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Chapter 1

THE RISE OF INTELLIGENT FARMING: AI AGENTS AND IMAGE ANALYTICS IN DIGITAL AGRICULTURE

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1. Introduction

1.1. The Transformation Process of Digital Agriculture

The term "digital agriculture" describes a modern agricultural strategy developed through the integration of information systems. This technology's essential components include global positioning systems, geographic information systems, remote sensing systems, and data analysis (Göl and Tarhan, 2024).

The agricultural industry is now facing significant challenges such as resource constraint, population growth, and climate change. By 2050, agricultural productivity must be increased by 60–100%. Digital solutions that go deeper than conventional approaches are crucial for addressing this requirement. Particularly, machine learning as well as artificial intelligence have the possibility of becoming to boost agricultural output while guaranteeing sustainability. By enabling precision agriculture applications using instruments like drones, sensors, and robotic systems, smart farming technologies maximize resource utilization. For instance, plant development and health status may be tracked in real time, and planting, irrigation, and harvesting schedules can be precisely planned thanks to the abundant data gathered from the farm. But there are drawbacks to this change as well, like high expenses, low digital literacy, and data security (Raj & Prahadeeswaran, 2025).

1.2. The Conceptual Framework of Artificial Intelligence (AI) Agents

In agriculture, an "AI agent" is a smart system that gathers and evaluates operational data to produce recommendations or decisions for farm management. To provide prompt and data-driven interventions, it can automatically identify critical situations, develop management plans, and interact with linked devices including irrigation networks, unmanned aerial vehicles, and autonomous field equipment (Virtual Workforce AI, 2026).

AI agents have recently attracted a lot of interest from a range of sectors, including finances, medical care, intelligent cities, transportation, and agriculture. These days, AI agents can interact intelligently in dynamic situations and learn on their own to improve their performance (Murad et al., 2026).

The usage of several AI agents cooperating in harmony can greatly improve the models' overall performance and efficiency in a smart precision farming setting. A specialized mission, such as tracking soil moisture, identifying pests, examining weather trends, and controlling irrigation, might be given to each agent. Although these agents work independently, they communicate with one another in actual time, allowing prompt and well-informed decision-making. To reduce crop stress and minimize the use of chemicals, a pest detection agent can notify the nutrient and irrigation agents when it detects an early infestation. Timely actions, resource optimization, and less human involvement result from this type of agent synchronization. A more responsive and adaptable agricultural system is produced by the agents' combined intelligence and collaboration, which eventually increases crop output, conserves resources, and promotes long-term sustainability (Srinivasu et al., 2025). The several agricultural domains where an AI agent may be implemented for intelligent management are shown in Figure 1.

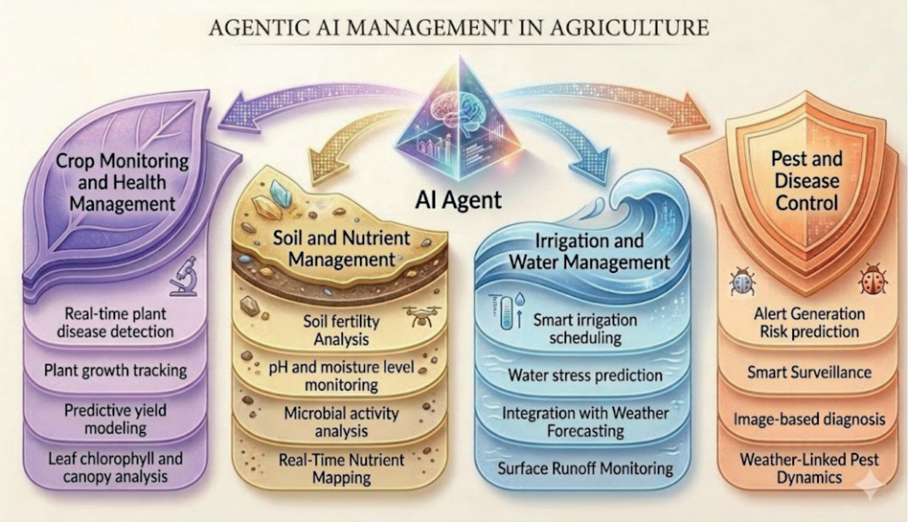

Figure 1. *Theoretical Framework for AI Agent Integration in Smart Agricultural Management*

