economic problems. Rising input costs, climate change, dwindling water resources, and the decline of young people in agriculture are among the significant issues. Furthermore, sugar policies, quota applications, and debates surrounding starch-based sugar production directly affect beet growers. Strengthening the institutional capacity of cooperatives, promoting professional management, and increasing transparency will play a crucial role in overcoming these problems.

Sugar Beet Growers' Cooperatives are one of the oldest and most effective examples of agricultural cooperatives in Türkiye. Historically, these cooperatives have evolved from structures solely supporting production to actively participating in industry and trade, increasing the economic power of growers. Supported by sound policies, strong organization, and sustainable agricultural practices, Sugar Beet Growers' Cooperatives will continue to play a significant role in the future of Turkish agriculture and the sugar industry.

7. Conclusion

In Türkiye, sugar beet production constitutes one of the strongest examples of integration between agriculture and industry, and the sustainability of this structure has largely been made possible through the cooperative model. Sugar Beet Growers' Cooperatives have ensured the continuity of sugar beet farming by solving economic, technical, and marketing problems that growers find difficult to address individually, within a collective structure. In this respect, cooperativism has become not only a form of organization but also one of the fundamental pillars of the production process.

Cooperatives provide support to growers in a wide range of areas in sugar beet production, from input supply to financing, from production planning to marketing. This structure, which operates within the framework of contract farming and a quota system, significantly reduces production risks by providing growers with purchase and price guarantees. Thus, sugar beet has become a product with lower marketing uncertainty and higher income stability compared to many other agricultural products. This situation stands out as an important factor encouraging small and medium-sized growers to remain in agriculture.

Another significant contribution of cooperatives is that they enable growers to gain a stronger position in the agricultural-industrial chain. The participation of Sugar Beet Growers' Cooperatives in sugar factories or their direct industrial investments have allowed growers to receive a greater share of added value. This development has transformed cooperatives from classical solidarity organizations into economically powerful institutional structures. It has also yielded significant results in terms of job creation in rural areas and the revitalization of local economies.

However, the structural problems facing the cooperative structure should not be overlooked. Factors such as increasing input costs, climate change, dwindling water resources, and the decline of young people in agriculture are challenging sugar beet production and, consequently, the effectiveness of cooperatives. Furthermore, management problems, lack of institutional capacity, and insufficient awareness of cooperatives among members, as observed in some cooperatives, can prevent them from fully realizing their potential.

In this context, strengthening the role of cooperatives in sugar beet production in Türkiye requires the development of their institutional structures and the widespread adoption of transparent and professional management practices. Providing growers with training, consultancy, and digital agriculture applications through cooperatives will both increase productivity and support a sustainable production approach. The state's pursuit of cooperative policies with a long-term and grower-focused approach will also be crucial for the success of this process.

In conclusion, cooperatives form the economic, social, and institutional foundation of sugar beet production in Türkiye. Thanks to strong cooperative structures, growers become more resilient to market fluctuations, and agricultural-industrial integration continues in a sustainable manner. Therefore, supporting and developing cooperatives is of strategic importance not only for sugar beet growers but also for the future of Turkish agriculture and rural development.

REFERENCES

Aygen, M., Duman, M., (2021). Public Economic Enterprises and Privatization Applications: Sugar Factories Example. *Journal of Social and Humanities Sciences Research*, 8(75), 2629-2637.

Çalışkan, M.E., Çalışkan, S., Demirel, U., Aksoy, E., Arıoğlu, H.H., (2020). Current Situation and Future in Starch and Sugar Plant Production, Türkiye Agricultural Engineering IX. Technical Congress, 13-17 January 2020, Ankara, pp.439-461.

Çiçek, O., (2021). Alternative Approaches in the Face of the Privatization Process in the Sugar Industry: A Critical Evaluation Through the Example of Pankobirlik, In: Agriculture and Cooperatives in 21st Century Türkiye: Theory, Practice, Vision, Ed. E.Ç.Şahin, NotaBene Publications, Istanbul, pp.83-106.

Çiçek, Ö., (2022). Seeking an Alternative Model for Producer and Worker Solidarity in the Turkish Sugar Industry, *Journal of Faculty of Economics and Administrative Sciences of Mehmet Akif Ersoy University*, 9(1),.455-482.

Çiçek, Ö., Acar, O.K., (2019). Discussing the Near Future of Producer Cooperative's in Türkiye while the Sugar Mill's Privatizing: The Case of the Union of Beet Growers Cooperatives (Pankobirlik), *Fiscaoeconomia,* 3(2), 99-127.

Çiçek, Y., Uludağ, A., Gülbandılar, E., (2022). Artificial Intelligence Techniques in Sugar Beet Production, *Journal of Eskisehir Turkish World Application and Research Center Informatics*, 3(2), 54-59.

Demirdöğen, A., (2022). Sugar in Türkiye: A Short Discussion of Production, Consumption, Trade and Policies, *Journal of Agricultural Economics Research*, 8(1), 85-95.

Erdinç, Z., (2017). The Development of Sugar Industry in Türkiye and the Politics of Sugar Industry, *Anadolu University Journal of Social Sciences*, 17(3), 9 -26.

Ertan, A., (1997). A Proposed Approach to the Problem of Privatization of Agricultural State-Owned Enterprises in Türkiye with Cooperatives and the Example of Pankobirlik in the Turkish Sugar Industry, Pankobirlik Publication No: 5, Ankara.

Eştürk, Ö., (2018). An Assessment on Importance and Future of the Sugar Industry in Türkiye, *Anatolian Journal of Economics and Business*, 2(1), 67- 81.

Fedai, R., (2016). Sugar and Sugar Beet as a Policy Area. *Journal of History School*, 9(28), 455-471.

FAOSTAT, (2025). Sugar Beet and Sugar Production and Trade Statistics, https://www.fao.org/faostat, Access date: 16 December 2025.

Kadakoğlu, B., Karlı, B., Taşçı, N., Özyürek, H., (2023). Sugar Beet Production Cost and Profitability Analysis: The Case of Burdur Province, *Kahramanmaraş Sütçü İmam University Journal of Agriculture and Nature*, 26(2), 385- 392.

Kadıoğlu, Y., (2009). Geographical Features of Sugar Beet Agriculture in Çivril, *Eastern Geographical Review*, 14(22), 107-124.

Kanat, Z., (2023). Product Report: Sugar Beet and Sugar-2023, Agricultural Economics and Policy Development Institute Publication No: 388, Ankara.

Karabulut, T., Topak, A., (2007). The Cost and Productivity at Sugar Industry: The Comparison of Public and Private Sector, *Journal of Social Sciences Vocational School of Selçuk University*, 10(1-2), 1-20.

Koç, B., Yıldırım, İ., (1997). Socio-Economic Structures and Annual Activity Results of a Selected Group of Sugar Beet Growing Enterprises in Gevaş District of Van Province, *Yüzüncü Yıl University Journal of Science Institute*, 4(1), 17-32.

Koç, H., Ergün, A., Kartal, F., (2018). Problems of Sugar Beet Producers in Sivas Province and Proposals for Solutions, *International Journal of Geography and Geography Education*, 38, 247-265.

MAF, (2025). Agricultural Organization Statistics in Türkiye, General Directorate of Agricultural Reform, Ankara.

Oğuz, H., Mete, O., (2017). Branding in Cooperatives and Relationship Between Consumer-Cooperative Products: Torku Case, *Third Sector Social Economic Review*, 52 (Special edition), 386-424.

Özer Topaloğlu, E., (2021). Example of Agricultural Cooperative in Türkiye: Historical Development of Konya Sugar Inc., *Journal of Social and Humanities Sciences Research*, 8(71), 1498-1502.

Özüdoğru, H., (2010). Marketing in Cooperatives, *Agricultural Engineering*, 354: 58-64.

Pankobirlik, (2025). General Information and History, https://www.pankobirlik.com.tr/AnaSayfa/Genel_Bilgi_ve_Tarihce, Access date: 15 December 2025.

Paksoy, H., (2023). A Study on Beet Growers and Irrigation Cooperative Members: The Case of Konya Province, Journal of Social, *Humanities and Administrative Sciences*, 9(70), 3851-3855.

Taşpınar, T., (2019). Cooperatives and Their Importance in the Sugar Sector, https://www.tarimorman.gov.tr, Accessed: 13 December 2025.

Timurkaynak, İ., (2017). An Evaluation of Satisfaction of Members in the Beet Growers Cooperatives-Kayseri, MSc Thesis, Institute of Science of Aydın Adnan Menderes University, Aydın.

Tuğcu, G., (2009). Evaluation of the Significance of Pankobirlik in the National Sugar Market in Terms of Sugar Beet Producer within the Framework of 4634 Sugar Act, MSc Thesis, Institute of Science of Namık Kemal University, Tekirdağ.

TURKSTAT, (2025). Sugar Beet and Sugar Production, Trade and Price Statistics, https://data.tuik.gov.tr, Access date: 15 December 2025.

Türkşeker, (2024). Sector Report-2024, Turkish Sugar Factories Inc., Ankara.

Ünsal, Y., (2024). Agricultural Products Markets: Sugar Beet, Agricultural Economics and Policy Development Institute, Ankara.

Yıldız, S., (2020). Agricultural Marketing and Place of Agricultural Cooperatives in Agricultural Marketing, *Journal of International Social Research*, 13(72), 879-893.

Yılmaz, H., Dağ, M.M., Kaştan, M.A., (2023). Analysis of The Factors Affecting Producers' Crop Rotation Practices for Sustainable Sugar Beet Production, *Academic Journal of Agriculture*, 12(1), 83-90.

Yücel Engindeniz, D., Yercan, M., (2024). Farmers Collective Action: Agricultural Cooperatives, In: International Studiıes and Evaluations in the Field of Agriculture, Forestry and Aquaculture Sciences, (Edit.: K. Özrenk, A. Bolat), Serüven Publications, Ankara, pp.15-34.

Yücel, B., (2023). The Importance of Sugar Beet for the Food Industry, *International Journal of Sivas University of Science and Technology*, 2(2), 54-64.

Chapter 11

AERIAL PHOTOGRAMMETRY AND DEEP LEARNING IN FORESTRY

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1. INTRODUCTION

Forestry practices depend heavily on intensive fieldwork; however, the wide and heterogeneous geographical distribution of forests across the country makes the use of aerial photographs indispensable. Moreover, identifying the spatial and structural characteristics of forest resources and integrating this information into planning processes constitutes one of the core responsibilities of the forestry sector (Erdin, 1992).

Considering the distribution characteristics of forests in our country, access to each forested area is not always easy, and it is often impossible to carry out effective and safe work in these areas. Within the scope of forestry practices, it is necessary to visit these areas to take measurements and make observations, collect samples, and monitor these areas periodically. However, access to these sites, which are mostly located in steep and mountainous areas, is not always possible; even when access is possible, the work is often time-consuming, laborious, and costly. On the other hand, assessments carried out by a limited number of personnel or teams covering a limited area in thousands of hectares of land generally remain at a local scale and do not adequately represent the overall structure of the forest ecosystem. For this reason, the use of modern technologies in the effective monitoring, integrated planning, and sustainable management of forest areas is becoming increasingly important.

In this context, aerial photogrammetry stands out as one of the fundamental methods that enables the rapid, accurate, and comprehensive determination of the spatial and structural characteristics of forested areas. Thanks to high-resolution images obtained via aerial platforms, many forestry applications can be carried out effectively, such as forest inventory creation, forest structure analysis, biomass and volume estimates, forest road detection, damage detection, and monitoring of temporal changes. In recent years, the widespread use of unmanned aerial vehicles (UAVs) in photogrammetric studies has made data collection processes safer, more cost-effective, and more flexible in areas that are difficult to access and risky.

Aerial photogrammetry is considered an indispensable technological approach that reduces dependence on terrain in forestry studies, strengthens decision support processes, and contributes to sustainable forest management. This study aims to examine the applications of aerial photogrammetry and deep learning in the field of forestry. The second section introduces the fundamental concepts related to aerial photogrammetry and forestry, the third section explores application areas of aerial photogrammetry and deep learning in forestry, and the final section discusses the results based on the study's findings.

2. FORESTRY AND AERIAL PHOTOGRAMMETRY

The demand for reliable, objective, cost-effective, and periodically obtainable information covering the entire forest ecosystem is increasing. In this context, photogrammetric techniques play a crucial role in forestry research and applications.

Photogrammetry is a scientific discipline that is constantly evolving with technological advances and is widely used in many different disciplines. Photogrammetry is generally divided into two main groups: terrestrial photogrammetry and aerial photogrammetry, depending on the platform from which the photograph is obtained. Terrestrial photogrammetry is the photogrammetry technique used on the ground or near the ground. Aerial photogrammetry, on the other hand, is a special mapping technique that allows large areas to be easily mapped by taking pictures from high above the ground in areas that cannot be reached by terrestrial shooting techniques.

When examining the historical development of aerial photogrammetry, it can be seen that balloons, pigeons, kites, zeppelins, rockets, airplanes, helicopters, and satellites have been used as image acquisition platforms. In recent years, UAV's, which are widely used for a variety of purposes, have been added to these platforms and have gained an important place in aerial photogrammetry applications.

In recent years, UAV systems have emerged as a new platform for photogrammetric data acquisition, gaining prominence due to the advantages they offer, particularly in areas that are difficult or hazardous to access. In this respect, UAV systems are especially well suited for use in forested environments and provide an effective alternative to existing systems and methods.

Data sources used in forestry applications within the scope of aerial photogrammetry have diversified significantly in parallel with rapid developments in sensor technologies, and each data type offers unique advantages for different analysis requirements. In this context, UAV-based RGB images, multispectral and hyperspectral aerial photographs, thermal camera images, aerial LiDAR data, and LiDAR-photogrammetry fusion are among the basic data types commonly used in current forestry studies.

High-resolution RGB images obtained with UAV's are widely used for detailed visual interpretation and geometric analysis. In addition, multispectral and hyperspectral aerial photographs enable the separation of spectral characteristics of vegetation cover, providing significant contributions to applications such as species classification, stress detection, and forest health monitoring. Thermal camera images provide valuable information for assessing plant water status, temperature anomalies, and fire risk. Aerial LiDAR data enables high-accuracy three-dimensional modeling of forest structure, while fusion approaches that combine LiDAR and photogrammetric data integrate both geometric and spectral information, allowing for more comprehensive, reliable, and effective analysis in forestry studies.

Aerial photogrammetry has extensive applications in forestry, largely attributable to its high spatial resolution resolution and ability to produce three-dimensional data. Using digital surface models, point clouds, and orthomosaic images obtained through photogrammetric methods, tree crown detection can be performed; the crown position, crown diameter, and crown cover ratio can be determined with high accuracy on an individual tree basis (Zarco-Tejada et al., 2014; Zhou et al., 2020). These data form the basis for analyzing stand structure and calculating tree density.

Within the scope of tree species classification, spectral, textural, and geometric features derived from aerial photographs can be used to distinguish between different tree species or species groups.In particular, multispectral and high-resolution images, when used in conjunction with machine learning and deep learning-based classification algorithms, significantly increase the accuracy of species discrimination (Puliti et al. 2015; Franklin et al. 2015; Nevalainen et al., 2017). It is possible to classify tree species using spectral, textural, and geometric features obtained from aerial photographs (Ke et al., 2010; Fassnacht et al., 2016). In particular, high-resolution images based on UAVs, when used in conjunction with object-based and machine learning methods, significantly increase classification accuracy (Nevalainen et al., 2017).

Aerial photogrammetry enables the rapid and up-to-date production of data over large areas by reducing dependence on field conditions in forest inventory studies. Basic dendrometric parameters, such as tree height, canopy height, and canopy closure, can be estimated from photogrammetric 3D data; when integrated with traditional inventory data, this information yields more comprehensive and reliable inventory results.Three-dimensional point clouds obtained from aerial photogrammetry are effectively used in forest inventory studies to estimate basic parameters such as tree height, stand density, and volume (Bohlin et al., 2012;White et al., 2013). UAV-based photogrammetry, in particular, offers a low-cost and flexible inventory approach for small and medium-sized areas (Puliti et al., 2015).

The obtained three-dimensional structural information also offers significant potential for estimating biomass and carbon stocks. Three-dimensional point clouds and crown metrics obtained from aerial photogrammetry enable the estimation of structural parameters such as tree height and volume; and these parameters are effectively used in calculating biomass and carbon stocks through allometric equations (Lim, 2004; Vastaranta et al., 2013). This contributes significantly to carbon monitoring and reporting efforts in the context of combating climate change.

In the context of forest health monitoring, time-series airborne photogrammetric data can be used to detect signs of desiccation, insect damage, disease, and stress. Changes in image color, deterioration in crown structure, and variations in canopy closure enable the early detection of adverse developments in forest health. High-resolution images obtained from aerial photogrammetry and three-dimensional crown structure information enable the early detection of signs of desiccation, stress, and damage in forest health monitoring (Dandois et. al., 2013; Näsi et al., 2015; Lehmann, 2015; Dash, 2017). UAV-based photogrammetry, in particular, provides substantial advantages in temporal monitoring and detailed analysis at the local scale (Nevalainen et al., 2017).

In addition, aerial photogrammetry is an effective tool for generating pre-fire risk maps. Topographic models derived from photogrammetric data, together with parameters such as fuel load distribution and vegetation structure, when integrated with fire behavior models, enable the identification of high-risk areas. High-resolution orthomosaics and three-dimensional surface models obtained from aerial photogrammetry contribute significantly to the creation of pre-fire risk maps by being used to determine fuel load distribution and vegetation structure(Hirschmugl et al., 2007; Fernández-Guisuraga et al., 2016). UAV-based photogrammetry is an effective tool, particularly for detailed and up-to-date risk analyses at the local scale (Varga et. al., 2016).

Digital terrain models and orthomosaic images obtained from aerial photogrammetry are effectively used in the planning of forest road routes, slope analyses, and the optimization of transportation systems (Contreras et al., 2012; Akgul et al., 2016; Buğday, 2018; Kınalı et al., 2022). UAV-based photogrammetry enables the rapid and objective assessment of structural damage to roads and haulage routes (Pierzchała et al., 2014).

Finally, in post-disturbance damage assessments following fires, storms, insect infestations, or human-induced impacts, aerial photogrammetry provides rapid and objective data. It contributes significantly to the identification of affected areas, the quantitative assessment of damage levels, and the planning of remediation efforts. High-resolution orthomosaics and 3D point clouds derived from aerial photogrammetry enable the precise quantification of the spatial distribution and severity of damage caused by fires, storms, and insect outbreaks. (Fernández-Guisuraga et al., 2016). In particular, UAV-based photogrammetry offers rapid and objective analyses based on the comparison of pre- and post-damage data (White et al., 2016).

3. AERIAL PHOTOGRAMMETRY AND DEEP LEARNING-BASED ANALYSES

High-resolution data produced by aerial photogrammetry can be automatically analyzed using deep learning networks. In recent years, advances in deep learning–based approaches have enabled high–spatial-resolution photogrammetric data to be utilized far more effectively and comprehensively in forestry applications. In particular, orthophotos, dense point clouds, and digital surface and terrain models generated by UAV's and conventional aerial platforms provide rich and multidimensional input datasets for deep learning networks. As a result, these approaches offer a significantly higher level of accuracy and automation compared with classical image processing and statistical methods.

Photogrammetric products (orthophotos, SYM, SAM, dense point clouds, and 3D models) can be used in conjunction with different deep learning architectures to obtain detailed information on both horizontal and vertical forest structure. In this context, the main deep learning models commonly used in forestry in aerial photogrammetry are summarized below.

Convolutional Neural Networks (CNNs), which are widely used in deep learning, represent one of the most common architectures for analyzing aerial photogrammetry data (Oh et al., 2021). CNNs achieve high accuracy in tasks such as land cover classification, tree species differentiation, and stand type determination by automatically learning spatial and spectral features from orthophotos and multi-band aerial imagery. In this context, single-tree detection can be performed with high accuracy using deep learning–based object detection and semantic segmentation approaches; in particular, individual tree crowns can be automatically delineated from RGB and multispectral aerial images (Weinstein et al., 2020). When applied to high-resolution RGB and multispectral data, these approaches yield more accurate and reproducible results than traditional methods (Fujimoto, 2019; Kattenborn, 2019 Kattenborn,2020; Onishi, 2021). Dendrometric parameters such as crown diameter and crown area can also be automatically derived from orthophotos and 3D point clouds generated from photogrammetric data. These analyses provide important inputs for evaluating tree growth conditions and forest structure and are effectively supported by deep learning–based crown segmentation approaches(Silva et al., 2016;Jing et al., 2017).

Tree species classification is another important application that exploits the spectral and spatial characteristics of aerial photogrammetry data. In particular, the analysis of multispectral and hyperspectral aerial imagery using convolutional neural networks has demonstrated high success in discriminating between tree species with similar morphological characteristics(Fassnacht et al., 2016; Kattenborn et al., 2021). Early detection of forest pests is critical for monitoring biotic and abiotic stress factors in forest ecosystems. The integrated use of aerial photogrammetry and imaging spectroscopy data with deep learning models enables the early identification of physiological changes caused by insect infestations and diseases(Näsi et al., 2015; Brodrick et al., 2019). In forestry studies, thermal and multispectral aerial imagery plays a significant role in drought and plant stress monitoring. Analyses based on surface temperature and vegetation indices enable the temporal tracking of plant water stress and drought effects, while deep learning approaches facilitate the automation of these processes(Dash, et.al., 2004; Zhang et al., 2019).

The U-Net architecture excels in semantic segmentation problems that require pixel-level classification. Within the scope of aerial photogrammetry, U-Net and its derivatives are effectively used in applications such as determining tree canopy boundaries, distinguishing between vegetation and soil, and detecting roads and open areas. Its ability to produce successful results even with limited training data makes U-Net attractive for forestry studies(Schiefer, 2020;Kattenborn, et al., 2021).

Object detection-based models such as YOLO and Faster R-CNN are used to automatically identify trees, logs, damage areas, and infrastructure elements in aerial images. These models offer high speed and accuracy advantages in individual tree detection, post-fire damage analysis, and identification of forest structures (roads, storage areas, etc.). YOLO architectures, in particular, provide suitable solutions for real-time or near real-time applications(Hossain et al. 2020). Transformer-based models developed in recent years (Vision Transformer – ViT, Swin Transformer, etc.) have demonstrated significant potential in the analysis of large-scale and complex forest areas. These models are used in studies such as land cover classification, change analysis, and monitoring forest dynamics in large-scale aerial photogrammetry data, thanks to their ability to consider long-range spatial relationships (Tolan, 2024; Tony, 2025). They can demonstrate superior performance compared to classical CNN architectures, especially when trained on large datasets.

The integrated use of deep learning-based approaches with aerial photogrammetry data has provided new opportunities for the automatic detection and mapping of forest roads. CNN and U-Net-based segmentation models trained on high-resolution orthophotos enable the extraction of forest road networks across large areas with high accuracy(Zhang et al., 2018; Caliskan 2022a;Caliskan 2022b). These methods produce faster, more objective, and more repeatable results than manual digitization processes. The integrated use of aerial photogrammetry and deep learning provides substantial contributions not only to road detection but also to road condition monitoring and risk analysis. Photogrammetric products derived from UAV imagery, together with machine learning–based analyses, enable the effective identification of road surface degradation, erosion features, and road segments susceptible to landslides(Jaafari et al., 2017; İbrahim et al., 2024). These types of analyses help prioritize maintenance and repair work and prevent potential environmental damage.

Three-dimensional point cloud–based deep learning networks (e.g., PointNet, PointNet++, RandLA-Net) are designed to analyze dense point clouds derived from photogrammetric mapping or LiDAR data. These networks enable the automatic extraction of key forest parameters, including tree height, crown volume, vertical canopy closure, and stand structure, thereby providing detailed insights into the three-dimensional characteristics of forest ecosystems. Point cloud–based models offer substantial advantages, particularly for applications requiring detailed vertical structure analysis, such as biomass and carbon stock estimation. (Ma, 2023; Liu, 2024). Automatic mapping of burned areas after a fire is one of the most critical applications of aerial photogrammetry data. Deep learning-based classification and segmentation methods enable the rapid and accurate identification of areas damaged by fire, thereby making significant contributions to rehabilitation and management efforts(Key et al., 2006; Huang et al., 2018). Aerial Photogrammetry and Deep Learning Processes in Forestry are shown in Table 1.

Table 1. Aerial Photogrammetry and Deep Learning Processes in Forestry

Stage	Process	Output
1	Acquisition of Aerial Images (UAV / Aircraft)	Raw images
2	Pre-processing	Camera calibration Image alignment
3	Generation of Photogrammetric Products (SfM)	Orthophoto Digital Surface Model (DSM) Digital Terrain Model (DTM)
4	Dense Point Cloud Generation	3D point cloud
5	Deep Learning Analysis	Segmentation (U-Net, DeepLab) Object Detection (YOLO, Faster R-CNN) Classification (CNN, Transformer-based models) 3D Analysis (PointNet, RandLA-Net)
6	Integration into Forest Information Systems (FIS / GIS)	Spatial database
7	Mapping and Decision Support Processes	Management outputs

In conclusion, deep learning models used in aerial photogrammetry are complementary to each other depending on different data types and analysis objectives, offering a robust methodological framework for automation, accuracy, and scalability in forestry. The integration of these models plays a key role in the development of smart forestry applications.

4. DISCUSSION AND CONCLUSION

This study provides a comprehensive review of the use of aerial photogrammetry and deep learning methods in forestry applications and evaluates the contributions of these technologies to forest inventory, planning, and decision-support processes. Orthophotos, digital surface and terrain models, and three-dimensional point clouds generated through the photogrammetric processing of high–spatial-resolution aerial imagery enable a detailed representation of both the horizontal and vertical components of forest structure.

Aerial photogrammetry combined with deep learning–based approaches allows for the analysis of very large areas within a short time frame without the need for extensive field visits. High–spatial-resolution aerial imagery supports the generation of detailed, tree-level information, offering a significant advantage for inventory, monitoring, and planning studies. The application of deep learning algorithms reduces reliance on manual interpretation, facilitating automated, objective, and repeatable analyses. Moreover, these approaches minimize labor demands and time-consuming fieldwork, resulting in substantial time and cost efficiencies in forest management processes.

However, there are some limitations to the integration of aerial photogrammetry and deep learning. High-resolution images and dense point clouds generate large volumes of data, increasing data storage, processing power, and infrastructure costs. Optical-based systems are sensitive to cloud cover, shadow effects, and variable light conditions, which can negatively impact data quality. The need for large amounts of labeled data for deep learning models to operate with high accuracy poses a significant constraint, particularly in heterogeneous ecosystems such as forestry. Furthermore, the performance of photogrammetric methods may be limited in detecting understory and juvenile layers under dense canopy cover. This can lead to the underrepresentation or misrepresentation of certain ecosystem components. The difficulties encountered in determining the understory in forests with dense canopy cover, in particular, highlight the need for the integrated use of photogrammetric data with LiDAR and multispectral data. In this context, the use of multimodal data fusion and advanced deep learning architectures offers significant potential for overcoming current limitations.

The integration of deep learning–based analyses with these photogrammetric products substantially enhances accuracy and efficiency diverse applications, including individual tree detection and tree species classification, crown geometry estimation, biomass and carbon stock assessment, and forest health monitoring. In particular, the application of CNN-, U-Net–, YOLO-, and Transformer-based models enables faster, more objective, and more repeatable results than traditional manual interpretation approaches. Consequently, these methods provide significant time and cost advantages for large-scale forestry studies.

In the future, aerial photogrammetry and deep learning applications in forestry are expected to advance substantially through the integration of ultra-high-resolution UAV imagery with Transformer-based deep learning models. Multimodal data fusion approaches combining LiDAR, RGB, multispectral, and thermal data will enable more accurate and comprehensive modeling of both the horizontal and vertical components of forest structure. Advances in real-time data processing are anticipated to improve the effectiveness of fire early-warning and risk monitoring systems. Furthermore, the development of three-dimensional digital twin forest models will create new opportunities for forest ecosystem simulation and scenario analysis. The use of autonomous UAV swarms for continuous and periodic data acquisition is expected to make monitoring and decision-support processes in forestry more dynamic, flexible, and sustainable.

REFERENCES

Akgül M., Yurtseven H., Demir M., Akay A., Gülci S., **Öztürk T.**, (2016). İnsansız Hava Araçları ile Yüksek Hassasiyette Sayısal Yükseklik Modeli Üretimi ve Ormancılıkta Kullanım Olanakları. Journal of the Faculty of Forestry Istanbul University, 66(1): 104-118

Bohlin, J., Wallerman, J., Fransson, J. E. S. (2012). Forest variable estimation using photogrammetric matching of digital aerial images in combination with field plots. Scandinavian Journal of Forest Research, 27(7), 692–699.

Brodrick, P. G., Davies, A. B., Asner, G. P., Vaughn, N. R. (2019). Using imaging spectroscopy and deep learning to map forest health indicators across landscapes. Remote Sensing of Environment, 231, 111270. https://doi.org/10.1016/j.rse.2019.111270

Bugday, E. (2018). Capabilities of Using UAVs in Forest Road Construction Activities. European Journal of Forest Engineering, 4(2), 56-62.

Contreras, M., Aracena, P., Chung, W. (2012). Improving accuracy in earthwork volume estimation for proposed forest roads using a high-resolution digital elevation model. Croatian Journal of Forest Engineering: Journal for Theory and Application of Forest Engineering, 33(1), 125–142.

Çalışkan, E., and Sevim, Y. (2022a). Forest road detection using deep learning models. Geocarto International, 37(20), 5875–5890.

Çalışkan, E.,and Sevim, Y. (2022b). Forest road extraction from orthophoto images by convolutional neural networks. Geocarto International, *37*(26), 11671–11685.

Dash, J., Curran, P. J. (2004). The MERIS terrestrial chlorophyll index. International Journal of Remote Sensing, 25(23), 5403–541.

Dash, J.P.; Watt, M.S.; Pearse, G.D.; Heaphy, M.; Dungey, H.S.(2017). Assessing very high resolution UAV imagery for monitoring forest health during a simulated disease outbreak. ISPRS J. Photogramm. Remote Sens, 131, 1–14.

Dandois, J. P., Ellis, E. C. (2013). High spatial resolution three-dimensional mapping of vegetation spectral dynamics using computer vision. Remote Sensing of Environment, 136, 259–276.

Erdin, K**., (**1992), Fotogrametri, İ.Ü. Üniversitesi Orman Fakültesi Yayınları İ.Ü. Yayın No. : 3674, O.F. Yayın No. : 421, İstanbul, ISBN 975-404-251-9.

Fassnacht, F. E., Latifi, H., Stereńczak, K., Modzelewska, A., Lefsky, M.,Waser, L.T., Straub, C., Ghosh, A., (2025). Review of studies on tree species classification from remotely sensed data. Remote Sensing of Environment, 186, 64–87.

Fernández-Guisuraga,J.M.,Suárez-Seoane,S.,Calvo,L.,and Fernández-García,V.(2016). Use of unmanned aerial vehicles and photogrammetry to estimate fuel characteristics in fire-prone ecosystems. International Journal of Applied Earth Observation and Geoinformation, 52, 1–11.

Franklin, S. E., Ahmed, O. S., Wulder, M. A., et al. (2015). Large area mapping of tree species using airborne hyperspectral data. Remote Sensing of Environment, 156, 49–60.

Fujimoto, A.; Haga, C.; Matsui, T.; Machimura, T.; Hayashi, K.; Sugita, S.; Takagi, H.(2019). An End to End Process Development for UAV-SfM Based Forest Monitoring: Individual Tree Detection, Species Classification and Carbon Dynamics Simulation. Forests 10, 680.

Hirschmugl, M., Steinegger, M., Gallaun, H., Schardt, M. (2007). Mapping forest fuel models using airborne laser scanning and orthophotos. Remote Sensing of Environment, 111(4), 450–463.

Hossain, F.A.; Zhang, Y.M.; Tonima, M.A. (2020). Forest fire flame and smoke detection from UAV-captured images using fire-specific color features and multi-color space local binary pattern. J. Unmanned Veh. Syst, 8, 285–309.

Huang, X., Wang, P., and Zhang, L. (2018). Deep learning for post-fire burned area mapping using aerial imagery. ISPRS Journal of Photogrammetry and Remote Sensing, 142, 201–214.https://doi.org/10.1016/j.isprsjprs.2018.06.011

Ibrahim, H.B., Salah, M., Zarzoura, F.,Mewafi, M.E.(2024). Smart monitoring of road pavement deformations from UAV images by using machine learning. *Innov. Infrastruct.* Solut. 9, 16 .

Ke, Y., L.J. Quackenbush, J. Im.,(2010). Synergistic use of QuickBird multispectral imagery and LIDAR data for object-based forest species classification, Remote Sens. Environ., 114 (6) (2010), pp. 1141-1154,

Key, C. H., and Benson, N. C. (2006). Landscape assessment: Ground measure of severity, the Composite Burn Index. USGS General Technical Report.

Kattenborn, T.; Eichel, J.; Fassnacht, F.E. (2019). Convolutional Neural Networks enable efficient, accurate and fine-grained segmentationof plant species and communities from high-resolution UAV imagery. Sci. Rep. 9, 17656.

Kattenborn, T.; Eichel, J.; Wiser, S.; Burrows, L.; Fassnacht, F.E.; Schmidtlein, S. (2020). Convolutional Neural Networks accurately predict cover fractions of plant species and communities in Unmanned Aerial Vehicle imagery. Remote Sens. Ecol. Conserv., 6, 472–486.

Kınalı, M., and Çalışkan, E. (2022). Use of unmanned aerial vehicles in forest road projects. Bartın Orman Fakültesi Dergisi, 24(3), 530–541.

Lehmann, J.R.K.; Nieberding, F.; Prinz, T.; Knoth, C. (2015).Analysis of Unmanned Aerial System-Based CIR Images in Forestry—A New Perspective to Monitor Pest Infestation Levels. Forests, 6, 594–612.

Lim, K.S.; Treitz, P.M. (2004). Estimation of above ground forest biomass from airborne discrete return laser scanner data using canopy-based quantile estimators. Scand. J. For. Res. 19, 558–570.

Liu, H., Zhong, H., Lin, W., Wu, J. (2024). Tree species classification based on PointNet++ deep learning and true- colour point cloud. International Journal of Remote Sensing, 45(16), 5577–5604. https://doi.org/10.1080/01431161.2024.2377837

Jaafari, A., Rezaeian, J., Omrani, M.S.O. (2017). Spatial Prediction of Slope Failures in Support of Forestry Operations Safety. Croatian Journal of Forest Engineering, 38(1), 107-118.

Jing, L., and Hu, B. (2017).Individual tree crown delineation from UAV imagery using convolutional neural networks. Remote Sensing, 9(9), 930. https://doi.org/10.3390/rs9090930

Ma, Zhibin., Dong, Yanqi, Z.Jial., Xu, F., Chen, F. (2023). Forest-PointNet: A Deep Learning Model for Vertical Structure Segmentation in Complex Forest Scenes. Remote Sensing. 15. 4793. 10.3390/rs15194793.

Näsi, R.; Honkavaara, E.; Lyytikäinen-Saarenmaa, P.; Blomqvist, M.; Litkey, P.; Hakala, T.; Viljanen, N.; Kantola, T.; Tanhuanpää, T.; Holopainen, M.(2015) Using UAV-Based Photogrammetry and Hyperspectral Imaging for Mapping Bark Beetle Damage at Tree-Level. Remote Sens, 7, 15467-15493. https://doi.org/10.3390/rs71115467

Nevalainen, O., Honkavaara, E., Tuominen, S., Viljanen, N., Hakala, T., Yu, X., Hyyppä, J., Saari, H., Pölönen, I., Imai, N. N., & Tommaselli, A. M. G. (2017). Individual Tree Detection and Classification with UAV-Based Photogrammetric Point Clouds and Hyperspectral Imaging. Remote Sensing, 9(3), 185.

Oh, G., Ryu, J., Jeong, E., Yang, J. H., Hwang, S., Lee, S. ve Lim, S. (2021). Drer: Deep learning– based driver's real emotion recognizer. Sensors, 21(6), 1–29doi:10.3390/s21062166

Onishi, M.; Ise, T.(2021). Explainable identification and mapping of trees using UAV RGB image and deep learning. Sci. Rep., 11, 903.

Pierzchała, M., Talbot, B., Astrup, R. (2014). Estimating soil displacement from timber extraction trails using UAV-based photogrammetry. International Journal of Forest Engineering, 25(3), 122–133.

Silva, Carlos A.; Hudak, Andrew T.; Vierling, Lee A.; Loudermilk, E. Louise; O'Brien, Joseph J.; Hiers, J. Kevin; Jack, Steve B.; Gonzalez-Benecke, Carlos; Lee, Heezin; Falkowski, Michael J.; Khosravipour, A. (2016). Imputation of individual longleaf pine (Pinus palustris Mill.) tree attributes from field and LiDAR data. Canadian Journal of Remote Sensing. 42(5): 554-573.

Schiefer, F.; Kattenborn, T.; Frick, A.; Frey, J.; Schall, P.; Koch, B.; Schmidtlein, S.(2020) Mapping forest tree species in high resolution UAV-based RGB-imagery by means of convolutional neural networks. ISPRS J. Photogramm. Remote Sens., 170, 205–215.

Puliti, S., Ørka, H. O., Gobakken, T., & Næsset, E. (2015). Inventory of small forest areas using an unmanned aerial system. Remote Sensing, 7(8), 9632–9654.

Tolan, J.; Yang, H.I.; Nosarzewski, B.; Couairon, G.; Vo, H.V.; Brandt, J.; Spore, J.; Majumdar, S.; Haziza, D.; Vamaraju, J.; Moutakanni, T., Bojanowski, P., Johns, T., White, B., Tiecke, T., Couprie, C.,(2024). Very high resolution canopy height maps from RGB imagery using self-supervised vision transformer and convolutional decoder trained on aerial lidar. Remote Sensing of Environment 300 -113888.

Tony, C., Kiarie, N., Andreas, G., Vincent, A. L., Luke J. Z., Bogdan, S., Mitchell A. G., Colton W. M., Nathan E. R., and Scott, C., (2025) VibrantVS: A High-Resolution Vision Transformer for Forest Canopy Height Estimation, Remote Sens., 17(6), 1017

Varga, I. V. D., and Asenjo, F. (2016). Assessment of fire risk using UAV imagery and photogrammetric techniques. International Journal of Applied Earth Observation and Geoinformation, 48, 1–12.

Vastaranta, M., Wulder, M. A., White, J. C., Pekkarinen, A., Tuominen, S., Ginzler, C., Hyyppä, H. (2013). Airborne laser scanning and digital stereo imagery measures of forest structure: comparative results and implications to forest mapping and inventory update. Canadian Journal of Remote Sensing, 39(5), 382–395.

Zarco-Tejada, P. J., Diaz-Varela, R., Angileri, V. Loudjani, P. (2014). Tree height quantification using very high resolution imagery acquired from an unmanned aerial vehicle. International Journal of Applied Earth Observation and Geoinformation, 27, 173–182.

Zhang, Y., Wu, H., Yang, W. (2019). Forests growth monitoring based on tree canopy 3D reconstruction using UAV aerial photogrammetry. Forests, *10*(12), 1052.

Zhou, X., Zhang, X.,(2020). Individual Tree Parameters Estimation for Plantation Forests Based on UAV Oblique Photography, IEEE Access, (8), 96184-961198

Weinstein, B. G., Marconi, S., Bohlman, S. A., Zare, A., and White, E. P. (2020). Individual tree-crown detection in RGB imagery using deep learning neural networks. Remote Sensing, 12(6), 1–19. https://doi.org/10.3390/rs12060930

White, J. C., Wulder, M. A., Vastaranta, M., Coops, N. C., and Pitt, D. (2013). The utility of image-based point clouds for forest inventory. Remote Sensing of Environment, 140, 372–384.

White, J. C., Coops, N. C., Wulder, M. A., Vastaranta, M., and Hilker, T. (2016). Remote sensing technologies for enhancing forest inventories: A review. Canadian Journal of Remote Sensing, 42(5), 619–641

Chapter 12

THE POTENTIAL OF AGRICULTURAL RESIDUES AS SUSTAINABLE RAW MATERIALS IN CEMENT-BONDED PARTICLEBOARD PRODUCTION

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1. INTRODUCTION

The construction industry is one of the largest consumers of resources worldwide and has a significant impact on the environment. The rising demand for construction materials resulting from rapid urbanization prompts the need for sustainable construction practices (Li vd. 2022; El Hamri vd., 2025). The circular economy provides a strategic way to address these challenges by reducing waste, emissions, and dependence on virgin materials. The circular economy has recently gained widespread attention as a key approach to sustainable development (Tura vd. 2019; El Hamri vd., 2025).

Cement-bonded particleboards (CBPBs) are usually composed of cement as a binder, water as a hydration initiator, wood as a reinforcing/filling material, and small amounts of chemical additives (e.g., $CaCl_2$ and $MgCl_2$) as cement-setting accelerators to enhance the compatibility of wood with cement. CBPBs represent a versatile class of construction materials widely used in both new building projects and the rehabilitation or retrofitting of existing structures (Nunes et al., 2021). CBPBs exhibit outstanding advantageous properties, such as low production cost, high mechanical performance, low density, exceptional long-term weathering resistance, and good acoustic and thermal insulation. They also have high-dimensional stability, enhanced toughness, and strong resistance to water, fire, fungal degradation, and insect attack (Nasser et al., 2016; Yel, 2022).

The growing demand for forest resources in wood-based industries has prompted a sustained and systematic search for alternative lignocellulosic materials to replace forest wood. Therefore, extensive research efforts to identify and evaluate such alternative resources have been conducted by both industrial stakeholders and academic research institutions (Nasser et al., 2011).