1.3. Multi-Agent Systems

The need for more adaptable and useful systems grew as robots integrated more and more into daily life. Although quite sophisticated, early robotic systems were costly and complicated. Multi-Agent Systems (MAS) evolved as a reliable and affordable solution to get around these restrictions. A MAS is a system made up of several independent agents working together to accomplish a shared goal. MAS offers more resilience, adaptability, and flexibility than single-robot systems. Effective operation necessitates skills including environmental interaction, formation control, obstacle avoidance, and higher-level decision-making in dynamic environments. Each agent in the system contributes to the overall aim while carrying out particular duties (Chevalier et al., 2016).

2. Digital Agriculture Ecosystem and Data Infrastructure

2.1. Agriculture 4.0 and Smart Production Paradigm

The term "agriculture 4.0" describes a new stage of agricultural development in which automation, precise data analysis, and digital technology are transforming traditional farming (Sai et al., 2025). In this paradigm, data-driven production models are created through remote sensing (satellite, drone, etc.), the integration of IoT (Internet of Things), and artificial intelligence. These technologies improve resource management efficiency, provide quick reactions to environmental changes, cut manufacturing waste, and improve product traceability, all of which boost resilience and transparency. However, this transition is also beset by challenges including inadequate infrastructure, incompatible data, a lack of expertise, and expensive installation. By combining diverse agricultural data sources (sensor data, satellite photos, climate model outputs, etc.), the agriculture 4.0 method opens the door for intelligent decision systems and autonomous applications. The development of digital infrastructure, such as big data and cloud computing platforms, is crucial in this situation (da Silveira et al., 2025).

2.2. Internet of Things, Drone and Satellite Systems

Combining the terms "Internet" and "Thing (IoT)," is a worldwide network of interconnected, uniquely identifiable objects that exchange data using common communication protocols. This idea has developed over time into a worldwide network of intelligent, networked gadgets that can sense, recognize, and react to their surroundings using sensors and actuators. Every object in an IoT system has a unique identity and is instantly connected to the internet, allowing for remote monitoring and control. Because of this, the Internet is becoming more prevalent in both daily life and enterprises, where technologies run smoothly in the background and react quickly to consumer demands. With almost five billion smart connected devices in use globally, IoT is widely considered to be the next significant development of the Internet (Verdouw et al., 2016). The Food and Agriculture Organization (FAO) projects that there will be about ten billion individuals on the planet by 2050, which will increase demand for agricultural output (FAO, 2017). Researchers are creating technological solutions to increase production and resource efficiency to solve this problem. Smart agricultural systems have been made possible by innovations like wireless sensor networks, sensor technologies, and IoT. By streamlining processes and cutting waste, IoT-based agriculture promotes automation and increases crop output. The development of contemporary agricultural automation is further aided by the widespread use of IoT technology in fields including farm management, environmental monitoring, animal tracking, irrigation control, greenhouse management, autonomous machinery, and drone-based applications (Kim et al., 2020).

Unmanned aerial vehicles (UAVs) containing multispectral sensors are evolving into more significant tools for managing agricultural fields as a result of the increasing need for precision agriculture, which requires high accuracy in both temporal and spatial crop data (Zhang et al., 2025).

A completely autonomous ecosystem where IoT sensors, drones, and robotic systems are seamlessly linked to accomplish data-driven, sustainable farming is illustrated in Figure 2, which demonstrates the practical implementation of IoT inside the agriculture 4.0 framework.

Figure 2. *Integration of IoT Sensors, Drones, and Robots in Smart Farming Systems*

2.3. Big Data in Agriculture

Big Data stands for the use of large datasets and digital technologies for gathering, combining, and analyzing them (Bronson & Knezevic, 2016).

A deeper comprehension of complicated and dynamic agricultural ecosystems is necessary to meet the challenges of smart farming and agricultural sustainability. This is made possible by new digital technologies that continually tracks environmental conditions and produce massive amounts of data. This makes it necessary to gather, store, process, and analyze diverse agricultural data on a big scale. Because of this, agricultural "big data" needs sophisticated infrastructure that can handle data in almost real-time for uses like animal illness diagnosis, pest monitoring, and weather forecasting. As a consequence, Big Data Analytics has become a crucial strategy that allows farmers and associated organizations to quickly acquire, identify, and analyze data to extract economic value from massive and diverse datasets (Kamilaris et al., 2017).

3. Agricultural Image Processing: Technical Fundamentals

3.1. Image Acquisition Systems

The image processing approach is a way to alter an image from a picture or frame video after recording taken by a camera, scanner, or sensors are converted into digital format, and then apply certain algorithms to obtain some valuable details from the digital data. This method involves rearranging pictures using a variety of procedures that ultimately provide significant outcomes. Descriptive parameters that indicate significant information in the picture are found during these procedures. In this manner, the qualities to be assessed are identified and separated, picture distortions are corrected, some attributes are made more visible, and the background is thresholded. Since the beginning of the use of image processing techniques in agricultural operations, research has been done on a variety of concerns, such as the identification of diseases, pests, and weeds, the identification of plant stresses, the prediction of yield, the tracking of crop development, the modeling of irrigation techniques, and the identification of soil properties. Furthermore, The experience obtained from implementing these research efforts, together with artificial intelligence, modeling, deep learning (DL) machine learning, and simulation uses, has resulted in the development of immediate and computerized expertise systems, autonomous tractors or agricultural machines, and agricultural robotics technologies (Özgüven, 2023).

For general mapping and looking at crops, RGB (Red, Green, Blue) cameras are used. They take in light that is visible in the range of 400 to 700 nm (Guebsi et al., 2024). RGB cameras are able to observe fine spatial textures, but they lack the ability to have the spectral specificity needed to measure crop health (Zhang et al., 2025). The RGB spectrum is helpful for seeing how the quantities of pigments content in plants vary. Chlorophyll mainly absorbs light in the blue and red ranges, which is why it stands out so much in the green range (Bestas et al., 2025).

UAVs are commonly utilized in Precision agriculture, integrated with multiple imaging sensors. thermal cameras, multispectral, and RGB are the most popular among them. RGB cameras are mostly used for field mapping and general crop monitoring. They collect pictures in the visible spectrum. The evaluation of agricultural conditions and vegetation health is made possible by multispectral cameras, which record many distinct spectral bands, usually ranging from three to ten bands, including visible, red-edge, and near-infrared wavelengths. In contrast, thermal cameras monitor plant water stress, soil moisture, and irrigation efficiency by detecting radiation in the thermal infrared region and translating it into temperature data. When combined, these sensors offer useful information for enhancing precision agricultural decision-making and crop monitoring (Martínez-Heredia et al., 2023).

Multispectral images have been applied a lot in agricultural research to find out things like biomass, crop yield, soil degradation, and chlorophyll content (Lu et al., 2020). These sensors collect reflectance data across various spectral bands, typically ranging from the visible spectrum (400–700 nm) to the near-infrared (700–1000 nm). Most multispectral systems capture four to six spectral bands (Guebsi et al., 2024) so that they can pick up on tiny changes in plant spectrum reflectance that the human eye is enabled to see. The Normalized Difference Vegetation Index (NDVI) is one vegetation index that regularly uses this spectral data. It uses reflected bands of electromagnetic radiation to figure out a scalar measure of plant health and vigor (Lum et al., 2016). Vegetation indices based on multispectral images give us numbers that tell us how stressed plants are, what amount of photosynthesis is currently going on, and how healthy they are. Because of these factors, multispectral sensing has become more important as a tool for monitoring agriculture, helping with crop yield analysis, early stress detection, and plant health evaluation.