According to a World Bank report, world waste production is estimated to reach 2.6 billion tons by 2030 (Kaza et al., 2018). Agricultural residues comprise a significant portion of total waste, and they represent 30-40% of the total crop volume (Lackner and Besharati, 2025). Agricultural residues are typically disposed of through methods such as burial, open burning, and abandonment. They cause significant environmental issues (air pollution, greenhouse gas emissions, soil pollution, water pollution) and economic losses due to the underutilization of biomass resources (Rao et al., 2024; Lackner and Besharati, 2025). In the search for environmentally sustainable and resource-efficient alternatives to conventional construction materials, agricultural residues have attracted increasing interest as reinforcement/filling materials in cement-based composites (El Hamri et al., 2025). Much research was conducted on the utilization of agricultural residues as alternative lignocellulosic materials in the production of cement-bonded particleboards.

2. SUITABILITY OF AGRICULTURAL RESIDUES FOR CEMENT-BONDED COMPOSITE PRODUCTION

2.1. Sunflower Stalks

A high amount of sunflower stalk residues is generated by sunflower cultivation. The cultivated area of sunflowers in the world was 26.5 million hectares in 2017. This led to 80–186 million tons of sunflower stalk residues (Jiang et al., 2024). Taş and Kul (2020) investigated the utilization of sunflower stalks in the production of cement-bonded particleboards. The cement-bonded particleboards with a target density of 1300 kg/m3 were produced by replacing wood particles with sunflower stalk particles at ratio levels of 0%, 25%, 50%, 75%, and 100%. The water absorption, thickness swelling, screw withdrawal resistance, and the bending properties were evaluated in the cement-bonded particleboards. The test results demonstrated that the use of sunflower stalks considerably affected the physical and mechanical properties. A replacement ratio of up to 25% was feasible without a loss in the mechanical performance. However, the replacement levels exceeding this ratio did not meet the requirements specified in the EN 634-2 standard.

In another study, Yel (2022) made experimental cement-bonded particleboards with a target density of 1200 kg/m^3 and a wood-cement ratio of 1/3 using sunflower stalks and different types of accelerators ($CaCl_2$, $AlCl_3$, and $MgCl_3$) and tested the produced boards for physical, mechanical, thermal, and morphological properties. The researcher treated the sunflower stalks with 1% NaOH extraction process before the production. The obtained results demonstrated that the highest mechanical properties were recorded for the boards made from a mixture of pretreated sunflower stalks (40%) and poplar particles (60%) with the addition of $CaCl_2$. The researcher stated that the boards with 100% sunflower stalks subjected to 1% NaOH extraction, and a $CaCl_2$ chemical additive met the requirements stipulated in the EN 634-2 standard. The NaOH pretreatment and the chemical additives enhanced the mechanical properties, and reduced the water absorption and the thickness swelling. The researcher also concluded that the sunflower stalks significantly reduced the thermal conductivity.

2.2. Walnut Shells

Walnut shells are the endocarp of the walnut fruit. They are generated as agricultural residues during the process of separating kernels. World walnut production amounted to 3.66 million tons in 2018, and walnut shells comprised %50-%60 of the total walnut weight (Cebin et al., 2021). El Hamri et al. (2025) investigated the potential of walnut shells as an alternative reinforcement material in the manufacture of cement-bonded particleboard and produced experimental cement-bonded particleboards with a target density of 1300 kg/m³ using super white cement and walnut shells in proportions ranging from 10% to 50%. The test results showed that the highest modulus of rupture and modulus of elasticity were recorded for the boards produced using 30% walnut shells. The lowest thermal conductivity was obtained from the boards containing 50% walnut shells. However, the water absorption and thickness swelling values of the boards increased as the walnut shell content increased. They also noted that the test results demonstrated the potential of walnut shells to enhance the performance of building materials. Therefore, this composite can contribute to sustainable and environmentally responsible construction practices.

In another work, Tichi and Razavi (2023) determined the mechanical, physical, and morphological properties of cement-bonded composites produced using 10%, 20%, and 30% walnut shells and 0%, 1%, 2%, and 3% nanocellulose. The obtained results indicated that the addition of nanocellulose enhanced the boards' mechanical properties. The highest mechanical values were recorded at the boards with nanocellulose, containing 10% walnut shells. As the walnut shell content increased, the boards' bending strength, modulus of elasticity, and internal bond strength values increased. However, higher proportions of both nanocellulose and walnut shell led to a reduction in fire resistance. Increasing the walnut shell content also caused a significant rise in both board density and thickness swelling values.

2.3. Tea Residues

In the world, 6.6 million tons of tea are produced each year (FAO, 2023). Most of the generated tea waste is disposed via incineration or landfilling (Thiruvengadam et al., 2023). Therefore, the utilization of these wastes is very important for both economic and environmental sustainability (Vu et al., 2022). Demirbaş and Aslan (1998) produced cement-bonded composites containing 0%, 2%, 5%, 7.5%, and 10% tea wastes to investigate the utilization of tea waste as a reinforcement material in cement-bonded composites and tested these boards for compressive and flexural strength. The obtained results demonstrated that tea waste had a negative influence on cement hydration, and increasing the tea waste content reduced both flexural and compressive strength. Furthermore, it was also reported that the cement-bonded composites with 10% tea waste could not be tested due to structural weakness.

In another study, Yel et al. (2011) experimentally produced the cement-bonded particleboards with target densities of 800 kg/m³ and 1200 kg/m³ by partially replacing poplar particles with tea factory wastes and tested the produced boards for the physical and mechanical properties. The obtained results revealed that the cement-bonded particleboards produced using only tea wastes (%100) were not feasible for both density levels mentioned above. The boards could only be manufactured with a density of 1200 kg/m³ using a mixture of poplar particles (50%) and tea waste (50%). However, their mechanical properties did not fulfill the relevant standard requirements. The tea waste exhibited a high degree of incompatibility with cement. The authors concluded that pre-treatment such as cold/hot-water extraction or 1% NaOH extraction, was applied to the tea wastes to overcome this incompatibility, before the composite board production.

2.4. Olive Mill Wastes

In the world, olive oil production generates 40 million tons of solid waste each year (Enaime et al., 2024). Converting these wastes into value-added products can contribute to environmental protection and economic benefits. Aras et al. (2022) explored the utilization of olive mill solid wastes (OSW) in cement-bonded particleboard production. They made some cement-bonded particleboards using olive mill solid waste (OSW) and poplar wood particles. The olive mill solid wastes were subjected to a 1% NaOH extraction method before the manufacture. After the production, some mechanical, physical, thermal, and morphological tests were performed on the boards. They found that the boards produced using Super White cement showed better mechanical and physical properties than those produced using Portland cement. The water absorption and thickness swelling values increased, and the moisture content remained unchanged as the OSW content increased. The high replacement ratios led to a reduction in the modulus of rupture, the modulus of elasticity, and the internal bond strength. In spite of these reductions, the boards made of olive mill solid wastes up to 20% met the requirements specified in the EN 634-2 standard. Therefore, it was concluded that cement-bonded particleboards can be produced using olive mill solid wastes up to 20% as a partial replacement for wood particles.

In another study, Taş and Sarı (2022) aimed to investigate the suitability of olive pruning residues for cement-bonded particleboard production. They produced the cement-bonded particleboards using three different accelerators ($CaCl_2$, KCl_2, and DARASET 580), two wood-cement ratios (1/2 and 1/3), and 0%, 25%, and 50% olive pruning residues. They reported that increasing the olive pruning residue content led to higher water absorption and thickness swelling than that of the control boards. Moreover, the modulus of rupture and the modulus of elasticity decreased with increasing the replacement levels, and $CaCl_2$ exhibited the highest performance.

2.5. Wheat Straw

World wheat straw production is estimated to reach 687–740 million tons annually by 2050. But its widely use as a fuel source caused significant environmental concerns due to the air, water, and soil pollution (Durand et al., 2024). Wheat straw has good geometric and mechanical characteristics that make it a promising alternative to wood particles in cement-bonded particleboard production. However, its inhibitory effect on cement hydration reaction is a major obstacle for the successful development and widespread adoption of cement-bonded boards containing wheat straw (Soroushian et al. 2004).

Nazerian and Sadeghiipanah (2013) searched for the evaluation of wheat straw in the production of cement-bonded particleboard. In their study, experimental cement-bonded particleboards were made using a mixture of wheat straw and poplar wood. After producing the boards, they determined the boards' physical and mechanical properties such as density, water absorption, thickness swelling, and flexural strength of the boards. The study indicated that some mechanical properties significantly decreased with an increase in wheat straw ratio in the boards. On the other hand, it was observed that the acceptable board properties could be achieved when the wheat straw was used at suitable ratios. However, the surface characteristics and chemical components of wheat straw affected the cement hydration and limited the bonding performance of the cement. Therefore, it was reported that the optimal mixing ratio is very important for both mechanical performance and raw material sustainability. It was concluded that wheat straw is a potential alternative raw material for wood particles in cement-bonded composite production when used in suitable processing and ratios.

In another study, Soroushian et al. (2004) determined the effects of accelerated processing techniques on the production of cement-bonded boards produced using wheat straw. The researchers stated that the soluble sugars and organic components in the wheat straw retarded the cement hydration process. Therefore, they applied some accelerating methods, such as chemical additives and heat treatment, in the cement-bonded particleboard production. The accelerated processing methods improved the cement hydration reactions, increased the early-age strength, and considerably decreased the production times. In addition, it was observed that the pretreated straw fibers showed a good bonding performance with the cement matrix and increased the board stability. The author also noted that process optimization is very important for good performance in the cement-bonded composites produced using wheat straw. It was concluded that the low-cost fibers, such as wheat straw, can be converted into high-performance cement-bonded boards by using suitable processing techniques.

2.6. Fruit Tree Pruning Residues

Valorization of agricultural residues from pruning has many advantages such as employment, social and economic benefits, rural development, natural forests, increased energy efficiency, and lower costs for raw material production in the panel industry (Gilanipoor et al., 2020). 2.85 thousand trees were grown in one hectare of orchard, and 3-3.5 tons of pruning waste per hectare was generated each year (Dursun, 2024). According to FAOSTAT, apple orchards were 4.8 million hectares in 2022 worldwide (FAO, 2024). Global average annual apple pruning residues are 1.9 tons per hectare (Bisaglia et al., 2018). Tas and Acar (2022) researched the utilization of fruit tree pruning residues as an alternative lignocellulosic raw material for wood in the cement-bonded wood composite manufacturing and produced experimental cement-bonded particleboards using mixtures of apple tree pruning chips and red pine wood chips at five different ratios: 100/0, 75/25, 50/50, 25/75, and 0/100. The obtained results demonstrated that the boards' mechanical properties such as modulus of rupture, modulus of elasticity, and screw withdrawal strength, decreased, whereas the water absorption and thickness swelling values increased, as the use ratio of apple pruning residues in the boards increased. It was concluded that cement-bonded particleboards produced using apple pruning residues up to 25% met the requirements specified in the standard for general-purpose use.

Taş (2016) researched the suitability of olive tree pruning wastes for cement-bonded particleboard manufacturing. In this study, CaCl2, KCl, and DARASET 580® were added to increase the compatibility of olive tree pruning wastes with cement. The results indicated that the addition of olive pruning waste exhibited poor properties in the cement-bonded particleboards. The boards produced with KCI hardener exhibited better results than those produced with other hardeners. it was concluded that the produced boards are not suitable for structural applications, but can be used for insulation applications.

2.7. Banana Pseudostem

Banana pseudostems (BPS), which account for approximately 60% of the total biomass of the banana plant, represent a major waste fraction in banana production systems, as they are removed after each harvest (Castillo et al., 2023). According to FAOSTAT, total global banana production was reported as 135 million tons in 2022 (FAO, 2023). It is reported that approximately 3 tons of pseudostems are generated for each ton of banana fruit harvested (Castillo et al., 2023). In a work investigating the use potential of banana pseudostems in the production of cement-bonded particleboards, Nunes et al. (2021) examined the bulk density, the thermal conductivity, the dimensional stability, and the mould susceptibility of cement-bonded particleboards made of the mixtures of maritime pine (Pinus pinaster) and banana pseudostems at different ratios: 100/0, 75/25, 50/50, and 25/75. The results revealed that the boards' thermal conductivity values increased as the proportion of banana pseudostems increased. Banana pseudostems also caused a significant increase in the bulk density values of the boards. However, banana pseudostems led to a reduction in the thickness swelling values of the boards. On the other hand, mould development in the boards increased with the increase in the proportion of banana fibre. In another study, Owoyemi and Opeyemi (2021) produced the cement-bonded particleboards with wood-cement ratios of 1:2 and 1:3 using the mixtures of banana pseudostems and wood sawdust at different proportions: 100/0, 90/10, 80/20, 70/30, and 0/100. The results demonstrated that banana pseudostem fibers led to a significant redcution in the water absorption and thickness swelling values of the boards. The boards'desnity increased with increasing the proportion of banana pseudostems. Moreover, addition of banana pseudostems led to a significant increase in the modulus of rupture and modulus of elasticity of the boards.

2.8. Rice Husk/Ash

Rice production generates several agricultural by-products, including rice straw, husk, and bran (Figure 1). Rice husk constitutes approximately 20% of the total grain weight (Marques et al., 2021). Annual global rice production exceeds 750 million tons of grain, generating approximately 150 million tons of rice husk as a by-product (Kordi et al., 2024). Rice husk ash is obtained by burning rice husk to produce silica. Rice husk biochar is generated by burning rice husk in limited oxygen conditions (Kordi et al., 2024).

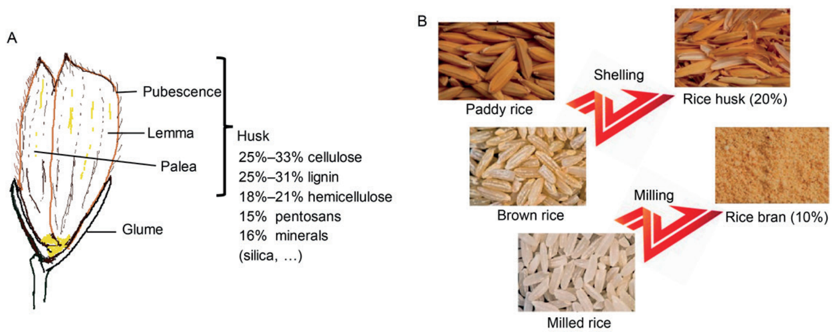

Figure 1. Rice grain components (A) and grain process (B) (Kordi et al., 2024)

Marques et al. (2021) searched for the utilization of rice husk as a lightweight aggregate in the cement-bonded board production to develop a suitable building material for acoustic barriers and thermal insulation elements. They made cement-bonded boards using different cement-rice husk ratios and tested the produced boards for density, thermal conductivity, sound absorption capacity, and mechanical properties. The obtained results showed that the rice husk improved the thermal insulation properties by reducing the board density. Moreover, the rice husk increased the sound absorption properties, whereas it caused a slight reduction in the boards' mechanical properties. The authors concluded that rice husk can be used as an effective biomass additive in the cement-bonded board manufacturing.

Bamisaye (2007) produced cement-bonded particleboards using different cement/rice husk ratios and aluminium chloride as a cement setting accelerator to improve the compatibility between the rice husk and the cement. The results indicated that linear expansion increased, whereas impact strength, modulus of rupture, and modulus of elasticity decreased with increasing proportion of rice husk. Moreover, it was reported that the board density decreased, whereas the moisture content, thickness swelling, and water absorption values increased with the addition of rice husk.

2.9. Sugarcane Bagasse

Bagasse is the residue left after the crushing of sugarcane for juice extraction (Aggarwal, 1995). Sugarcane bagasse is generated in large quantities globally, with annual production estimated at about 490 million tons, corresponding to roughly 0.3 tons of wet bagasse per ton of processed sugarcane (Meghana and Shastri, 2020). Sugarcane bagasse is primarily composed of cellulose, hemicellulose, and lignin, whose fibrous structure and biochemical characteristics make it a promising reinforcing material in cement-bonded composites (Cabral et al., 2017). However, the sugarcane bagasse fiber can disrupt or delay Portland cement hydration reactions because it has extractives and impurities. This situation can delay the cement setting and reduce the composite quality (Cabral et al., 2018). Therefore, before production, sugarcane bagasse fibers should be treated by cold/hot water extraction or NaOH extraction to improve the compatibility between the sugarcane bagasse and the cement for high-quality cement-bonded composites.

Cabral et al. (2018) experimentally fabricated cement-bonded composites using untreated and treated sugarcane bagasse subjected to hot-water extraction at 100 ^{0}C for 30 minutes before the production. They determined the inhibition index values of untreated and treated sugarcane bagasse. The obtained findings demonstrated that the boards' water absorption and thickness swelling decreased with the sugarcane bagasse. The boards produced with treated bagasse showed better physical properties than those made with untreated bagasse. Moreover, the boards' mechanical properties decreased with the sugarcane bagasse. However, the utilization of the treated bagasse caused better mechanical properties than those obtained with untreated bagasse.

Aggarwal (1995) treated sugarcane bagasse fibers by soaking in water containing a chemical admixture for 2 hours and produced the cement-bonded particleboards using these fibers. The obtained results indicated that the physical and mechanical properties of cement-bonded particleboards produced using the treated sugarcane bagasse met most of the requirements of various standards on the cement-bonded particleboards.

2.10. Coconut Shells

In the world, coconuts are harvested as 62.8 billion tons, and coconut shells are generated as 9 billion tons each year (Bellow et al., 2016). To utilize these coconut shells in the cement-bonded board manufacturing, Weeranukul and Suweero (2016) made cement-bonded boards using 12%, 13%, 14%, 15%, 16% coconut shell ash. The obtained results indicated that the thermal conductivity of the boards increased by using the coconut shell ash up to 13%, but decreased when higher proportions were used. The highest bending strength values were recorded for the boards containing 12% coconut shell ash. The highest modulus of elasticity values were obtained from the boards containing 14% coconut shell ash. Moreover, the tensile strength perpendicular values were found in the boards containing 16% coconut shell ash.

In another study, Almeida et al. (2002) fabricated cement-bonded particleboards with/without adding %4 $CaCl_2$ at two densities of 1200 kg/m_3 and 1400 kg/m_3 using coconut shells. Hydration, physical, and mechanical tests were performed. The results revealed that the boards containing coconut shell exhibited a low inhibitory index on cement setting. CaCl2 improved only the mechanical performance of cement-bonded particleboards containing coconut shells. An increase in density led to an improvement in the mechanical and physical properties of the boards. It was also reported that it was possible to produce cement-bonded particleboards using coconut shells.

2.11. Corn Stover

The global yield of corn stover reaches 1661 million tons per year and this accounts for approximately 27.2% of the total agricultural waste generated worldwide. Corn stover is composed of 34.5% stems, 32.3% leaves, 14.3% husks, 12.3% cobs, and 6.6% flowers (Li et al., 2020). Corn stover contains 45% cellulose, 30% hemicellulose, and 20% lignin. Corn stover posses significant potential as a valuable lignocellulosic biomass resource for various industrial and bioenergy applications (Zabed et al., 2023).

To utilize the corn cobs as alternative lignocellulosic raw materials in the manufacture of cement-bonded composites, Rindayatno et al. (2023) experimentally produced the cement-bonded particleboards using corn cobs with different particle sizes (20 mesh, 40 mesh, and 50 mesh). It was observed that the corn cob with smaller particle sizes resulted in higher density, modulus of rupture, and internal bond strength. However, moisture content, water absorption, thickness swelling, and modulus of elasticity exhibited a declining trend as the corn con particle size decreased. The physical properties of the cement-bonded particleboards produced from corn cobs complied with the requirements specified in ISO 8335 (1987) and MS 934 (1986). However, their mechanical properties did not meet the respective standard criteria.

In another study, Adelusi et al. (2021) experimentally produced cement-bonded boards using two fiber-cement ratios (1:2.5 and 1:3) and five mixing proportions of corn cob particles to gmelina arborea sawdust (100:0, 75:25, 50:50, 25:75, 0:100). The test results showed that as the contents of cement and corn cob particles in the boards increased, modulus of rupture and modulus of elasticity increased, whereas water absorption and thickness swelling values decreased. They also reported that corn cobs are suitable for the production of cement-bonded particleboards.

2.12. Coffee Husk

According to the USDA Foreign Agricultural Service, global coffee production in the 2024/2025 season was reported to be between 10.1 and 10.5 million tons. Coffee husk is a significant byproduct of the dry processing of coffee beans, constituting approximately 40–45% of the total coffee yield (Ali and Bhowmik, 2025).

To utilize coffee husk in cement-bonded board composites, Zhu (2020) fabricated cement-bonded composites using coffee husk treated with water or %1, %2, %3, %4, and %5 NaOH solution, and tested the composites for compressive strength, bulk density, water absorption, and microstructure analysis (SEM, XRD). The test results showed that pretreatments removed the inhibitory organic compounds from the coffee husk and improved its compatibility with Portland cement. The treated coffee husks exhibited more compressive strength values compared to untreated coffee husks. The composites containing coffee husks treated with 4% NaOH solution yielded the best properties. SEM and XRD analysis revealed that the treated coffee husks had good interfacial adhesion with the cement matrix and caused compact-structure composites. It was concluded that coffee husk waste offered high potential as a sustainable reinforcing material for the production of cement-bonded composites when appropriate modification techniques are applied.