In agriculture, thermal cameras usually work in the thermal infrared range of 7.5 to 14 μm. They have a normal thermal resolution of 0.05–0.1 °C, which makes it possible to find small changes in temperature in crops. Thermal cameras are generally used for checking on the health of plants and finding out if plants are stressed from lack of water (Guebsi et al., 2024). Thermal infrared imagers also allow for mapping of canopy temperature and soil moisture (Zhang et al., 2025).

3.2. Preprocessing and Segmentation Techniques

The initial step in getting an image ready for more advanced processing is called image preprocessing. The objective is in two ways: to extract desired characteristics that represent important information in the picture and eliminate unwanted features that would impede further processing. At this point, the computer lowers noise and sometimes enhances specific object characteristics that are essential for understanding the image. Pre-processing is an important step after image capturing since raw image data is frequently noisy, fragmentary, or inaccurate. It acts as a first step to raise the accuracy of later processing stages, including item recognition and classification, and to increase the quality of the data. Depending on the application, several preprocessing methods might be used. These include techniques that reduce undesired distortions and improve crucial picture attributes needed for additional analysis, as well as geometric changes including rotation, scaling, and translation. Preprocessing methods enhance picture quality and get the data ready for more dependable and effective processing later by taking use of the inherent redundancy in images (Sethi & Bawa, 2022).

A key task in computer vision is image segmentation, which separates a picture at the pixel level into meaningful sections. Semantic segmentation, instance segmentation, and panoptic segmentation are often its three primary subtasks. Image segmentation is crucial for agricultural applications including crop and soil health monitoring, yield estimation, and plant disease detection. However, noise, uneven lighting, and complicated backdrops are common in agricultural photos, and inaccurate dataset labeling and comparable visual traits across disease stages can make reliable segmentation difficult. Before analysis, photographs are usually pre-processed using techniques like color balance, noise reduction, and image correction to solve these problems. Following preprocessing, the target item (such as a plant or leaf) is separated from the background (soil or surrounding environment) using segmentation techniques. Thresholding (such as the Otsu method), edge-based segmentation, region expanding, k-means clustering, watershed algorithms, and graph-based techniques are examples of traditional segmentation techniques. Nevertheless, these methods are frequently susceptible to changes in the environment and image quality. Deep learning-based segmentation algorithms have been popular in agricultural picture analysis in recent years. Accurate pixel-level separation of crops, weeds, and disease areas is made possible by architectures including Encoder–Decoder networks, U-Net, DeepLabv3+, graph convolutional networks, and Transformer-based models. Segmentation is an essential stage for plant health research and automated agricultural monitoring since these techniques offer increased resilience and accuracy in challenging agricultural situations (Lei et al., 2024).

3.3. Deep Learning Architectures

The use of deep learning technologies has expanded quickly in recent years. Deep learning systems are becoming increasingly similar to human cognitive processes like data-driven learning, problem-solving, and decision-making. These models, in compared to traditional methods, can automatically extract patterns from massive datasets without the need for tedious human programming. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are two deep learning approaches that have been extensively researched and used in a range of industries, including agriculture (Altalak et al., 2022). These models are often applied to applications including video processing, segmentation, speech recognition, object identification, natural language processing and picture classification. LeNet, AlexNet, and VGGNet are just a few of the well-known CNN designs that have made A significant influence on the development of deep learning research and real-world applications (Purwono et al., 2022).