Bhandary et al. (2023) produced cement-bonded composites using 2%, 4%, 6%, and 8% coffee husk ash as a partial replacement for fine aggregate. The test results showed that the composite with 4% coffee husk ash exhibited remarkable increments of 28.4% in compressive strength, 19.35% in flexural strength, and 1.66% in splitting tensile strength, compared to the control composite.

2.13. Arhar Stalks

High quantities of stems and branches (arhar stalks) remain as agricultural residues after harvesting arhar for pulse production. These dry stalks are a promising reinforcing/filling material for the manufacture of cement-based building products because they have their low cost, favorable strength characteristics, and inherent durability (Aggarwal et al., 2008).

Aggarwal et al. (2008) explored the possibility of using arhar stalks as alternative raw materials in the manufacture of cement-bonded composite building products and fabricated the cement-bonded particleboards using arhar stalks at 0%-32% ratios. The test results indicated that the water-soluble extractives in arhar stalks delayed the cement hydration reaction and reduced the compressive strength up to 20%. However, these negative effects could be overcome by a chemical additive or cold water extraction. The researchers also reported that the bending strength and the internal bond strength values of cement-bonded composites produced using arhar stalks satisfied the minimum requirements specified in International Standard (ISO:8335-1987). Cement-bonded particleboards could be produced using arhar stalks as a reinforcing material.

2.14. Vine Stalks

According to The International Organisation of Vine and Wine (OIV), the world grape production reached 77 million tons in 2024 (OIV, 2024). Vine stalks, as a byproduct, are generated either from vineyard pruning operations or during wine production. Under conventional agricultural management, a significant proportion of vine stalks remains on-site or is eliminated through open-field burning. Therefore, they led to considerable environmental hazards (Wei et al., 2022).

Wang et al. (2013) investigated the suitability of vine stalks as an alternative raw material in the manufacture of cement-bonded particleboard. For this purpose, they fabricated the cement-bonded particleboards using vine stalks in different vine stalk-cement ratios, water-cement ratios, and particle sizes. The produced boards' physical and mechanical properties were assessed. The obtained results demonstrated that increasing the vine stalk-cement ratio reduced the modulus of rupture, the modulus of elasticity, the internal bond strength, and the thermal conductivity, while increasing the thickness swelling values. Moreover, an increase in water-cement ratio led to reductions in the modulus of rupture, the modulus of elasticity, the internal bond strength, the thickness swelling, and the thermal conductivity.

In another work, Nasser et al. (2011) produced experimentally cement-bonded particleboards using vine stalks by applying various pretreatments and adding chemical additives. The obtained results demonstrated that untreated vine stalks were incompatible with the cement and unsuitable for the cement-bonded particleboard manufacturing. They noted the hot-water extraction of vine stalks or the addition of 3% CaCl2 significantly improved the compatibility of the vine stalks with the cement. It was concluded that the vine stalks, after hot-water extraction or % 3% $CaCl_2$ addition, could be utilized for the manufacture of cement-bonded particleboard.

2.15. Oil Palm

Oil palm cultivation and processing generate significant volumes of by-products and residues each year in the world. These byproducts and residues are largely unused and not valorized into value-added products. Recently, the researchers reported that oil palm vascular bundles from empty fruit bunches and fronds can be effectively utilized as cellulosic raw materials for the manufacture of cement-bonded boards (Hermawan et al., 2001).

Hermawan et al. (2001) investigated the utilization of the palm oil fronds in the production of cement-bonded particleboards and experimentally produced cement-bonded particleboards using oil palm fronds in different wood-cement ratios. They determined the compatibility of the oil palm fronds with the cement when magnesium chloride by a hydration test. The test results demonstrated that the 5% magnesium chloride significantly improved the compatibility of oil palm fronds with the cement matrix and increased their compatibility levels up to 90%. Moreover, magnesium chloride enhanced the cement hydration and the boards' strength performance. The cement-bonded particleboards containing oil palm fronds and magnesium chloride fulfilled the related standard requirements.

In another study conducted by Pazai and Soh (2025), the cement boards were produced by using oil palm empty fruit bunch fiber. Oil palm fruit brunch fibers were subjected to a hot-water extraction to improve their compatibility with cement and increase the cement boards. The test results concluded that extending the curing period of cement boards from 7 to 28 days caused a decline in modulus of rupture, modulus of elasticity, and internal bond strength, while resulting in an increase in thickness swelling, water absorption, and density values.

2.16. Hazelnut Shells

Hazelnuts are cultivated worldwide on approximately one million hectares across 38 countries, resulting in a global production exceeding 1.1 million tonnes in the 2020/2021 season, and Turkey is the leading producer, accounting for 665,000 tonnes during the same period (Manterola-Barroso et al., 2024). Hazelnut shells constitute more than 50% of the total mass of the hazelnut fruit and are structurally composed of cellulose (26–32%), hemicelluloses (25–30%), lignin (40–43%), and other H_2O-soluble extractives (3.3–4%) (Manterola-Barroso et al., 2024).

To investigate the possibility of hazelnut shells as lignocellulosic raw material in cement composite manufacturing, Demirbaş and Aslan (1998) experimentally produced cement composites incorporating 2%, 5%, 7.5%, and 10% hazelnut shells and evaluated the changes in board strength over curing periods ranging from 7 to 90 days. The test results indicated that an increase in the curing time led to an increase in the boards' compressive strength and bending strength values. However, an increase in hazelnut shell content caused a decline in the boards' bending strength and compressive strength.

3. CONCLUSION

In this section, the potential that agricultural residues have as alternative raw materials in cement-bonded particleboard production has been examined. In many studies carried out in cement-bonded particleboard production, it has been seen that many agricultural wastes such as sunflower stalks, walnut shells, olive mill residues, wheat straw, rice husk, sugarcane bagasse, banana pseudostems, vine stalks, hazelnut shells, and various pruning residues, can be used effectively when appropriate processing methods are applied. The evaluation of these residues reduces the dependence on forest-based materials, contributes to the solution of problems related to the disposal of agricultural residues, and supports a more sustainable approach in the construction sector within the scope of the circular economy.

The performance of cement-bonded particleboards produced from agricultural residues depends on many factors, such as the type of biomass used, chemical composition, particle geometry, substitution ratio, and interaction with cement hydration. Many of these residues contain water-soluble sugars, extractive substances, or other organic components that can negatively affect cement hydration and strength development. However, studies show that these negative effects can be effectively eliminated by various methods, such as hot/cold water extraction, sodium hydroxide extraction, or the addition of chemical accelerators such as calcium chloride and magnesium chloride, in production. Many agricultural residues can meet the required standard values for certain substitution ratios, especially in non-structural and semi-structural applications.

The utilization of agricultural residues in cement-bonded particleboards generally caused a decrease in density and thermal conductivity, improving the insulation properties of cement-bonded particleboards. Because of the multifunctional feature of cement-bonded particleboards produced using agricultural waste, they can be used in various applications such as wall panels, insulation boards, acoustic barriers, and partition elements. However, excessive replacement ratios can increase the water absorption and the thickness swelling, and decrease the mechanical strength. This situation shows that the mixture ratios and production conditions should be carefully optimized.

As a result, agricultural residues are sustainable and promising alternative materials to traditional wood particles in the production of cement-bonded particleboard when the limitations specific to each material are addressed. Additional works are needed to investigate long-term durability, conduct life cycle analyses, evaluate large-scale industrial applicability, and develop standardized production protocols for the commercial use of these agricultural waste-based cement-bonded particleboards.

4. REFERENCES

Adelusi, E.A., Olaoye, K. O., Adelusi, F. T., Adedokun, S. A. (2021). Physico-mechanical properties of cement-bonded boards produced from mixture of corn cob particles and gmelina arborea sawdust. *Journal of Forest and Environmental Science* 37(1): 79-89.

Aggarwal, L.K. (1995). Bagasse-reinforced cement composites. *Cement and Concrete Composites 17*(2): 107-112.

Aggarwal, L.K., Agrawal, S.P., Thapliyal, P.C., Karade, S.R. (2008). Cement-bonded composite boards with arhar stalks. *Cement and Concrete Composites 30*(1): 44-51.

Ali, M.A., Bhowmik, S. (2025). Bioactive compounds in coffee husk: extraction, functional properties, applications, and sustainable approach in circular economy. *RSC sustainability 3*(10): 4410-4425.

Almeida, R.R., Del Menezzi, C.H.S., Teixeira, D.E. (2002). Utilization of the coconut shell of babaçu (Orbignya sp.) to produce cement-bonded particleboard. *Bioresource Technology 85*(2): 159-163.

Aras, U., Kalaycıoğlu, H., Yel, H., Kuştaş, S. (2022). Utilization of olive mill solid waste in the manufacturing of cement-bonded particleboard. *Journal of Building Engineering 49*: 104055.

Bamisaye, J.A. (2007). Cement-bonded particleboard production from rice husk in Southwestern Nigeria. *Journal of Engineering and Applied Science* 2(1): 183-185.

Bellow, S.A., Agunsoye, J.O., Adebisi, J.A., Kolawole, F. O., Hassan, S. B. (2016). Physical properties of coconut shell nanoparticles. *Kathmandu University Journal of Science, Engineering and Technology 12*(1): 63-79.

Bisaglia, C., Brambilla, M., Cutini, M., Bortolotti, A., Rota, G., Minuti, G., Sargiani, R. (2018). Reusing pruning residues for thermal energy production: A mobile app to match biomass availability with the heating energy balance of agro-industrial buildings. *Sustainability 10*(11): 4218.

Bhandary, R.P., Rao, A.U., Shetty, P.P., Blesson, S., Thomas, B.S. (2023). Application of coffee husk ash as partial replacement of fine aggregate in concrete. *Sustainability 15*(18): 13328.

Cabral, M. R., Nakanishi, E. Y., Fiorelli, J. (2017). Evaluation of the effect of accelerated carbonation in cement–bagasse panels after cycles of wetting and drying. *Journal of Materials in Civil Engineering 29*(6): 04017018.

Cabral, M.R., Nakanishi, E.Y., Dos Santos, V., Palacios, J.H., Godbout, S., Savastano, H., Fiorelli, J. (2018). Evaluation of pre-treatment efficiency on sugarcane bagasse fibers for the production of cement composites. *Archives of Civil and Mechanical Engineering 18*(4): 1092-1102.

Castillo, M., de Guzman, M. J. K., Aberilla, J. M. (2023). Environmental sustainability assessment of banana waste utilization into food packaging and liquid fertilizer. *Sustainable Production and Consumption* 37, 356-368.

Cebin, A.V., Ralet, M.C., Vigouroux, J., Karača, S., Martinić, A., Komes, D., Bonnin, E. (2021). Valorisation of walnut shell and pea pod as novel sources for the production of xylooligosaccharides. *Carbohydrate polymers 263*:117932.

Demirbaş, A., Aslan, A.(1998). Effects of ground hazelnut shell, wood, and tea waste on the mechanical properties of cement. *Cement and concrete research*, *28*(8): 1101-1104.

Durand, K., Daassi, R., Rodrigue, D., Stevanovic, T. (2024). Study of purified cellulosic pulp and lignin produced by wheat straw biorefinery. *Macromol 4*(3): 650-679.

Dursun, N. (2024). Estimation of pruning wastes and biochar production potential of Turkey. *BioResources 19*(2): 2503.

El Hamri, A., Mouhib, Y., Chkala, H., Oulhakem, O., Chigr, M., El Mansouri, N. E. (2025). Investigating the potential of using walnut shell particles for manufacturing cement-bonded particle boards. *Journal of Composites Science* 9(4):183.

Enaime, G., Dababat, S., Wichern, M., Lübken, M. (2024). Olive mill wastes: From wastes to resources. *Environmental Science and Pollution Research 31*(14): 20853-20880.

Food and Agriculture Organization of the United Nations. (2022). Michurin's legacy, or selection, is a strict teacher: Like tree, like fruit. Retrieved from https://www.fao.org/russian-federation/news/news-detail/michurin-s-legacy--or-selection-is-a-strict-teacher.-like-tree--like-fruit/en/

Food and Agriculture Organization of the United Nations. (2023). *FAOSTAT* statistical database: Crops – Bananas, 2022 production. FAO. Retrieved from https://www.fao.org/faostat/

Food and Agriculture Organization of the United Nations. (2023). FAOSTAT*:* Crops and livestock products – Tea production statistics. Food and Agriculture Organization of the United Nations.

Gilanipoor, N., Spinelli, R., Naghdi, R., Najafi, A. (2020). Utilization of woody pruning residues of apple trees. *Forest Science and Technology 16*(4): 216-223.

Hermawan, D., Subiyanto, B., Kawai, S. (2001). Manufacture and properties of oil palm frond cement-bonded board. *Journal of Wood Science 47*(3): 208-213.

International Organization of Vine and Wine (2024). OIV statistical brief: Wine, table grapes, and dried grapes in 2024.

Jiang, H., Wang, S. Y., Wang, H. R., Jing, Y. Y., Qu, H., Sun, L., Wang, J., Lui, B., Gao, F.Q. (2024). Influence on the fermentation quality, microbial diversity, and metabolomics in the ensiling of sunflower stalks and alfalfa. *Frontiers in Plant Science 15*: 1333207.

Kaza, S., Yao, L., Bhada-Tata, P., Van Woerden, F. (2018) . What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050. World Bank Publications, Washington, DC, USA.

Kordi, M., Farrokhi, N., Pech-Canul, M. I., Ahmadikhah, A. (2024). Rice husk at a glance: from agro-industrial to modern applications. *Rice Science 31*(1): 14-32.

Lackner, M., Besharati, M. (2025). Agricultural waste: Challenges and solutions, a review. *Waste* 3(2):18.

Li, X., Qin, D., Hu, Y., Ahmad, W., Ahmad, A., Aslam, F., Joyklad, P. A. (2022). Systematic review of waste materials in cement—based composites for construction applications. *Journal of Building Engineering* 45: 103447.

Li, C.L., Kerner, P., Williams, C.L., Hoover, A., Ray, A.E. (2020). Characterization and localization of dynamic cell wall structure and inorganic species variability in harvested and stored corn stover fractions as functions of biological degradation. Sustainable Chemistry and Engineering Journal 8(18): 6924–6934.

Manterola-Barroso, C., Padilla Contreras, D., Ondrasek, G., Horvatinec, J., Gavilán CuiCui, G., Meriño-Gergichevich, C. (2024). Hazelnut and walnut nutshell features as emerging added-value byproducts of the nut industry: A review. *Plants 13*(7): 1034.

Marques, B., Almeida, J., Tadeu, A., António, J., Santos, M. I., de Brito, J., Oliveira, M. (2021). Rice husk cement-based composites for acoustic barriers and thermal insulating layers. *Journal of Building Engineering 39:* 102297.

Meghana, M., Shastri, Y. (2020). Sustainable valorization of sugar industry waste: Status, opportunities, and challenges. *Bioresource technology 303*: 122929.

Mehdikhani, H., Jalali Torshizi, H., Dahmardeh Ghalehno, M. (2019). Deeper insight into the morphological features of sunflower stalk as biorefining criteria for sustainable production. *Nordic Pulp & Paper Research Journal* 34: 250–263.

Nasser, R.A., Salem, M.Z.M., Al-Mefarrej, H.A., Aref, I.M. (2016). Use of tree pruning wastes for manufacturing of wood reinforced cement composites, *Cement and Concrete Composite* 72: 246–256.

Nasser, R.A., Al-Mefarrej, H.A., Abdel-Aal, M.A. (2011). Suitability of vine (Vitis vinifera L.) prunings for wood-cement industry. *American-Eurasian Journal of Agricultural & Environmental Sciences 11*(6): 903-910.

Nazerian, M., Sadeghiipanah, V. (2013). Cement-bonded particleboard with a mixture of wheat straw and poplar wood. *Journal of Forestry Research 24*(2): 381-390.

Nunes, L., Cintura, E., Parracha, J. L., Fernandes, B., Silva, V., Faria, P. (2021). Cement-bonded particleboards with banana pseudostem waste: physical performance and bio-susceptibility. *Infrastructures 6*(6): 86.

Owoyemi, J.M., Opeyemi, A.H. (2021). Assessment of “Musa spp” fibre inclusion on the strength and sorption properties of cement-bonded particleboard. *Indonesian Journal of Innovation and Applied Sciences (IJIAS) 1*(1): 1-11.

Pazai, A.R.M., Soh, N.M.Z.N. (2025). Dimensional stability of oil palm empty fruit bunch fibre (opefb) cement board over the curing period. *Journal of Structural Monitoring and Built Environment 5*(1): 1-11.

Rao, M.M., Botsa, S.M., Rao, T.P., Goddu, S. R., Vijayasanthi, C. (2024). A comprehensive review on agricultural waste production and onsite management with circular economy opportunities. *Discover Sustainability 5*(1): 288.

Rindayatno, A., Fahmi, A. N. (2023). Particle cement board quality from corn cob (Zea mays L.) based on differences in particle size. *International Journal of Scientific Multidisciplinary Research* 1(7): 893-902.

Soroushian, P., Aouadi, F., Chowdhury, H., Nossoni, A., Sarwar, G. (2004). Cement-bonded straw board subjected to accelerated processing. *Cement and Concrete Composites 26*(7): 797-802.

Taş, H. H., Sari, U. (2022). Feasibility of olive tree pruning as an alternative raw material for cement-bonded particleboard. *ProLigno* 18(4): 10-15.

Taş, H.H., Acar, K. (2022). Investigation of the usability of apple tree pruning chips as an alternative raw material to produce cement-bonded particleboard. *International Journal of Technological Science 14*(3): 132-137.

Taş, H.H., Kul, F.M. (2020). Sunflower (Helianthus annuus) stalks as an alternative raw material for cement-bonded particleboard. *Drvna industrija*, *71*(1): 41-46.

Thiruvengadam, M., Rajakumar, G., Chung, I. M., Yang, D. C. (2023). Environmental concerns and valorization pathways of tea waste: A comprehensive review. *Environmental Research*, 216: 114742.

Tichi, A. H., Razavi, M. (2023). Construction of cement composite using walnut shell reinforced with bacterial nanocellulose gel. *BioResources*, *18*(4).

Tura, N., Hanski, J., Ahola, T., Stahle, M., Piiparinen, S., Valkokari, P. (2019). Unlocking circular business: A framework of barriers and drivers. *Journal of Cleaner Production*, 212: 90–98.

Vu, H.P., Nguyen, L.N., Vu, M.T., Nguyen, H.Q. (2022). Tea waste: Generation, characteristics, and emerging applications. *Waste Management*, 138: 134–150.

Wang, C.G., Zhang, S.G., Wu, H. (2013). Performance of cement-bonded particleboards made from grapevine. *Advanced Materials Research 631*: 765-770.

Weeranukul, P., Suweero, K. (2016). Development of cement boards from coconut shell ash for energy and environment conservation. *Engineering and Applied Science Research 43*: 173-175.

Wei, M., Ma, T., Ge, Q., Li, C., Zhang, K., Fang, Y., Sun, X. (2022). Challenges and opportunities of winter vine pruning for the global grape and wine industries. *Journal of Cleaner Production 380*: 135086.

Yel, H. (2022). Effect of alkaline pre-treatment and chemical additives on the performance of wood cement panels manufactured from sunflower stems. *Journal of Building Engineering 52*: 104465.

Yel, H., Dönmez Çavdar, A., Kalaycioğlu, H. (2011). Mechanical and physical properties of cement-bonded particleboard made from tea residues and hardboards. *Key Engineering Materials 471*: 572-577.

Zabed, H. M., Akter, S., Yun, J., Zhang, G., Zhao, M., Mofijur, M., Awasthie, M.K, Kalamf, M.A., Ragauskas, A., Qi, X. (2023). Towards the sustainable conversion of corn stover into bioenergy and bioproducts through biochemical route: Technical, economic and strategic perspectives. *Journal of Cleaner Production 400:* 136699.

Chapter 13

AN INNOVATIVE TECHNIQUE FOR QUANTIFYING EPISTEMIC AND ALEATORIC UNCERTAINTY IN ARTIFICIAL INTELLIGENCE–BASED MODELING OF FOREST ATTRİBUTES: EVIDENTIAL DEEP LEARNING

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Introduction

Over the past twenty decades, artificial intelligence (AI) techniques—ranging from early applications of artificial neural networks (ANNs) to more recent implementations of deep learning algorithms (DLAs)—have demonstrated substantial improvements in predictive performance across a wide range of forestry applications. The gradual integration of AI-based methods into forest science has provided researchers with powerful alternatives to conventional statistical modeling approaches, particularly in contexts where complex, nonlinear relationships and high-dimensional interactions are present. Unlike traditional regression-based methods, which often require strict assumptions regarding data distribution, linearity, and error structure, AI-based models offer greater flexibility in representing complex ecological processes.