Many digital instruments and technologies used in agriculture rely heavily on vision. By automating the process of locating, recognizing, and detecting different things across expansive agricultural landscapes, object detection plays a crucial part in digital farming. You Only Look Once (YOLO), a single-stage detection algorithm, has become well-known in agriculture in a comparatively short amount of time because of its cutting-edge effectiveness with regard to of accuracy, speed, and network size. YOLO is applied in a diversity of agricultural studies, such as monitoring, surveillance, sensing, automation, and robotics operations, and provides Real-time detection results with excellent accuracy. Although they are dispersed and diverse in character, YOLO studies and their applications related to agriculture are expanding at an incredible rate (Badgujar et al., 2024).

4. Image Processing Integration Architecture with Artificial Intelligence Agents

4.1. Agent-Based Workflow Model

Agentic frameworks are computational structures that allow AI systems to function more autonomously in a variety of situations and problem areas. These frameworks create coherent structures that facilitate goal-directed behavior by integrating perceptual modules, reasoning engines, planning mechanisms, and execution systems. Agentic AI has internal representations of the environment that enable planning, prediction, and adaptability to new situations, in contrast to classic reactive systems that map inputs to outputs through predefined routes. These systems' sophisticated architecture enables them to function over a variety of time horizons, from short-term reactions to long-term strategic planning, while preserving consistency between goals and actions. The environmental awareness skills of agentic systems have been significantly improved by recent developments in perception technology and sensor integration, laying the groundwork for more complicated decision-making processes in challenging real-world contexts (Garg, 2025).

4.2. Real-Time Decision Support Systems

In smart agriculture, decision support systems facilitate data analysis, inference, and knowledge base creation. The management of irrigation resources, task planning, climate change adaptation, waste avoidance and management, agricultural supply chains, and sustainability challenges are areas where the application of decision support systems in agriculture is particularly noteworthy (Ayberkin, 2025).

By integrating smart machines with decision support systems, applications in agriculture enable real-time analyses of soil tillage, compaction of soil, organic material and moisture detection, surveying the soil, weed identification through remote sensing, plant development monitoring, and spraying and fertilization processes. With the use of variable-rate technology, these systems enable quick or real-time operations. The main advantage is the reduction of needless applications and the enhancement of quality and efficiency through optimal input use. The beneficial effects of these technologies on cost reduction and operational efficiency are further demonstrated by academic research and field surveys, which also emphasize the significance of field-based training and implementation programs to assist successful adoption (Kubilay, 2025).

4.3. Drone–Edge–Cloud Integration

Distributed computing models that vary in their degree of decentralization and closeness to end users include cloud, fog, and edge computing. While fog computing expands this paradigm by providing processing power closer to the network edge to enhance reaction time and service quality, cloud computing offers centralized computing resources provided over the internet. This idea is further developed by edge computing, which makes it possible to analyze data directly at the device or sensor level, enabling real-time analysis and minimizing the need to send massive large volumes of data that are sent to faraway servers. By spreading data collecting, processing, and storage over many levels, cloud, fog, and edge computing integration helps get around the drawbacks of entirely cloud-based systems. In this architecture, fog computing works at the network infrastructure level and can support several IoT applications, increasing system efficiency, lowering latency, and enhancing reliability in data-intensive environments, while edge computing mainly functions at the IoT device level (Kalyani et al., 2023).

In smart agriculture, where massive amounts of heterogeneous data are produced from several sources including sensors, robots, autonomous tractors, drones, and actuators, this architecture is very crucial. Actuators including irrigation systems, ventilation systems, lighting units, automated greenhouse windows, and nutrient pumps react automatically to the agricultural data that this equipment continually gathers, which includes humidity, soil conditions, pH levels, and temperature. To enable real-time monitoring, data analysis, and decision-making processes across several agricultural domains, such as crop production, animal management, and greenhouse operations, cloud-, fog-, and edge-based infrastructures are essential (Kalyani and Collier, 2021).