The emergence of artificial neural networks (ANNs) has marked a significant shift in predictive modeling by enabling data-driven learning without the need for predefined functional forms. ANNs are capable of approximating complex nonlinear relationships directly from data, making them particularly well suited for modeling forest attributes such as growth, yield, biomass, and structural characteristics. Their ability to learn from examples rather than relying on explicit statistical assumptions has contributed to their widespread adoption in forestry since the early 2000s. This flexibility allows ANNs to maintain predictive stability even when relationships among variables are highly nonlinear or when interactions among predictors are difficult to specify a priori.

Another important advantage of ANNs lies in their robustness to noisy and imperfect data, which are common features of forest inventory and ecological datasets. Through adaptive weight optimization, neural networks can identify dominant patterns in the data while reducing sensitivity to outliers and measurement errors. As a result, ANN-based models often achieve improved generalization performance compared to traditional parametric approaches, particularly when modeling complex systems characterized by spatial and temporal variability.

Recent advances in deep learning have further expanded the modeling capacity of neural network–based approaches. Deep Learning Algorithms (DLAs) represent an extension of conventional ANNs, characterized by multi-layer network architectures that include at least three hidden layers and, in many cases, substantially deeper structures. These architectures may consist of five to ten or even dozens of hidden layers, with hundreds or thousands of interconnected neurons. Such depth enables DLAs to learn hierarchical representations of data, where low-level features are progressively transformed into higher-level abstractions through successive network layers.

The increased representational power of deep learning models allows them to capture highly complex patterns and interactions that are difficult to model using shallow networks or traditional statistical techniques. By leveraging multiple layers of nonlinear transformations, DLAs can approximate intricate functional relationships and decision boundaries, thereby enhancing predictive accuracy in challenging modeling tasks. This hierarchical learning capability has been widely interpreted as an attempt to emulate certain aspects of human learning and decision-making processes, albeit in a highly simplified and abstracted form.

In the context of forestry, the application of deep learning has enabled more accurate and flexible modeling of forest dynamics under diverse environmental and management conditions. However, while deep learning models offer remarkable predictive performance, their increasing complexity also introduces challenges related to interpretability, transparency, and uncertainty awareness. These challenges underscore the importance of developing modeling frameworks that not only achieve high predictive accuracy but also provide meaningful insights into model confidence and reliability, particularly in decision-support applications.

The increasing use of artificial intelligence (AI) and deep learning techniques in forestry has significantly advanced the modeling of complex forest attributes such as growth, yield, biomass, and structural dynamics. Deep neural networks are particularly effective in capturing nonlinear relationships and high-dimensional interactions that are difficult to represent using traditional statistical models. However, despite their strong predictive performance, most AI-based forestry applications remain deterministic in nature and provide limited information regarding the reliability and confidence of their predictions. In forestry-related decision-making processes, predictive models are increasingly expected to support not only estimation tasks but also risk-aware planning and management. Forest management decisions often involve long temporal horizons, irreversible interventions, and trade-offs among economic, ecological, and social objectives. Under such conditions, deterministic predictions without explicit uncertainty information may lead to overly confident interpretations and suboptimal decisions. Consequently, the integration of uncertainty quantification into AI-based forestry models has become a critical requirement rather than an optional enhancement.

Uncertainty quantification has therefore emerged as a critical component of machine learning applications in environmental and ecological systems, where data are inherently noisy, heterogeneous, and often sparse. Predictive uncertainty is commonly decomposed into two fundamental components: *aleatoric uncertainty*, which arises from irreducible noise and natural variability in the data, and *epistemic uncertainty*, which reflects limitations in model structure, parameter estimation, or insufficient training data (Kendall and Gal, 2017). This distinction is particularly important, as aleatoric uncertainty cannot be reduced through additional data, whereas epistemic uncertainty can potentially be mitigated by improved modeling strategies or expanded data coverage. In the context of forest ecosystems, aleatoric uncertainty is closely linked to inherent ecological variability, including site heterogeneity, climatic fluctuations, and biological processes that cannot be fully controlled or observed. Epistemic uncertainty, on the other hand, arises from incomplete knowledge of forest dynamics, limited sample sizes, measurement errors, and simplifications inherent in modeling assumptions. Distinguishing between these two uncertainty components is particularly valuable in forestry, as it allows practitioners to identify whether uncertainty is driven by irreducible system variability or by limitations that could potentially be addressed through improved data collection or model refinement.

Early approaches to uncertainty estimation in deep learning relied heavily on Bayesian neural networks, Monte Carlo dropout, and deep ensemble techniques (Gal and Ghahramani, 2016; Lakshminarayanan et al., 2017). Although these methods provide principled uncertainty estimates, they typically depend on repeated sampling or multiple model realizations, leading to substantial computational cost and increased inference complexity. Such limitations can restrict their practical applicability in large-scale or operational forestry problems, where efficiency and interpretability are essential. From an operational forestry perspective, computational efficiency and methodological transparency are particularly important, as predictive models are often applied across extensive forest areas and repeated simulation scenarios. The reliance on multiple forward passes or ensemble members may significantly increase computational burden, thereby limiting the scalability of uncertainty-aware deep learning approaches in applied forest management contexts.

A major conceptual breakthrough in uncertainty-aware deep learning was introduced by Sensoy et al. (2018), who first proposed the Evidential Deep Learning (EDL) framework. In this pioneering work, learning was reformulated as an evidence accumulation process grounded in the theory of evidence and subjective logic. By enabling neural networks to predict the parameters of a Dirichlet distribution rather than point estimates, EDL allowed predictive uncertainty to be represented explicitly within a single deterministic model, without resorting to Bayesian weight sampling or ensemble-based approximations. This evidential formulation marked a conceptual shift in how uncertainty is represented in deep learning models. Rather than interpreting uncertainty as a by-product of stochastic sampling, EDL treats uncertainty as an explicit model output that reflects the strength of evidence supporting a prediction. This perspective aligns well with the needs of environmental and forestry applications, where interpretability and consistency of uncertainty estimates are essential for decision support. Building upon this foundational idea, Amini et al. (2020) extended evidential learning to continuous regression problems through the formulation of deep evidential regression. By placing conjugate priors over Gaussian likelihood functions, this approach enabled the simultaneous estimation of predictive targets and their associated aleatoric and epistemic uncertainties. These developments demonstrated that evidential learning could achieve calibrated uncertainty estimates with substantially lower computational overhead than sampling-based methods, while maintaining competitive predictive accuracy. Despite these advantages, recent studies have raised important critiques regarding the interpretation and reliability of uncertainty estimates produced by evidential deep learning. In particular, Shen et al. (2024) argued that evidential models may, in some cases, exhibit counterintuitive uncertainty behavior, such as assigning high epistemic uncertainty to in-distribution samples or insufficiently penalizing confident but incorrect predictions. Their findings suggest that EDL may be more robust as a detector of out-of-distribution samples than as a universally reliable uncertainty quantifier, especially in complex or highly noisy learning environments. Similarly, Meinert et al. (2023) highlighted potential limitations related to the overparameterization of evidential distributions and the sensitivity of uncertainty estimates to loss function design and regularization strategies. They emphasized that epistemic uncertainty inferred through evidential formulations may be influenced by optimization dynamics rather than purely reflecting model ignorance.

These critiques are particularly relevant for forestry applications, where complex ecological interactions, heterogeneous data sources, and scale-dependent processes may challenge the faithful interpretation of uncertainty estimates. Accordingly, uncertainty-aware AI models must be evaluated not only in terms of predictive accuracy but also with respect to the ecological plausibility and stability of their uncertainty representations. These critiques underscore that evidential uncertainty should be interpreted with caution and that its decomposition into aleatoric and epistemic components does not automatically guarantee faithful uncertainty representation across all problem settings. These critical perspectives do not diminish the value of evidential deep learning but rather emphasize the need for careful interpretation, methodological transparency, and domain-specific evaluation when applying EDL. Particularly in forestry, where data heterogeneity, measurement error, and complex ecological processes are prevalent, understanding both the strengths and limitations of evidential uncertainty modeling is essential.

The primary aim of this study is to provide a concise and structured overview of Evidential Deep Learning as an innovative technique for uncertainty quantification. Specifically, this chapter aims to present essential theoretical and methodological insights into how epistemic and aleatoric uncertainty can be numerically represented within the EDL framework, while also acknowledging current limitations and ongoing debates in the literature. In doing so, the study seeks to offer a balanced reference for researchers interested in applying uncertainty-aware artificial intelligence approaches to forestry and related environmental sciences.

Epistemic and Aleatoric Uncertainty

Uncertainty is an inherent component of predictive modeling and arises whenever a model is used to infer unknown outcomes from observed data. In the context of artificial intelligence and machine learning, uncertainty reflects the degree of confidence that can be attributed to a model's predictions and determines how reliably model outputs can be interpreted. Quantifying uncertainty is particularly important in environmental and forestry applications, where observational data are often affected by measurement errors, sampling limitations, and natural variability across space and time. Moreover, forest-related datasets are frequently incomplete and heterogeneous, as they are collected under diverse ecological conditions and management regimes. Because model outputs in forestry are commonly used to support planning, policy formulation, and operational decision-making, the absence of explicit uncertainty information may lead to misleading conclusions or overly confident interpretations, even when predictive accuracy appears high.

In practical forestry applications, uncertainty-aware predictions allow decision makers to assess the robustness of alternative management strategies and to evaluate potential risks associated with different intervention scenarios. Without explicit uncertainty quantification, model-based recommendations may obscure the limits of knowledge and create a false sense of precision. Consequently, incorporating uncertainty into predictive modeling is essential for promoting transparency, supporting risk-aware decision making, and improving the credibility of artificial intelligence–based tools in forest science.

Predictive uncertainty is commonly decomposed into two fundamental components: aleatoric uncertainty and epistemic uncertainty. Aleatoric uncertainty represents the inherent variability or noise present in the data-generating process and arises from stochastic natural processes, environmental fluctuations, and measurement imprecision. This type of uncertainty is irreducible, even with an infinite amount of data, as it reflects randomness intrinsic to the system being modeled. In forestry, aleatoric uncertainty is often associated with site heterogeneity, microclimatic variation, and biological processes that cannot be fully observed or controlled.

In contrast, epistemic uncertainty arises from incomplete knowledge of the underlying system and is closely linked to limitations in model structure, parameter estimation, and data availability. This form of uncertainty reflects what the model does not know and can potentially be reduced through improved model formulations, additional observations, or more informative training data. In forest modeling, epistemic uncertainty may stem from sparse sample plots, unobserved explanatory variables, or simplified representations of complex ecological interactions. The decomposition of predictive uncertainty into aleatoric and epistemic components is therefore crucial, as it enables a more meaningful interpretation of model reliability by distinguishing between uncertainty that is intrinsic to the system and uncertainty that is attributable to model limitations. This distinction provides valuable guidance for both model improvement and data acquisition strategies, particularly in uncertainty-aware forest management and planning. From a probabilistic perspective, the total predictive uncertainty of a model can be expressed using the law of total variance. For a target variable conditioned on input features , the total predictive variance is given by:

$$\mathrm{Var}(y \mid \mathbf{x}) = \mathbb{E}_{\theta}\left[\mathrm{Var}(y \mid \mathbf{x}, \theta)\right] + \mathrm{Var}_{\theta}\left[\mathbb{E}(y \mid \mathbf{x}, \theta)\right] \tag{1}$$

where denotes the model parameters. The first term on the right-hand side corresponds to aleatoric uncertainty, representing the expected data noise conditioned on the model, while the second term corresponds to epistemic uncertainty, capturing the variability in predictions induced by uncertainty in the model parameters.

In evidential deep learning frameworks, this uncertainty decomposition is achieved without sampling or ensemble-based approximations. Instead, the model is trained to predict the parameters of a higher-order evidential distribution over the likelihood function. In the regression setting, this is commonly formulated using a Normal–Inverse-Gamma (NIG) distribution, where the likelihood parameters are treated as random variables. Under this formulation, the predictive mean is given by:

$$\mathbb{E}(y \mid \mathbf{x}) = \mu, \tag{2}$$

while aleatoric and epistemic uncertainties can be expressed as:

$$\begin{aligned} \text{Aleatoric Uncertainty} &= \mathbb{E}[\sigma^2], \\ \text{Epistemic Uncertainty} &= \mathrm{Var}(\mu). \end{aligned} \tag{3}$$

$$\begin{aligned} \text{Aleatoric Uncertainty} &= \mathbb{E}[\sigma^2], \\ \text{Epistemic Uncertainty} &= \mathrm{Var}(\mu). \end{aligned} \tag{4}$$

This explicit representation enables the numerical quantification and separation of epistemic and aleatoric uncertainty within a single deterministic neural network. As a result, evidential deep learning provides a principled and computationally efficient framework for uncertainty-aware modeling, allowing model predictions to be interpreted not only in terms of accuracy but also in terms of their associated confidence and reliability.

Python-Based Libraries for Training Evidential Deep Learning Models

The training and implementation of Evidential Deep Learning (EDL) models can predominantly be carried out using Python-based machine learning frameworks, owing to their flexibility, extensive ecosystem, and strong community support. Python has become the de facto programming language for deep learning research, offering a comprehensive environment for neural network development, numerical computation, and uncertainty-aware modeling. Its readability, modular structure, and compatibility with a wide range of scientific libraries make it particularly suitable for interdisciplinary fields such as forestry, where modeling workflows often integrate statistical analysis, data preprocessing, and visualization. Within this ecosystem, EDL frameworks are commonly implemented by extending standard deep learning architectures with customized output layers and loss functions that allow neural networks to estimate the parameters of evidential distributions rather than producing simple point predictions. Among the available deep learning frameworks, PyTorch is currently the most widely used library for developing EDL models. Its dynamic computation graph provides flexibility in model design and facilitates the implementation of complex loss functions required for evidential learning. This feature is particularly advantageous when modeling epistemic and aleatoric uncertainty, as it allows for fine-grained control over gradient flow and regularization mechanisms. PyTorch's modular architecture enables researchers to construct custom neural network heads that output evidential parameters associated with Dirichlet or Normal–Inverse-Gamma distributions, depending on whether the task involves classification or regression. Furthermore, PyTorch seamlessly integrates automatic differentiation, enabling efficient optimization of evidential loss functions that combine data likelihood terms with regularization components designed to penalize unsupported or misleading evidence during training.

In practical EDL workflows, PyTorch is typically complemented by a suite of auxiliary Python libraries. NumPy and SciPy are widely used for efficient numerical operations, statistical computations, and scientific processing, while scikit-learn supports data preprocessing, feature scaling, model evaluation, and comparison with conventional machine learning approaches. These libraries collectively facilitate the development of reproducible and well-structured modeling pipelines, from raw data ingestion to uncertainty-aware performance assessment. For data management and exploratory analysis, pandas plays a central role in handling structured and tabular datasets commonly encountered in forestry applications. Visualization libraries such as Matplotlib and Seaborn are frequently employed to inspect training dynamics, explore data distributions, and analyze predictive uncertainty components. In EDL studies, visualizing epistemic and aleatoric uncertainty across input variables or spatial and temporal gradients is particularly important for interpreting model behavior and identifying regions of high uncertainty. To support model monitoring and diagnostics, TensorBoard and PyTorch-compatible logging tools are often integrated into training workflows, enabling real-time tracking of loss convergence, predictive accuracy, and the evolution of uncertainty components throughout the training process.

Recent and future EDL studies increasingly rely on cloud-based computational environments, with Google Colab being one of the most widely adopted platforms. Google Colab provides free and on-demand access to GPU and TPU resources, substantially reducing the computational barriers associated with training deep neural networks. Its browser-based interface allows researchers to develop, execute, and share Python notebooks without requiring local hardware installation or complex software configuration. This accessibility is particularly beneficial for researchers in forestry and environmental sciences, where access to high-performance computing resources may be limited.

Within Google Colab, typical EDL workflows involve importing standard Python libraries, loading datasets from cloud storage or external repositories, defining neural network architectures using PyTorch, and training models with stochastic gradient-based optimization algorithms such as Adam or its variants. The integration of Colab with cloud storage services, especially Google Drive, facilitates efficient dataset management, model checkpointing, version control, and result archiving. This integration also enhances reproducibility and collaboration, allowing researchers to share complete modeling pipelines, including code, data, and trained models. Consequently, Google Colab has emerged as a practical, transparent, and accessible environment for implementing Evidential Deep Learning models, particularly in research contexts where computational efficiency, methodological transparency, and reproducibility are of primary importance.

Discussion

In this study, Evidential Deep Learning (EDL)-originally introduced by Sensoy et al. (2018) for classification problems and subsequently extended to regression tasks by Amini et al. (2020)-has been discussed as an innovative framework for quantifying predictive uncertainty in artificial intelligence–based modeling of forest attributes. Rather than proposing new predictive models or presenting empirical performance comparisons, the primary contribution of this study lies in providing a structured, theoretical, and methodological overview of EDL, with particular emphasis on the numerical representation and decomposition of epistemic and aleatoric uncertainty.

The discussion underscores a key limitation of many existing AI-based applications in forestry: the predominance of deterministic predictions that offer limited insight into prediction reliability. By explicitly distinguishing between aleatoric uncertainty, which arises from irreducible data noise and natural variability, and epistemic uncertainty, which reflects model limitations and insufficient knowledge, EDL provides a richer interpretative framework than conventional deep learning approaches. This distinction is particularly relevant in forestry, where measurement errors, site heterogeneity, and complex ecological processes often constrain model performance and interpretation.

From a methodological perspective, this study highlights that evidential deep learning represents a conceptual alternative to traditional sampling-based uncertainty estimation techniques. Unlike Bayesian neural networks, Monte Carlo dropout, or deep ensemble methods, EDL estimates uncertainty within a single deterministic neural network by learning the parameters of a higher-order evidential distribution. This characteristic offers important practical advantages in terms of computational efficiency and scalability, making EDL especially attractive for large-scale or operational forestry applications. The discussion of Python-based libraries and the widespread use of Google Colab further illustrates how EDL can be implemented in accessible and reproducible computational environments.

At the same time, the study acknowledges that evidential uncertainty estimates should be interpreted with caution. Recent critiques by Shen et al. (2024) and Meinert et al. (2023) have shown that EDL models may exhibit sensitivity to loss function design, regularization strategies, and optimization dynamics, potentially leading to counterintuitive uncertainty behavior. These findings suggest that epistemic uncertainty inferred through evidential formulations does not always exclusively reflect genuine model ignorance and may, under certain conditions, be influenced by training dynamics. By explicitly recognizing these limitations, this study adopts a balanced perspective that neither overstates nor dismisses the capabilities of EDL.

Within the scope of this work, the principal value of evidential deep learning lies in its ability to provide a transparent and computationally efficient mechanism for decomposing predictive uncertainty. By synthesizing theoretical foundations, mathematical formulations, and practical implementation considerations, this study contributes to a clearer understanding of how epistemic and aleatoric uncertainty can be quantified and interpreted. Such clarity is particularly important for forestry-related applications, where uncertainty information can support risk-aware decision making, guide data acquisition strategies, and inform model refinement.

In conclusion, this study positions Evidential Deep Learning as a promising and evolving framework for uncertainty-aware artificial intelligence in forestry. By presenting EDL as an informational and methodological reference rather than a model development or validation study, the discussion highlights both its potential advantages and its current limitations. Future research should focus on empirical evaluations of evidential uncertainty in real-world forestry applications and on systematic comparisons with alternative uncertainty quantification approaches to further clarify the role of EDL in forest science and management.

References

Amini, A., Schwarting, W., Soleimany, A., and Rus, D. (2020). Deep evidential regression. Advances in Neural Information Processing Systems (NeurIPS), 33, 14927–14937.

Gal, Y., & Ghahramani, Z. (2016). Dropout as a Bayesian approximation: Representing model uncertainty in deep learning. Proceedings of the 33rd International Conference on Machine Learning (ICML), 1050–1059.

Kendall, A., and Gal, Y. (2017). What uncertainties do we need in Bayesian deep learning for computer vision? Advances in Neural Information Processing Systems (NeurIPS), 30, 5574–5584.

Lakshminarayanan, B., Pritzel, A., & Blundell, C. (2017). Simple and scalable predictive uncertainty estimation using deep ensembles. Advances in Neural Information Processing Systems (NeurIPS), 30, 6402–6413.

Meinert, N., Gawlikowski, J., Lavin, A. (2023). The unreasonable effectiveness of deep evidential regression. Proc. AAAI Conf. Artif. Intell. 37, 9134–9142

Sensoy, M., Kaplan, L., and Kandemir, M. (2018). Evidential deep learning to quantify classification uncertainty. Advances in Neural Information Processing Systems (NeurIPS), 31, 3179–3189.

Shen, M., Ryu, J. J., Ghosh, S., Bu, Y., Sattigeri, P., Das, S., and Wornell, G. (2024). Are uncertainty quantification capabilities of evidential deep learning a mirage?. Advances in Neural Information Processing Systems, 37, 107830-107864.