5. Examples of Agricultural Applications

In Figure 3, different application areas of deep learning technology in agriculture are illustrated, such as yield estimation and disease detection.

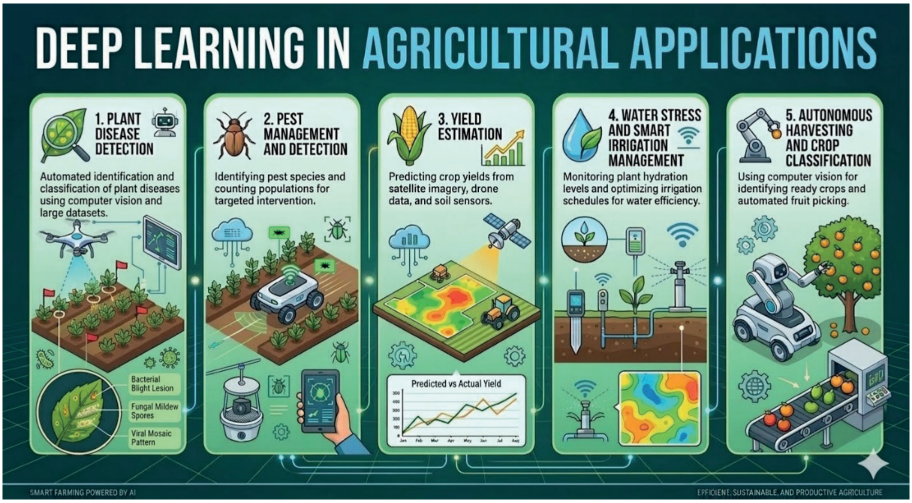

Figure 3. *Real-World Examples of How Deep Learning Architectures Can Be Used in Smart Farming*

5.1. Plant Disease Detection

The diagnosis of diseases of plants by visual inspection of symptoms on leaf surfaces is quite complicated. Even seasoned agronomists and plant pathologists sometimes unsuccessful to accurately diagnose certain illnesses cause of this complexity, the vast variety of cultivated plants, and their current phytopathological issues, which lead to incorrect conclusions and treatments. An automated computational method for plant disease identification and diagnosis would be very helpful to agronomists who must make these diagnosis by examining the leaves of injured plants (Ferentinos, 2018).

Large-scale disease picture collection and labeling in leaf disease detection necessitates significant financial, material, and human resources. Additionally, it might be challenging to collect enough picture samples since certain plant diseases have brief occurrence periods. Two significant variables that adversely impact model performance in deep learning applications are short sample numbers and dataset imbalance. Therefore, creating efficient deep learning models for leaf disease detection requires growing the dataset. The quantity of training data may be increased by using data augmentation techniques, but these methods must be utilized carefully to guarantee accurate representations. For example, image augmentation techniques should refrain from changing the original color properties of the photos because color is a significant visual signal of many plant illnesses (Li et al., 2021).

According to the review studies conducted by Saleem et al. (2019), many deep learning algorithms have been applied for detecting to the plant disease using leaf images. CNN-based models, including VGG-16, AlexNet, GoogLeNet, VGG-19, ResNet, and Inception, have been extensively used in the literature to classify and identify plant diseases. These algorithms achieve great performance in disease identification tasks by automatically extracting discriminative characteristics from photos of plant leaves. According to the review, one of the most popular methods in the detection for plant disease research is transfer learning using pre-trained CNN architectures, which greatly enhances classification performance in agricultural picture analysis.

5.2. Pest Management and Detection

One of the most significant factors of upholding effective insect management and control are required under commercial food standards. Crop pests may have a major effect on crop output and quality, frequently resulting in large financial losses. As a result, it is crucial to create and apply cutting-edge instruments and techniques for early detection and diagnosis of pest-related illnesses before they seriously harm crops (Chithambarathanu and Jeyakumar, 2023).