Chapter 14

CHEMICAL COMPOSITION AND FIBER PROPERTIES OF PEDUNCULATE OAK: A LITERATURE REVIEW

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INTRODUCTION

Quercus robur (L.) or *Quercus pedunculata* (Ehrh.), commonly known as pedunculate oak, is a broad-leaved tree species belonging to the Fagaceae family. Pedunculate oak is a long-lived forest tree that can reach 30–40 m in height and 2 m in diameter, and generally live for 400–500 years (rarely 1000 years). It has thick and deeply cracked bark, and it has a broad and spreading crown structure (Anşin and Özkan, 1997). Oak trees are mainly divided into three types based on the anatomical structure of their wood, the ripening time of their fruits, and the characteristics of their leaves and bark: white oaks, red oaks, and evergreen oaks. Pedunculate oak belongs to the white oak group (Yaltırık, 1984). Among the thirteen European white oak species, pedunculate oak is one of the ecologically and economically most important deciduous forest tree species in Europe (Ducousso and Bordacs, 2004). Oak species are generally considered light-demanding and exhibit sensitivity to frost conditions. (Evans 1984). However, the pedunculate oak is especially resilient to the detrimental effects of flooding, storm damage, and drought, and it is extremely long-lived (Spiecker, 2021).

Pedunculate oak is distributed throughout Europe, North Africa, the Caucasus, and Türkiye (Figure 1). It is found from Scandinavia to the Iberian Peninsula. It may be found in northern Scotland and the Norwegian coast, as well as in Portugal, Greece, and southern Türkiye in the Mediterranean region. It can also be found eastward into continental central Russia, all the way up to the Urals (Eaton et al. 2016). In Türkiye, it is particularly widespread in the Black Sea, Marmara, Thrace, and Northwestern Anatolia regions (Anşin and Özkan, 1997). It is found in forests, on plains with high groundwater levels, and in stream beds, either in small groups or individually (Yaltırık, 1984). In plains, plateaus, and hills, pedunculate oak is a pioneer species. In valleys and floodplains, pedunculate oak grows alongside species such as sycamore, maple, ash, beech, and elm (Ducousso and Bordacs, 2004). These oaks can only compete in the early stages of stand development in oak-beech mixed woods; later on, beech frequently suppresses the oak. Only careful thinning, which benefits oak trees, can preserve the vitality of oak in these mixed woods (Spiecker, 2021).

The pedunculate oak has been an essential component of European human culture from ancient times. It provides wood for fuel, acorns for animals like jays, mice, squirrels, and pigs, bark for tanning, and timber for building (Eaton et al. 2016). In many European countries, oak is the typical wood used for high-quality construction projects. Traditionally, oak wood has been utilized for furniture, ships, and buildings. High-quality cabinetry, veneers, barrel staves, fences, and roof beams are also made using it (Ducousso and Bordacs, 2004). On the other hand, oak wood is a good firewood due to its high calorific value (18.6 MJ/kg) (Lunguleasa et al. 2022). Oak wood is especially valued for its high tannin content, which protects it from fungi and insects (Hart and Hillis, 1972). Pedunculate oak heartwood is thought to be resilient to biotic and abiotic degradation causes. In moist soil or water, this species' heartwood can endure for many years in relatively good condition (Krajewski et al. 2024).

Throughout Europe, oak trees have cultural value, and national or regional symbols often feature the trees or their leaves (Eaton et al. 2016). On the other hand, oak species play an important ecological role because acorns are a valuable food source for many birds and mammals; therefore, the tradition of grazing animals under the trees in autumns with abundant acorn yields (acorn years) is still practiced in some limited regions of Europe (Ducousso and Bordacs, 2004).

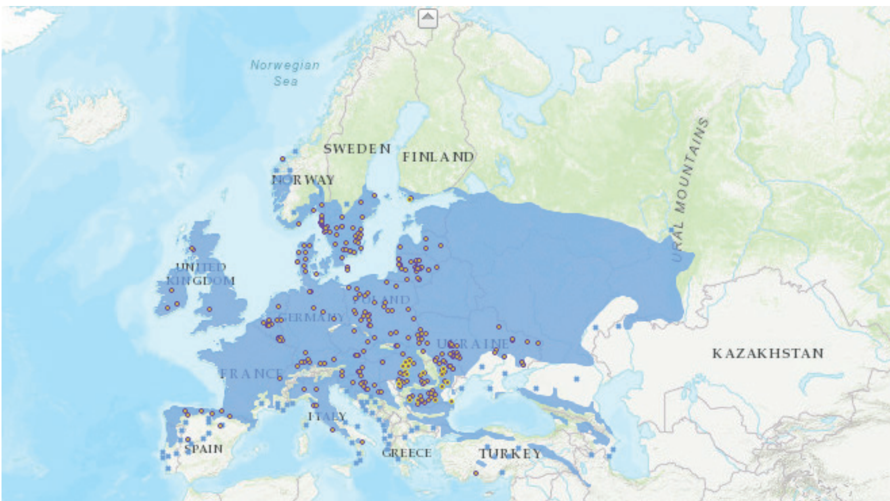

Figure 1. The distribution area of pedunculate oak (EUFORGEN, 2008).

CHEMICAL COMPOSITION OF PEDUNCULATE OAK WOOD

The chemical composition of pedunculate oak wood exhibits typical hardwood tree characteristics (Table 1). The wood consists mainly of holocellulose, cellulose, lignin, soluble fractions of hemicellulose origin, extractive substances, and a small amount of ash. Data from different geographical regions show that the chemical structure of the wood varies depending on growing conditions, tree age, wood texture (heartwood–sapwood), and sampling height.

It has been reported that the holocellulose content in pedunculate oak wood generally ranges from 58-80%, while the cellulose content mostly ranges from 36-49%. These values indicate that pedunculate oak has significant potential for fiber-based products and biopolymer applications. Differences in cellulose content appear to be related to the juvenile-mature wood difference, trunk height, and environmental factors.

The lignin content is approximately 17-29%, which is consistent with levels typically considered for hardwoods. The relatively high lignin content is one of the key factors explaining the mechanical strength, resistance to biological degradation, and long service life of oak wood. The chemical composition of European black pine is summarized in Table 1.

Table 1. Chemical composition of pedunculate oak from various regions.

Geographical Region	H (%)	C (%)	L (%)	HWS (%)	CWS (%)	1% NaOH (%)	E (%)	A (%)	Reference
-	-	41.10	29.60	12.20	-	-	0.40[1]	0.30	Fengel and Wegener (1989)
East of Slovak Republic	-	46.4	23.2	-	-	-	-	-	Košíková et al. (1992)
Bartın/Türkiye (NW)	68.00	42.40	24.50	9.90	6.50	22.30	6.60[1]	0.63	Gülsoy (2003)
Bartın/Türkiye (TW)	68.50	40.50	23.50	14.20	9.70	25.50	9.10[1]	0.60	Gülsoy (2003)
Bartın/Türkiye	73.60	43.00	21.00	10.70	8.50	23.50	-	-	Alkan (2004)
Voronezhskaya/ Russia	-	-	26.58	2.89	-	-	2.86[2]	-	Konovalova et al. (2006)
Iaşi/Romania	-	42.79	24.82	7.56	-	18.27	-	1.30	Bodîrlău et al. (2007)
Iaşi/Romania (1.30 m, 0-40 rings)	72.82	40.03	21.69	7.91	-	15.62	4.21[1]	-	Bodîrlău et al. (2007)
Iaşi/Romania (1.30 m, 40-70 rings)	71.57	42.81	23.75	7.85	-	18.95	2.29[1]	-	Bodîrlău et al. (2007)
Iaşi/Romania (1.30 m, 70-80 rings)	72.25	44.40	22.12	4.57	-	13.30	2.89[1]	-	Bodîrlău et al. (2007)
Iaşi/Romania (8 m, 0-40 rings)	67.03	42.04	25.77	9.87	-	18.35	3.12[1]	-	Bodîrlău et al. (2007)
Iaşi/Romania (8 m, 40-70 rings)	58.44	40.76	23.82	10.42	-	17.33	3.15[1]	-	Bodîrlău et al. (2007)
Iaşi/Romania (8 m, 70-80 rings)	70.48	46.97	20.73	4.61	-	14.12	2.33[1]	-	Bodîrlău et al. (2007)
Iaşi/Romania (15 m, 0-40 rings)	73.18	37.73	23.47	12.38	-	21.94	4.26[1]	-	Bodîrlău et al. (2007)
Iaşi-Romania (15 m, 40-70 rings)	67.92	36.81	24.71	10.72	-	19.59	3.17[1]	-	Bodîrlău et al. (2007)
Iaşi/Romania (15 m, 70-80 rings)	72.56	40.96	24.36	5.94	-	12.70	2.73[1]	-	Bodîrlău et al. (2007)
-	-	-	26.70	-	-	-	19.00[5]	-	Lindfors et al. (2008)
Zegrze/Poland (SW, butt-end)	-	49.20	21.80	-	-	-	3.10[1]	-	Krutul et al. (2010)
Zegrze/Poland (SW adjacent HW, butt-end)	-	48.80	22.60	-	-	-	3.80[1]	-	Krutul et al. (2010)

Zegrze/Poland (HW, butt-end)	-	48.10	22.90	-	-	-	3.70[1]	-	Krutul et al. (2010)
Zegrze-Poland (pith adjacent HW, butt-end)	-	46.30	23.10	-	-	-	4.20[1]	-	Krutul et al. (2010)
Zegrze/Poland (SW, middle)	-	49.10	22.10	-	-	-	3.50[1]	-	Krutul et al. (2010)
Zegrze/Poland (SW adjacent HW, middle)	-	49.00	22.70	-	-	-	3.90[1]	-	Krutul et al. (2010)
Zegrze/Poland (HW, middle)	-	48.80	23.10	-	-	-	3.60[1]	-	Krutul et al. (2010)
Zegrze/Poland (pith adjacent HW, middle)	-	47.40	23.40	-	-	-	4.20[1]	-	Krutul et al. (2010)
Zegrze/Poland (SW, top)	-	48.90	22.00	-	-	-	3.40[1]	-	Krutul et al. (2010)
Zegrze/Poland (SW adjacent HW, top)	-	48.40	23.00	-	-	-	3.60[1]	-	Krutul et al. (2010)
Zegrze/Poland (HW, top)	-	48.20	23.10	-	-	-	3.80[1]	-	Krutul et al. (2010)
Zegrze/Poland (pith adjacent HW, top)	-	47.50	23.50	-	-	-	4.00[1]	-	Krutul et al. (2010)
Golabki/Poland	66.40	38.50	26.00	-	-	-	3.49[6]	-	Sandak et al. (2010)
-	64.10	-	22.20	-	-	-	13.70[6]	-	Telmo and Lousada (2011)
Żółte/Poland	66.00	-	25.00	-	-	-	-	-	Łucejko et al. (2012)
-	70.64	44.98*	23.27	-	-	-	0.48[6]	0.36	Fišerová et al. (2013)
Limousin/ France	-	-	-	5.12	-	-	9.10[2]	-	Anjos et al. (2013)
Zegrze/Poland (SW, butt-end)	-	-	-	-	-	-	3.80[1]	-	Krutul et al. (2014)
Zegrze/Poland (SW, middle)	-	-	-	-	-	-	4.10[1]	-	Krutul et al. (2014)
Zegrze/Poland (SW, top)	-	-	-	-	-	-	4.50[1]	-	Krutul et al. (2014)
Zegrze/Poland (HW, butt-end)	-	-	-	-	-	-	4.20[1]	-	Krutul et al. (2014)
Zegrze/Poland (HW, middle)	-	-	-	-	-	-	4.90[1]	-	Krutul et al. (2014)
Zegrze/Poland (HW, top)	-	-	-	-	-	-	5.30[1]	-	Krutul et al. (2014)
Orozko/ Spain	-	46.37*	29.12	-	-	-	5.53[3]	0.52	Herrera et al. (2014)
Greater Poland	69.48	37.72	27.92	7.74	5.03	9.41	2.97[6]	1.05	Broda et al. (2015)
Continental Croatia	-	49.04	25.10	-	-	-	2.22[1]	0.17	Španić et al. (2018)
Central Poland	75.30	41.30	28.20	-	-	24.30	1.70[4]	-	Laskowska et al. (2018)

-	-	39.82	24.52	10.35	5.59	22.57	4.76[2]	0.17	Komorowicz et al. (2018)
Slovak Republic	76.96	-	21.78	-	-	-	5.57[6]	-	Čabalová et al. (2018)
Spain	78.15	49.31*	16.98	-	-	-	2.19[3]	0.47	Sillero et al. (2020)
Turek/Poland	73.00	36.00	23.80	-	-	-	-	-	Gąsecka et al. (2021)
Bratislava/ Slovak Republic (BW)	-	-	21.00	3.88	-	-	0.33[8]	0.50	Ihnát et al. (2021)
Zvolen-/Slovak Republic	73.16	33.79	22.86	-	-	-	3.97[3]	-	Zachar et al. (2021)
-	-	-	22.31	-	-	-	-	-	Barlović et al. (2022)
Central Bohemian/ Czech Republic	74.90	47.90	22.40	-	-	-	4.30[3]	-	Gaff et al. (2022)
Elbląg/Poland	-	38.43	27.35	7.70	1.88	18.84	1.56[2]	-	Lachowicz et al. (2024)
Vukovar-Srijem / Crotia	71.24	49.81	25.97				1.70[7]	0.25	Matin et al. (2024)
Pniewy/Poland	-	43.32	23.57	-	-	22.47	8.13[2]	-	Tomczak et al. (2024)
Mielno/Poland	80.00	42.90	25.36	-	-	-	-	-	Jurecki et al. (2025)
Morović/Serbia (Stump wood)	-	42.99	28.51**	9.27	-	-	3.63[3]	0.33	Popović et al. (2025)

H: Holocellulose, **C:** Cellulose, **L:** Lignin, **HWS:** Hot water solubility, **CWS:** Cold water solubility, **1% NaOH:** 1% NaOH solubility, **E:** Extractives, **A:** Ash, SW: Sapwood, HW: Heartwood, NW: Normal wood, TW: Tumorous wood, BW: Branch wood *α-cellulose, **Total lignin, [1]Alcohol/benzene, [2]Ethanol, [3]Ethanol/toluene, [4]Ethanol/chloroform, [5]Acetone/Water/dichloromethane, [6]Total extractives, [7]Methanol/benzene, [8]Dichloromethane

FIBER PROPERTIES OF PEDUNCULATE OAK WOOD

The fiber properties of pedunculate oak wood show typical and significant variability for broadleaf trees (Table 2). Basic parameters such as fiber length, fiber width, lumen diameter, and cell wall thickness vary depending on growing environment, trunk height, wood type (juvenile–mature, sapwood–heartwood), and ecological conditions. This directly affects the suitability of pedunculate oak wood for different industrial applications.

Fiber length in pedunculate oak wood generally ranges from 0.9–1.4 mm, indicating a moderate fiber length for broadleaf species. Fiber width and lumen width provide important information about the cell wall structure of the wood. The data in Table 2 show that fiber width is mostly between 16-23 µm. The cell wall thickness (generally ranges from 3-7 µm) is generally high, supporting the hard, dense, and durable character of oak wood. Although thick cell walls can limit fiber-to-fiber bonding in paper making by making it difficult to crush the fibers, they positively contribute to the tear strength of the final product.

Derived fiber parameters such as slenderness ratio, flexibility ratio, and Runkel ratio, shown in Table 2, reveal that pedunculate oak fibers have a moderately flexible and relatively rigid structure. In particular, the fact that the Runkel ratio is often above 1 in many studies indicates that the fibers have thick cell walls and narrow lumens, making them more suitable for packaging papers, cardboard, and sheet products rather than thin writing papers. However, regional and ecologically driven variability in fiber structure clearly highlights the importance of raw material characterization before industrial use. The fiber properties of European black pine are summarized in Table 2.

Table 2. Fiber properties of pedunculate oak from various regions.

Geographical Region	FL (mm)	VEL (mm)	FW (µm)	LW (µm)	CWT (µm)	SR	FR	RR	Reference
Potsdam/ Germany	1.21	-	-	-	-	-	-	-	Süß (1967)
Potsdam/ Germany (LW)	-	0.56	-	-	-	-	-	-	Süß (1967)
Potsdam/ Germany (EW)	-	0.44	-	-	-	-	-	-	Süß (1967)
Kew/England (trunk)	1.14	0.68	-	-	-	-	-	-	Gasson (1984)
Kew/England (BW)	0.59	0.42	-	-	-	-	-	-	Gasson (1984)
-	1.10	-	23.00	-	-	-	-	-	Ilvessalo-Pfäffli (1995)
Türkiye	1.35	-	18.60	-	6.10	-	-	-	Merev (2003)
Bartın/Türkiye	1.09	0.52	20.10	10.50	4.80	54.10	52.20	0.90	Alkan (2004)
Bartın/Türkiye (NW)	1.17	0.49	20.50	-	5.50	-	-	-	Gülsoy et al. (2005)
Bartın/Türkiye (TW)	1.02	0.41	21.20	-	6.95	-	-	-	Gülsoy et al. (2005)
Codlea/Romania	0.99	-	15.90	-	-	62.30	-	-	Lica and Coşereanu (2009)
Bratislava/ Slovak Republic (BW)	0.52	-	-	-	-	-	-	-	Ihnát et al. (2021)
Kastamonu/ Türkiye (Growing season-March)	1.22	-	21.9	5.35	2.37	-	-	-	Özden Keleş and Savacı (2021)
Kastamonu/ Türkiye (Growing season-September)	1.08	-	20.1	4.30	2.58	-	-	-	Özden Keleş and Savacı (2021)

Blata Malovanci /Bosnia and Herzegovina	1.34	-	-	18.89	5.92	-	-	-	Jokanović et al. (2022a)
Gornji Srem/ Serbia	1.35	-	-	20.14	6.58	-	-	-	Jokanović et al. (2022b)
Donji Srem/ Serbia	1.33	-	-	19.76	6.33	-	-	-	Jokanović et al. (2022b)
Türkiye	1.02	-	22.4	9.7	6.3	-	-	-	Elmas and Öztürk (2022)
Vinična-Žeravinac-Puk/ Croatia	1.38	-	-	20.21	6.06	-	-	0.60	Lozjanin et al. (2024)
Elbląg/Poland	1.33	-	19.30	5.50	6.90	70.30	28.14	-	Lachowicz et al. (2024)
Pniewy/Poland	1.07	0.38	-	-	-	-	-	-	Tomczak et al. (2024)

FL: Fiber length, **VEL:** Vessel element length **FW:** Fiber width, **LW:** Lumen Width, **CWT:** Cell wall thickness, **SR:** Slenderness ratio (FL/FW), **FR:** Flexibility ratio [(LW/FW)*100], **RR:** Runkel ratio [(2xCWT)/LW], EW: Earlywood, LW: Latewood, NW: Normal wood, TW: Tumorous wood, BW: Branch wood.

CONCLUSIONS

Pedunculate oak (*Quercus robur* L.) wood clearly offers strong potential for high value-added industrial applications in terms of both its chemical composition and fiber morphology. The high holocellulose and cellulose content of the wood provides a significant advantage for lignocellulosic biomaterials and fiber-based products, while the medium-to-high lignin content is one of the key elements supporting the mechanical strength and natural durability of oak wood.

The reported fiber length, cell wall thickness, and lumen dimensions in pedunculate oak wood indicate that the fibers have a relatively rigid and durable character. While this structure may present some limitations for paper types requiring fineness and high surface smoothness, it offers a significant advantage for products requiring high strength, such as packaging papers, cardboard, fiberboards, and biocomposites. Derived parameters of fiber morphology (fineness ratio, elasticity ratio, and Runkel ratio) also confirm that pedunculate oak fibers are more suitable for structural and strength-oriented applications.

Geographic region, growing environment, tree age, trunk height, and wood type (heartwood–sapwood) have a significant impact on the chemical and anatomical properties of pedunculate oak wood. This indicates that pedunculate oak wood should not be considered a single type of raw material in industrial applications; rather, selective raw material management and pre-characterization according to intended use are of great importance.

In conclusion, pedunculate oak wood is an extremely suitable raw material for building materials, packaging products, biocomposites, and long-lasting wood applications due to its high strength, rich extractive content, and characteristic fiber structure. Future research focusing on the targeted separation of chemical fractions of this species, the conversion of lignin and extractives into value-added products, and the optimization of fiber properties through process conditions will further advance the sustainable and efficient use of pedunculate oak wood.

REFERENCES

Alkan, Ç. (2004). Türkiye'nin Önemli Yapraklı ve Iğne Yapraklı Ağaç Odunlarının Migrografik Yönden Incelenmesi. Yüksek Lisans Tezi, Zonguldak Karaelmas Üniversitesi, Fen Bilimleri Enstitüsü, Orman Endüstri Mühendisliği Anabilim Dalı, Zonguldak.

Anjos, O., Carmona, C. P., Caldeira, I., & Canas, S. (2013). Variation of extractable compounds and lignin contents in wood fragments used in the aging of wine brandies. BioResources, 8(3): 4484-4496.

Anşin, R., Özkan, Z.C. (1997). Tohumlu Bitkiler (Spermatoptyta) Odunsu Taksonlar. Karadeniz Teknik Üniversitesi, Orman Fakültesi, Genel Yayın No: 167, Fakülte Yayın No:19, Trabzon.

Barlović, N., Pervan, S., Klarić, M., & Španić, N. (2022). Spectrometric analysis of lignin from abonos and oak wood (*Quercus robur* L.). Natural Resources, Green Technology and Sustainable Development 14th–16th September 2022, Zagreb, Croatia, pp. 49-53.

Bodîrlău, R., Spiridon, I., Teacă, C.A. (2007). Chemical investigation on wood tree species in a temperate forest, east-northern Romania. BioResources, 2(1): 41-57.

Broda, M., Mazela, B., Królikowska-Pataraja, K., Hill, C.A.S. (2015). The use of FT-IR and computed tomography non-destructive technique for waterlogged wood characterization. Wood Research, 60(5): 707–722.

Čabalová, I., Kačík, F., Lagaňa, R., Výbohová, E., Bubeníková, T., Čaňová, I., & Ďurkovič, J. (2018). Effect of thermal treatment on the chemical, physical, and mechanical properties of pedunculate oak (*Quercus robur* L.) wood. BioResources, 13(1), 157-170.

Ducousso, A., Bordacs, S. (2004). EUFORGEN Technical guidelines for genetic conservation and use for pedunculate and sessile oaks (*Quercus robur* and *Quercus petraea*). International Plant Genetic Resources Institute, Rome, Italy. 6 pages.

Eaton, E. G. S. D. J., Caudullo, G., Oliveira, S., & De Rigo, D. (2016). *Quercus robur* and *Quercus petraea* in Europe: distribution, habitat, usage and threats. European Atlas of Forest Tree Species, 14, 160-163.

Elmas, G. M., & Öztürk, D. Z. (2022). Suitability of some oak species for papermaking. In: Book of Proceedings of the XIII International Scientific Agricultural Symposium "Agrosym 2022", pp. 969-974.

Evans, J. (1984). Silviculture of broadleaved woodland. Forestry Commission Bulletin, 62: 1-32

EUFORGEN, (2008). European Forest Genetic Resources Programme. Distribution map of pedunculate oak (*Quercus robur*). https://www.euforgen.org/species/quercus-robur

Fengel, D., Wegener, G. (1989). Wood Chemistry, Ultrastructure, Reactions. Walter de Gruyter, Berlin.

Fišerová, M., Opálená, E., Illa, A. (2013). Comparative study of hemicelluloses extraction from beech and oak wood. Wood Research, 58(4): 543-554.

Gąsecka, M., Drzewiecka, K., Magdziak, Z., Piechalak, A., Budka, A., Waliszewska, B., Szentner, K., Goliński, P., Niedzielski, P., Budzyńska, S., Mleczek, M. (2021). Arsenic uptake, speciation and physiological response of tree species (*Acer pseudoplatanus*, *Betula pendula* and *Quercus robur*) treated with dimethylarsinic acid. Chemosphere, 263, 127859.

Gaff, M., Kačík, F., & Gašparík, M. (2019). Impact of thermal modification on the chemical changes and impact bending strength of European oak and Norway spruce wood. Composite structures, 216, 80-88.

Gasson, P. (1984). Recognition of characteristic features of secondary xylem of selected hardwoods. Ph.D. Thesis, University of London.

Gülsoy, S. K. (2003). Bazı Yapraklı Ağaçların Kanserli ve Normal Odunlarının Kimyasal-Anatomik Yapıları, Lif Morfolojisi ve Kağıt Özellikleri Yönünden Araştırılması. ZK Ü. Fen Bilimleri Enstitüsü, Yüksek Lisans Tezi, Bartın.

Gülsoy, S.K., Eroğlu, H., Merev, N. (2005). Chemical and wood anatomical properties of tumorous wood in a Turkish white oak (*Quercus robur* subsp. *robur* L.). IAWA Journal, 26 (4): 469-476.

Hart, J. H., & Hillis, W. E. (1972). Inhibition of wood-rotting fungi by ellagitannins in the heartwood of *Quercus alba*. Phytopathology, 62(6), 620-626.

Herrera, R., Erdocia, X., Llano-Ponte, R., Labidi, J. (2014). Characterization of hydrothermally treated wood in relation to changes on its chemical composition and physical properties. Journal of Analytical and Applied Pyrolysis, 107: 256–266.

Ihnát, V., Fišerová, M., Opálená, E., Russ, A., & Boháček, Š. (2021). Chemical composition and fibre characteristics of branch wood of selected hardwood species. Acta Facultatis Xylologiae Zvolen res Publica Slovaca, 63(2), 17-30.

Ilvessalo-Pfäffli, M.S. (1995). Fiber Atlas. Identification of Papermaking Fibers, Springer-Verlag, Berlin, Germany.

Jokanović, D., Ćirković-Mitrović, T., Jokanović, V. N., & Lozjanin, R. (2022a). Variability of wood fibres of mature pedunculate oak in flooded and non-flooded area. Wood Research, 67(4), 533-544.

Jokanović, D., Ćirković-Mitrović, T., Jokanović, V.N., Lozjanin, R., & Ištok, I. (2022b). Wood fibre characteristics of pedunculate oak (*Quercus robur* L.) growing in different ecological conditions. Drvna Industrija, 73(3), 317-325.

Jurecki, A., Szentner, K., Jarzębski, M., & Wieruszewski, M. (2025). Timber from historical foundation piles made of oak wood (*Quercus robur* L.). Applied Sciences, 15(17), 9322.

Komorowicz, M., Wróblewska, H., Fojutowski, A., Kropacz, A., Noskowiak, A., Pomian, I. (2018). The impact of 5 years' underwater exposure in the Baltic Sea (Puck Bay) on selected properties of English oak wood samples. International Biodeterioration & Biodegradation, 131: 40–50.

Konovalova, N. N., Konovalov, N. T., Bazhenov, A. N., Stasova, V. V., Varaksina, T. N., & Antonova, G. F. (2006). The effects of supersonic treatment on the structure and componenets of oak wood. In Proceedings of 5th IUFRO (Division 5) Symposium" Wood Structure and Properties (Vol. 6, pp. 59-65).

Košíková, B., Ebringerová, A., & Micko, M. (1992). Effect of aspen and oak wood rotting on the solubility of their main components. Holzforschung, 46(4): 289-291.

Krajewski, A., Witomski, P., & Drożdżek, M. (2024). The resistance of subfossil heartwood of oak (*Quercus robur* L.) from two sites in Poland to destruction by subterranean termites. Drewno, 67(214).

Krutul, D., Zielenkiewicz, T., Radomski, A., Zawadzki, J., Drożdżek, M., Antczak, A. (2010). Influence of urban environment originated heavy metals pollution on the content of extractives, cellulose and lignin in the oak wood. Annals of Warsaw University of Life Sciences–SGGW. Forestry and Wood Technology, 71: 410-416.

Krutul, D., Zielenkiewicz, T., Zawadzki, J., Radomski, A., Antczak, A., & Drozdzek, M. (2014). Influence of urban environment originated heavy metal pollution on the extractives and mineral substances content in bark and wood of oak (*Quercus robur* L.). Wood Research, 59(1), 177-190.

Lachowicz, H., Kulak, P., Komorowicz, M., Marcinkowski, M., & Sieńkowska, U. (2024). Technical quality of oak (*Quercus* sp.) wood from archaeological excavations in Elbląg Old Town. https://doi.org/10.21203/rs.3.rs-4348532/v1

Laskowska, A., Marchwicka, M., Boruszewski, P., Wyszyńska, J. (2018). Chemical composition and selected physical properties of oak wood (*Quercus robur* L.) modified by cyclic thermo-mechanical treatment. BioResources, 13(4): 9005-9019.

Lica, D., & Coşereanu, C. (2009). Influence of the pathological drying of pedunculate oak wood (*Quercus robur* L.) upon its structure. Pro Ligno, 5(1): 39-45.

Lindfors, E.-L., Lindström, M., Iversen, T. (2008). Polysaccharide degradation in waterlogged oak wood from the ancient warship Vasa. Holzforschung, 62(1): 57-63.

Lozjanin, R., Jokanović, D., Nikolić Jokanović, V., Živanović, K., Desimirović, I., & Marinković, M. (2024). Anatomical characteristics and assessment of wood fiber quality of mature pedunculate oak (*Quercus robur* L.) trees grown in different environmental conditions. Southeast European Forestry: SEEFOR, 15(1), 51-57.

Lunguleasa, A., Spirchez, C., & Olarescu, A. M. (2022). Calorific characteristics of larch (*Larix decidua*) and oak (*Quercus robur*) pellets realized from native and torrefied sawdust. Forests, 13(2), 361.

Łucejko, J. J., Zborowska, M., Modugno, F., Colombini, M. P., & Prądzyński, W. (2012). Analytical pyrolysis vs. classical wet chemical analysis to assess the decay of archaeological waterlogged wood. Analytica chimica acta, 745, 70-77.

Matin, B., Brandić, I., Matin, A., Ištvanić, J., & Antonović, A. (2024). Possibilities of liquefied spruce (*Picea abies*) and oak (*Quercus robur*) Biomass as an environmentally friendly additive in conventional phenol–formaldehyde resin wood adhesives. Energies, 17(17), 4456.

Merev, N. (2003). Odun Anatomisi. Karadeniz Teknik Üniversitesi, Orman Fakültesi, Genel Yayın No:209, Fakülte Yayın No:31, Trabzon.

Özden Keleş, S., & Savaci, G. (2021). Seasonal variation of morphological traits, wood formation, and soil properties differs between *Quercus robur* L. and *Robinia pseudoacacia* L. saplings. Scandinavian Journal of Forest Research, 36(5), 344-353.

Popović, J., Petković, G., Šuljagić, M., Popović, M., Điporović Momčilović, M., Lozjanin, R., & Stojiljković, I. (2025). The effects of natural degradation on the chemical composition of pedunculate oak stump (*Quercus robur* L.). In: 7th International Scientific Conference, Wood Technology & Product Design, Ohrid, Republic of North Macedonia, pp. 57-65.

Sandak, A., Sandak, J., Zborowska, M., Prądzyński, W. (2010). Near infrared spectroscopy as a tool for archaeological wood characterization. Journal of Archaeological Science, 37(9): 2093-2101.

Sillero, L., Barriga, S., Izaguirre, N., Labidi, J., & Robles, E. (2020). Fractionation of non-timber wood from Atlantic mixed forest into high-value lignocellulosic materials. Journal of Wood Chemistry and Technology, 40(3), 200-212.

Spiecker, H. (2021). Production of valuable oak wood in Europe. Annals of Forest Research, 64(1), 5-12.

Süß, H. (1967). Über die längenänderungen der parenchymstränge, holzfasern und gefäßglieder von laubhölzern im verlauf einer zuwachsperiode. Holz Als Roh-Und Werkstoff, 25(10): 369–377.

Španić, N., Jambreković, V., Klaric, M. (2018). Basic chemical composition of wood as a parameter in raw material selection for biocomposite production. Cellulose Chemistry and Technology, 52(3-4): 163-169.

Telmo, C., Lousada, J. (2011). The explained variation by lignin and extractive contents on higher heating value of wood. Biomass Bioenergy 35(5): 1663-1667.

Tomczak, K., Mania, P., Cukor, J., Vacek, Z., Komorowicz, M., & Tomczak, A. (2024). Wood quality of pendulate oak on post-agricultural land: A case study based on physico-mechanical and anatomical properties. Forests, 15(8), 1394.

Yaltırık, F. (1984). Türkiye Meşeleri, Teşhis Kılavuzu. Tarım, Orman ve Köy İşleri Bakanlığı Genel Mdürlüğü Yayını, 84 s.

Zachar, M., Čabalová, I., Kačíková, D., & Jurczyková, T. (2021). Effect of natural aging on oak wood fire resistance. Polymers, 13(13), 2059.

Chapter 15

THE ROLE OF PEAS IN FUTURE AGRO-ECOSYSTEMS: FUNCTIONAL BREEDING AND MULTI-CROPPING STRATEGIES FOR REGENERATIVE AGRICULTURE

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INTRODUCTION

Global agricultural systems currently confront multifaceted and interconnected crises, including climate change, soil degradation, biodiversity loss, and the escalating food demands of a growing population (Foley et al., 2011). The intensive, input-oriented monoculture practices of the post-Green Revolution era, while achieving short-term yield increases, have compromised the functionality of soil ecosystems and jeopardized environmental sustainability in the long term (Tilman et al., 2002). Aiming to reverse this trajectory, 'Regenerative Agriculture' presents a new paradigm that perceives soil not merely as a passive medium for production, but as a living biological entity requiring continuous restoration (Montgomery, 2017; Newton et al., 2020).

A cornerstone of the regenerative philosophy is legume-based systems, which aim to establish self-sustaining cycles by decoupling the ecosystem from dependence on external inputs. Within these cycles, the pea (*Pisum sativum L.*) emerges as one of the most potent instruments for ecological restoration, owing to both its historical lineage and physiological attributes (Jensen, 1996). Beyond atmospheric nitrogen fixation via symbiotic associations, peas provide essential "ecosystem services" such as enhancing soil aggregate stability, stimulating beneficial microbial populations, and increasing water-holding capacity. However, fully harnessing this potential necessitates a departure from traditional cultivation mindsets.

In modern agronomic approaches, the role of the pea is evolving from a mere "cash crop" to a "functional component" that enriches crop rotation systems (Lal, 2004). Specifically, its utilization as a cover crop and its application in cereal-based intercropping systems are fundamental determinants of the operational success of regenerative frameworks. These practices increase biodiversity per unit area while ensuring continuous soil coverage, thereby contributing directly to carbon sequestration. In this context, the success of peas within regenerative systems is intrinsically linked to the adaptability of the plant to these novel roles (Kazam et al.,2007).

The most critical threshold in achieving regenerative goals lies in the re-evaluation and development of existing genetic material according to the specific requirements of these systems. The priority of "maximum grain yield" in classical breeding programs is being superseded by "maximum system efficiency" in ecological restoration-oriented frameworks (Açıkgöz, 2001). This shift requires a comprehensive redefinition of pea breeding objectives, ranging from plant architecture and root phenotyping to nitrogen fixation efficiency and abiotic stress tolerance.

Polyculture systems, appearing as "mixed cropping" in the ancient agricultural traditions of Anatolia, are being reformulated today under the discipline of regenerative farming. Especially in Central Anatolia and transition zones, peas serve as a strategic rotation and production partner in narrowing fallow areas and mitigating the soil fatigue induced by monoculture wheat farming. With both winter and spring forms, peas demonstrate remarkable adaptability to Anatolia's variable climatic conditions, functioning as "green manure" that improves the physicochemical properties of the soil (Hauggaard et al., 2001).

The integration of peas into polyculture systems represents not only an ecological improvement but also a risk management tool for agricultural enterprises. Farmers, who are dependent on a single crop and its market fluctuations in monocultures, diversify their income streams by incorporating peas into the system. Post-harvest, peas can be integrated with livestock as forage or marketed directly as a high-protein food commodity. This versatility is one of the most significant factors reinforcing the economic resilience of polyculture. Peas act as a bridge from monoculture to polyculture restoring the soil, conserving water resources, and radically reducing input costs. For the sustainability of Anatolian lands, the intensive inclusion of legumes like peas in production patterns will be the ultimate guarantee of our food security.

1. The Role of Peas in the Transition from Monoculture to Polyculture

Industrial agriculture, primarily characterized by monoculture systems, focuses on achieving high yields within a narrow genetic pool. However, this model has precipitated severe ecological crises, including soil exhaustion, loss of biodiversity, and an escalating reliance on chemical pesticides. In the search for an escape from this unsustainable cycle, transitioning to polyculture (multi-cropping) systems has emerged as a strategic imperative. During this transformative process, the garden pea (*Pisum sativum L.*) stands out as a "facilitator" species due to its unique biological attributes and the ecosystem services it provides (Kazam et al., 2022). Integrating peas into polyculture systems does more than merely increase crop diversity; it imparts a restorative dynamism to the entire agricultural framework.

The most critical contribution of peas to polyculture is undoubtedly their capacity to restore soil fertility through the biological fixation of atmospheric nitrogen. While monoculture cereal farming leaves the soil dependent on external synthetic fertilizers, peas bind nitrogen to the soil via *Rhizobium* bacteria residing in their root nodules (Echarte et al., 2011). The simultaneous or sequential planting of peas alongside nitrogen-demanding crops, such as maize or wheat, minimizes the need for synthetic inputs. This preservation of the soil's chemical integrity supports the "self-sufficient ecosystem" model, which is the foundational philosophy of polyculture.

From an ecological perspective, peas promote biodiversity by creating micro-habitats within polycultural fields. The flowering period of the pea plant offers a nutrient-rich resource for pollinators and beneficial insects. This characteristic breaks the "biological desert" effect created by monocultures, allowing natural predators to regulate pest populations. The presence of peas within a polyculture pattern provides a natural contribution to Integrated Pest Management (IPM), thereby reducing the necessity for chemical interventions and enhancing the overall resilience of the system (Düzgüneş,1990).

Regarding soil structure and hydraulic management, peas function as a protective layer within polyculture systems. The rapid ground-covering architecture of the pea plant reduces evaporation, helping to conserve soil moisture and mitigate erosion risks. Furthermore, the crop residues remaining after harvest increase the organic matter content, strengthening the humic structure of the soil (Dhima et al., 2007). This organic enrichment results in a more friable and aerated soil profile that supports the root development of companion crops; thus, the soil compaction issues induced by monoculture are remediated through natural processes.

The transition from monoculture to polyculture depends on the precise orchestration of synergies between plant species. The pea plant occupies a central position in this synergy due to its nitrogen fixation, biological stabilization, and soil-improving properties. Recognized in academic literature as a core component of "regenerative agriculture," peas ensure not only the ecological health of polyculture systems but also their economic viability through reduced input costs (Peoples et al., 2009). To repair the degradation caused by traditional monocultures and to construct resilient agricultural models for the future, the expansion of pea-based polyculture applications is essential.

2. Breeding Peas as a Cover Crop

In contemporary agronomic practices, cover crops serve as strategic instruments employed to safeguard the soil and maintain ecosystem services following the harvest of the primary crop. Within this framework, the garden pea (*Pisum sativum L.*) is highly regarded for its robust adaptability and capacity for rapid biomass accumulation (Poggio, 2005). Nevertheless, as conventional pea varieties are predominantly developed for grain yield, specialized breeding programs are required to maximize the plant's soil protection and biological remediation potential.

The primary objective in breeding peas for cover crop use is achieving high biomass production and rapid ground coverage. Selection processes focus on vegetative growth rates and branching capacity to ensure the varieties can quickly establish a living carpet over the soil surface. This rapid colonization is essential for preventing erosion and suppressing weed competition (Rubiales and Mikic, 2015). Genetic manipulation in this direction provides physical protection to the soil while simultaneously creating a microclimate that fosters subterranean microbial activity.

Frost tolerance and winter hardiness constitute another vital pillar of cover crop breeding. Particularly in regions with harsh winters, it is desirable for peas to maintain viability throughout the winter and transition into active growth early in the spring (Pauli et al.,2016). Breeding programs target genes that regulate osmotic potential within plant cells to develop lines resistant to freezing stress. Consequently, the pea evolves from a mere summer catch crop into a perennial biological shield that keeps the soil active year-round.

Enhancing Biological Nitrogen Fixation (BNF) capacity is a fundamental element determining the economic and ecological value of pea cover crop breeding. Breeding efforts are directed toward identifying genotypes with high nodulation efficiency that can establish more effective symbiotic relationships with indigenous *Rhizobium* strains (Parihar et al., 2019). By increasing the biological nitrogen contribution to the soil, these cover crops play a pivotal role in reducing the nitrogenous fertilizer requirements of subsequent primary crops, thereby lowering the carbon footprint of agricultural production.

The ease of "termination" is considered a vital selection criterion. prior to planting the main crop, the cover crop must be easily decomposable through mechanical methods such as roller crimpers and capable of rapid mineralization in the soil. The fiber structure and lignin content of bred varieties must be balanced to create a persistent mulch layer without hindering the development of the following crop. This holistic breeding approach transforms the pea into an indispensable component of low-input, high-yield agricultural systems that remediate the damage caused by monoculture.

3. Morphological Breeding for Intercropping Systems

Intercropping systems are complex agro-ecosystems where two or more species are cultivated simultaneously on the same land to maximize resource-use efficiency. The success of the pea (*Pisum sativum* L.) in these systems depends not only on its genetic potential but also on its morphological compatibility with companion crops. While traditional monoculture breeding targets traits such as extreme height and large leaf areas, these characteristics can cause negative effects like light competition and excessive shading in intercropping setups. Therefore, morphological breeding specific to intercropping aims to select architectural structures that minimize competition and maximize synergy between plants (Vandermeer 1989).

One of the most critical components of breeding for intercropping is "leaf morphology" and light transmittance. Especially when peas are grown alongside cereals such as wheat, barley, or oats the breeding of "semi-leafless" traits is of great importance. In these genotypes, leaflets are transformed into tendrils. This morphological adaptation allows more light to penetrate the canopy, preserving the photosynthetic capacity of lower-tier plants (Sayre, 2003). Additionally, the abundance of tendrils enables the plant to remain upright, preventing excessive loading on the cereal crops and avoiding lodging issues within the system.

Another significant morphological objective is centered on "root architecture and distribution." To manage the competition for underground resources namely water and nutrients the root depth and proliferation rate of pea lines must be optimized. Breeding studies select genotypes that exhibit spatial niche differentiation relative to the primary crop (Varshney et al.,2021). For instance, developing pea varieties with deeper taproot systems alongside shallow-rooted cereals enhances total water-use efficiency and ensures a more homogenous uptake of nutrients from different soil strata.

"Plant height and growth habit" serve as strategic breeding parameters for system manageability. While indeterminate varieties risk smothering companion plants, determinate or semi-dwarf pea varieties integrate more easily into polyculture patterns. Breeding programs focus on a canopy architecture that correlates with the height of the main crop, does not disrupt mechanization at harvest, and does not overtop the companion species (Nemecek et al., 2008). This morphological harmony protects biodiversity while minimizing harvest losses.

"Synchronization of flowering and maturation" constitutes the temporal dimension of morphological breeding in intercropping systems. The goal is to develop pea lines with maturation periods similar to their companion crops or, conversely, to select for temporal niche differentiation where peak growth occurs at different times to reduce competition (Titi, 2002). Morphological traits such as the position of flowers on the plant and their capacity to attract pollinators are also included as breeding criteria, as they influence total fruit set and genetic sustainability.

Morphological breeding for intercropping systems involves redesigning the plant not as an isolated unit, but as a harmonious part of a complex community. Every morphological trait—from tendril structure to root depth, and from canopy architecture to phenological stages—must be calibrated to enhance ecosystem productivity. This "systems-oriented breeding" approach departs from the standardized plant models imposed by monoculture, opening the doors to a new agronomic era that supports the biological richness and resilience offered by polyculture.

4. Cultivation Strategies: No-Till and Minimum Input

At the core of sustainable agricultural paradigms, the "no-till" (zero tillage) system represents a holistic approach aimed at maximizing biological processes without disturbing the physical integrity of the soil ecosystem. Within this strategy, the pea (*Pisum sativum L.*) functions as a pivotal element determining the system's success. By preventing aggregate degradation and carbon loss associated with traditional tillage, the root architecture and post-harvest residues of the pea facilitate the soil's biological "self-tilling" process (Vandermeer, 1989).

Pea cultivation in no-till systems, when integrated with minimum-input principles, drastically reduces operational expenditures. Eliminating tillage machinery not only conserves fuel and labor but also prevents soil compaction, allowing roots to penetrate deeper soil strata more effectively. In this context, the pea acts as a "biological plow," creating macro-pores within the soil profile and establishing a prepared seedbed for the subsequent primary crop (Vazpotta, 2015).

The most prominent result of the minimum-input strategy is the minimization of synthetic fertilizer dependency, thanks to the pea's symbiotic nitrogen fixation capability. In no-till environments, the organic mulch layer remaining on the surface conserves moisture while providing an optimal micro-habitat for *Rhizobium* activity (Zander et al., 2016). This natural cycle reduces the demand for external nitrogenous fertilizers by 40% to 60%, offering an economic model that balances environmental burdens with production costs.

No-till pea farming also provides strategic advantages in weed suppression and water management. The rapid development of the pea canopy shades the soil surface, cutting off direct sunlight to decrease evaporation and inhibit the germination of weed seeds (Hauggaard-Nielsen et al., 2001). This morphological benefit aligns with minimum-input goals by reducing herbicide requirements to a baseline level. Furthermore, the enhancement of water-use efficiency makes no-till pea cultivation indispensable, particularly in regions facing high drought risks due to climate change.

Analysis of the cumulative effects on biodiversity and soil health reveals that integrating peas into no-till systems enriches the subterranean soil food web. By avoiding soil inversion, mycorrhizal fungal networks and earthworm populations are preserved (Lithourgidis et al., 2011). The protein-rich residues of the pea serve as a high-quality nutrient source for these microorganisms, accelerating the humification process. Consequently, this enhances the soil's long-term carbon sequestration capacity, transforming agricultural lands into active carbon sinks

Pea cultivation under no-till and minimum-input strategies sits at the intersection of energy conservation, soil restoration, and economic efficiency. Within this model, referred to in academic literature as "conservation agriculture," the pea disrupts the high-cost and destructive cycles of monoculture, enabling a production mode harmonious with ecological cycles. The adoption of these approaches in modern agronomy will not only restore soil health but also place global food security on a more resilient foundation.

5. Economic and Ecological Outcomes: Carbon Footprint Analysis

In sustainable agricultural economics, the carbon footprint is defined as the measurement of greenhouse gas emissions per unit of production, expressed in carbon dioxide equivalents (Stagnari et al., 2017) While traditional monoculture systems exhibit a high carbon intensity due to heavy fossil fuel consumption and synthetic fertilizer manufacturing, the integration of peas (*Pisum sativum L.*) provides a radical reduction in emissions (Gan et al., 2011). The primary impact of peas on the carbon footprint is a multidimensional ecological output manifested both in direct field operations and indirectly across the input supply chain (Nemecek et al., 2008).

The foremost factor lowering the carbon footprint of pea-based systems is the substitution of synthetic nitrogenous fertilizers. The production of these fertilizers via the energy-intensive Haber-Bosch process results in significant CO_2 emissions, while their field application triggers the release of nitrous oxide, a potent greenhouse gas. By biologically fixing atmospheric nitrogen, peas create a ready-to-use nitrogen pool in the soil (Gan et al.,2011). This fixation benefits not only the pea crop itself but also subsequent crops in the rotation, turning the system's total carbon budget positive.

From an economic perspective, the reduction in carbon footprint translates directly into cost advantages and market value. Regulations such as the European Green Deal and the Carbon Border Adjustment Mechanism incentivize low-carbon agricultural products through tax benefits and subsidies. Enterprises that minimize carbon emissions via pea production may also gain access to "carbon credit" systems, generating additional revenue. Therefore, a low carbon footprint is not merely an environmental parameter but a financial indicator that boosts the global competitiveness of agricultural businesses (Preissel et al., 2015).

The optimization of tillage requirements by peas directly influences fuel consumption and, consequently, carbon emissions related to mechanization

(West and Marland, 2002). In no-till or minimum-tillage systems, pea residues serve as a carbon sink on the soil surface (Gan et al., 2011). Avoiding soil inversion prevents stable organic matter from coming into contact with oxygen and being released into the atmosphere as CO_2 (Reicosky, 1997). This increases the soil's carbon sequestration potential, enabling agricultural lands to serve as active solution centers in the fight against climate change (Lal, 2004).

Logistical and supply chain analyses indicate that incorporating peas into local polyculture systems reduces "food miles," further lowering the carbon footprint. As a high-protein crop, the pea provides a local alternative to high-carbon-cost imported feed sources like soy. Considering the logistical emissions and deforestation impacts associated with transoceanic soy transport, local pea production is a strategy that alleviates the ecological footprint on a global scale. This strengthens local economies while preventing the accumulation of "ecological debt."

In conclusion, the role of the pea in polyculture systems is the most concrete example of a "green economy" model where economic profitability and ecological sustainability are optimized. Carbon footprint analysis proves that the pea is more than just a food commodity; it is a strategic ecosystem engineer that lightens the industrial burden of agriculture. Future agricultural policies should be constructed upon the mandatory integration of low-emission, high-restoration capacity crops like the pea into production patterns.

6. New Horizons in Pea Breeding: Precision Agriculture Technologies and Genomic Approaches

The efficacy of regenerative agricultural systems depends on the real-time and high-precision monitoring of plant responses to environmental dynamics. In this context, traditional selection methods in pea breeding are being superseded by "High-Throughput Phenotyping" (HTP) Technologies (Cayne et al., 2020). Through the use of drones and multispectral sensors, parameters such as canopy development, leaf area index, and responses to water stress can be measured instantaneously in the field. This technological integration provides a data-driven foundation for understanding the competitive dynamics of peas with other crops in polyculture systems and the ecosystem services they provide (Fulgosi and Spoliaric, 2021).

Genomic selection and gene-editing Technologies are accelerating the achievement of "functional restoration" goals in pea breeding. Specifically, the manipulation of genes controlling root architecture enables peas to extract nutrients from deeper soil layers and increases their resistance to drought stress. The "smart root" structure required in regenerative systems is no longer a matter of chance but emerges as a targeted breeding parameter thanks to advanced genetic mapping studies (Bhandari and Gupta, 2021).

Simulating the nitrogen fixation capacity of peas using Digital Twin models is revolutionizing cultivation strategies. By analyzing the interaction between soil microbial activity and pea genotypes through artificial intelligence algorithms, it is now possible to predict which pea variety will offer maximum ecosystem services in a specific location (Araus and Cains, 2014). This approach allows breeders to select specific lines that offer not only high yields but also the highest "restorative contribution" to a particular ecology.

Precision Agriculture applications are key to optimizing input costs in pea-based multi-cropping systems. Variable Rate Technology (VRT) maximizes pea performance by determining the optimal amount of seed and microbial inoculant required for every specific point in the field (Pauli et al., 2016). This technological layer transforms the "low-input" principle of regenerative agriculture from a theoretical concept into a measurable and scalable agricultural engineering discipline.

In the development of climate-resilient pea varieties, phenological modeling ensures that flowering time is optimized according to climate projections. Identifying genetic lines that minimize the impact of temperature fluctuations on pollen fertility ensures that the pea remains not just a cover crop, but also a reliable element of food security (Katam et al., 2022). This dynamic breeding approach synchronizes the plant's biological clock with changing climatic conditions, thereby guaranteeing the total productivity of polyculture systems.

In biodiversity-oriented breeding strategies, the pea should be viewed as a central data source for "smart polycultures." The genetic control of volatile organic compounds (VOCs), which facilitate inter-plant communication, can enhance the pea's capacity to repel natural pests. Such "ecological engineering" studies will allow future pea varieties to be designed not merely as a product, but as biological sensors and protectors that preserve the health of the field (Varshney et al., 2021).

The synthesis of technology and regenerative principles in pea breeding will transform agricultural production from an extractive activity into restorative ecosystem management (Foley et al., 2011; Newton et al., 2020) This next-generation breeding vision, which brings together the ancient heritage of Anatolian multi-cropping systems with modern science, is the most fundamental element for increasing the resilience of our food systems (Snapp et al., 2010).In the agricultural ecosystems of the future, the pea will continue to be the most tangible representative of sustainability at the intersection of data, genetics, and ecology (Foyer et al., 2016; Vaz Patto et al., 2015).

CONCLUSION

In the process of constructing future agricultural ecosystems, the garden pea (*Pisum sativum L.*) serves as an indispensable biological instrument for overcoming the ecological and economic constraints of monoculture. The morphological breeding strategies, no-till farming practices, and carbon footprint analyses examined throughout this study demonstrate that the pea is far more than a simple rotation crop; it is an "ecosystem engineer" that infuses regenerative dynamics into the entire agricultural system. Functional pea breeding integrated into polyculture frameworks optimizes both environmental sustainability and the resilience of agricultural production against the global climate crisis.

From an ecological perspective, the biological nitrogen fixation and soil structure enhancement provided by peas radically decrease agricultural carbon emissions by minimizing dependency on synthetic inputs. Economically, low input costs and income diversification establish a more secure financial foundation for producers. Combined with conservation agriculture techniques such as "no-till," pea production possesses the potential to restore soil health and ensure long-term food security, particularly in regions with fragile ecosystems like the Anatolian plateau.

Furthermore, the success of peas in regenerative systems generates a synergistic effect when integrated with agricultural digitalization and precision farming technologies. Monitoring next-generation varieties—optimized through morphological breeding—via Variable Rate Seeding (VRS) and smart sensor technologies enhances the measurability of ecosystem services. Specifically, the real-time tracking of parameters such as carbon sequestration and water-use efficiency proves that pea-based production models are not merely a biological preference but a data-driven, high-tech engineering solution. This technological alignment will also bolster the demographic sustainability of the agricultural transformation in Anatolia by increasing the interest of younger generation farmers in regenerative practices.

Ultimately, this transformation strategy centered on the pea is the key to complying with evolving global "regenerative food" standards. In a market where consumer consciousness is shifting toward "carbon-neutral" and "eco-friendly" products, the ecological value added by peas will enable local products to gain a premium identity in the international arena. This systems-oriented approach, manifested in every stage from scientific breeding to field-level planting norms, can position Turkey as a center of application in sustainable agriculture literature. The pea remains the most durable stone in the bridge built between the ancient wisdom of the past and the biotechnological possibilities of the future.

In conclusion, the efficacy of peas within polyculture and regenerative agriculture systems necessitates a transdisciplinary approach. It is essential to calibrate genetic breeding for morphological harmony, agronomic strategies for ecosystem services, and economic models for ecological outcomes. Supporting pea-based multi-cropping models at the policy level and expanding their adoption among farmers will be the cornerstone of a sustainable, low-carbon, and restorative agricultural revolution for Turkey's future.

References

Açıkgöz, E. (2001). *Yem Bitkileri*. Uludağ Üniversitesi Güçlendirme Vakfı Yayın No: 182, Bursa.

Altieri, M. A. (1999). The ecological role of biodiversity in agroecosystems. *Agriculture, Ecosystems and Environment*, 74(1-3), 19-31.

Anlar, B. and Çancı H. (2020). Baklagil ekim nöbeti sistemlerinde toprak organik madde ve azot dinamikleri. *Türkiye Tarımsal Araştırmalar Dergisi*.

Araus, J. L., and Cairns, J. E. (2014). "Field high-throughput phenotyping: the new crop breeding frontier." *Trends in Plant Science*, 19(1), 52-61.

Bedoussac, L., Journet, E. P., Hauggaard-Nielsen, H., Naudin, C., Corre-Hellou, G., Jensen, E. S., ... and Justes, E. (2015). "Ecological principles underlying the efficacy of cereal-legume intercropping in temperate systems to improve nitrogen use efficiency and global yield." *Agronomy for Sustainable Development*, 35(3), 711-735.

Bhandari, M., Das, A., and Gupta, S. C. (2021). "Artificial intelligence in plant breeding: Harnessing the power of machine learning for crop improvement." Plant Molecular Biology Reporter, 39, 1-18.

Coyne, C. J., Kumar, S., von Wettberg, E. B., Marques, E., Berger, J. D., and Redden, R. J. (2020).

Crews, T. E., and Peoples, M. B. (2004). "Legume versus fertilizer sources of nitrogen: ecological tradeoffs and operational efficiencies." *Agriculture, Ecosystems & Environment*, 102(3), 279-297.

Dhima, K. V., et al. (2007). Competition indices of common vetch and cereal intercrops in two seeding ratios. *Field Crops Research*, 100(2-3), 249-256.

Düzgüneş, O. (1990). *Bitki Islahı*. Ankara Üniversitesi Ziraat Fakültesi Yayınları, Ankara.

Echarte, L., et al. (2011). Models for prediction of the yield advantage in intercropping systems. *Field Crops Research*, 121(3), 323-333.

Foley, J. A., et al. (2011). "Solutions for a cultivated planet." *Nature*, 478(7369), 337-342.

Foyer, C. H., et al. (2016). "Neglecting legumes has compromised human health and sustainable food production." *Nature Plants*, 2(8), 1-10.

Foyer, C. H., Nguyen, H. T., Lam, H. M., Xu, C., Shen, J., Vaz Patto, M. C., ... and Varshney, R. K. (2016). "Neglecting legumes has compromised human health and sustainable food production." *Nature Plants*, 2(8), 1-10.

Fulgosi, H., and Špoljarić Marković, S. (2021). "Precision plant breeding: Genome editing in legumes for sustainable agriculture." *Sustainability*, 13(15), 8342.

Fustec, J., et al. (2010). Nitrogen rhizodeposition of legumes. A review. *Agronomy for Sustainable Development*, 30(1), 57-66.

Gan, Y., Hamel, C., O'Donovan, J. T., et al. (2011). "Diversifying crop rotations with pulses enhances system productivity and reduces the carbon footprint." *Renewable Agriculture and Food Systems*, 26(2), 141-155.

Hauggaard-Nielsen, H., Ambus, P., and Jensen, E. S. (2001). "Interspecific competition, N use and interference with weeds in pea–barley intercropping." *Field Crops Research*, 70(2), 101-109.

Hauggaard-Nielsen, H., et al. (2001). Evaluating pea–barley intercropping for yield stability, nitrogen use efficiency and ground water protection. *Biology and Fertility of Soils*, 34, 407-413.

IPCC (2019). *Special Report on Climate Change and Land*. Intergovernmental Panel on Climate Change.

Jensen, E. S. (1996). Grain yield, symbiotic nitrogen fixation and interspecific competition for inorganic nitrogen in pea-barley intercrops. *Plant and Soil*, 182, 25-38.

Kantar, F., et al. (2007). Biotic and abiotic stress factors limiting grain legume production in Turkey. *Journal of Biological Sciences*.

Katam, R., Shockey, J., Sakata, K., and Chen, S. (2022). "Omics and precision agriculture for crop improvement and environmental sustainability." *Frontiers in Plant Science*, 13, 1024563.

Lal, R. (2004). "Soil carbon sequestration to mitigate climate change." *Geoderma*, 123(1-2), 1-22.

Lal, R. (2004). Soil carbon sequestration impacts on global climate change and food security. *Science*, 304(5677), 1623-1627.

Lithourgidis, A. S., et al. (2011). Annual intercrops: an alternative pathway for sustainable agriculture. *Australian Journal of Crop Science*, 5(4), 396-410.

Montgomery, D. R. (2017). "Growing a Revolution: Bringing Our Soil Back to Life." *W. W. Norton & Company*.

Nemecek, T., et al. (2008). Environmental impacts of introducing grain legumes into European crop rotations. *European Journal of Agronomy*, 28(3), 380-393.

Newton, P., et al. (2020). "What is regenerative agriculture? A review of scholar and practitioner definitions based on processes and outcomes." *Frontiers in Sustainable Food Systems*, 4, 194.

Parihar, C. M., Nayak, H. S., Rai, V. K., Das, A., and Jat, M. L. (2019). "Soil health and global food security: A conservation agriculture perspective." *In Soil Health and Environmental Sustainability*. Springer, Cham.

Pauli, D., Chapman, S. C., Edwards, R., White, J. W., and Gore, M. A. (2016). "The quest for understanding the genetic basis of plant phenotype through high-throughput phenotyping with unmanned aerial systems." *Plant Phenomics*, 2016.

Peoples, M. B., et al. (2009). The contributions of nitrogen-fixing crop legumes to the productivity of agricultural systems. *Symbiosis*, 48, 1-17.

Poggio, S. L. (2005). Structure of weed communities in mixed swards of pea and barley in the Pampas. *Agriculture, Ecosystems & Environment*, 106(4), 389-402.

Reicosky, D. C. (1997). "Tillage-induced CO2 loss from soil." *Soil and Tillage Research*, 41(1-2), 105-118.

Rubiales, D., and Mikic, A. (2015). "Introduction: Legumes in sustainable agriculture." *Critical Reviews in Plant Sciences*, 34(1-3), 2-3.

Sayre, K. (2003). *No-till agriculture: a fundamental element of conservation agriculture*. CIMMYT, Mexico.

Smýkal, P., Aubert, G., Burstin, J., Coyne, C. J., Ellis, N. T., Flavell, A. J., ... and Duc, G. (2012). "Pea (*Pisum sativum L.*) in the genomic era." *Agronomy*, 2(2), 74-115.

Snapp, S. S., et al. (2010). "Biodiversity can support a greener revolution in Africa." *Proceedings of the National Academy of Sciences (PNAS)*, 107(48), 20840-20845.

Stagnari, F., Maggio, A., Galieni, A., & Pisante, M. (2017). "Multiple benefits of legumes for agriculture sustainability: an overview." *Chemical and Biological Technologies in Agriculture*, 4(1), 1-13.

Tilman, D., et al. (2002). "Agricultural sustainability and intensive production practices." *Nature*, 418(6898), 671-677.

Titi, A. (2002). *Soil Tillage and Crop Production*. CABI Publishing, UK.

Vandermeer, J. H. (1989). *The Ecology of Intercropping*. Cambridge University Press.

Varshney, R. K., Bohra, A., Roorkiwal, M., Barmukh, R., and Tuberosa, R. (2021). "Fast-forward breeding for a food-secure future." *Trends in Genetics*, 37(12), 1124-1136.

Vaz Patto, M. C., Amaral-Carneiro, A., Guimarães, L., and Rubiales, D. (2015). "The role of legumes in eco-efficient cropping systems." *Crop and Pasture Science*, 66(12), 1192-1206

Vaz Patto, M. C., et al. (2015). "The role of legumes in eco-efficient cropping systems." *Crop and Pasture Science*, 66(12), 1192-1206.

West, T. O., and Marland, G. (2002). "A synthesis of carbon sequestration, carbon emissions, and net carbon flux in agriculture: comparing tillage practices in the Southeast US." *Agriculture, Ecosystems & Environment*, 91(1-3), 217-232.

Zander, P., et al. (2016). Grain legume decline and environmental its impacts on European agriculture. *Environmental Science and Policy*.