Monitoring insects is essential for detecting pests early and diminishing the abuse of pesticides. To maximize crop management and enhance productivity and sustainability, Integrated Pest Management (IPM) systems monitor pests and only administer treatments when necessary. Smart Pest Monitoring (SPM), which automates data collecting, analysis, and decision-making, is made possible by developments in AI and IoT. While deep learning, which excels in image-based tasks like pest detection, employs neural networks to identify complicated patterns, machine learning (ML) enables computers to learn from data. Although there are AI techniques for counting and detecting insects automatically, completely dependable solutions are still difficult to come by (Teixeira et al., 2023).

5.3. Yield Estimation

Food security, food business decision-making, and agro-environmental management all depend on accurate and timely crop production forecast and crop mapping. Remote sensing (RS) data are useful methods for mapping crop extent and forecasting yield prior to harvesting because of their worldwide coverage, rich spectral and spatial information, and repeating nature. By considering the nonlinear interactions between variables, advanced machine-learning techniques, especially DL, can accurately capture the complex characteristics needed for crop mapping and yield prediction. The application of DL algorithms in agricultural monitoring is gradually growing, and they have shown impressive results in several RS domains (Joshi et al., 2023).

According to Jabed and Murad (2024), many research projects have researched the use of ML and DL techniques in agriculture, especially for crop yield estimation and tracking. While DL architectures like Long Short-

Term Memory (LSTM), CNN, RNN, and Deep Neural Networks (DNN) have drawn more attention due to their capacity to model intricate relationships in agricultural data, various ML algorithms like Support Vector Machines (SVM), Random Forest (RF), Logistic Regression (LR), and Neural Networks (NN) have been applied. These methods are often applied to data from sensors, meteorological sources, UAV photography, and remote sensing. In general, the evaluated research shows that deep learning techniques outperform conventional methods in agricultural picture processing and crop yield estimates.

5.4. Water Stress and Smart Irrigation Management

In dryland areas with high evapotranspiration, little rainfall, and high temperatures, water scarcity has emerged as a major barrier to sustainable agriculture and future food security. Water availability and agricultural output are seriously threatened by these extreme weather conditions and the growing effects of climate change. Improving irrigation efficiency has become a top issue since agriculture uses a significant amount of the world's freshwater resources. The idea of a "Blue Revolution," which seeks to produce more crops per drop of water, was inspired by this necessity. Smart irrigation systems have become an applicable option in this situation. These systems apply water at the appropriate moment, place, and amount through assessing factors like soil characteristics, crop necessities, and seasonal variations in the weather. Thus, smart irrigation may promote sustainable agriculture management while increasing crop output, conserving water resources, and improving water use efficiency (Ahmed et al., 2023).

According to Del-Coco et al. (2024), UAVs equipped with remote sensing technologies supply a successful option for monitoring soil and crop conditions, overcoming the restrictions of traditional ground sensors. To evaluate soil moisture and crop growth indicators, UAVs gather high spatial and temporal resolution images. Visible, near infrared, and thermal imaging are often used in studies to evaluate the health of plants, identify drought stress, and calculate evapotranspiration. Additionally, crop health is frequently assessed using vegetation indices that are generated from multispectral data. By regulating actuators like pumps, valves, and sprinklers, the data gathered from UAV analysis may also assist automated irrigation systems, increasing irrigation efficiency.

One of the methods used most frequently in Smart Irrigation Systems (SIS) is Machine Learning. Its main goal is to develop computer systems that automatically get smarter with time. ML approaches are known for their flexibility in adding fresh data to improve model accuracy and their capacity to autonomously solve difficult nonlinear problems utilizing datasets from many sources. These methods allow the creation of reliable machine learning models and offer better suggestions in the context of smart irrigation. In irrigation, ML is used to predict water table levels, measure soil moisture content, calculate reference evapotranspiration, and improve energy management. Overall, by utilizing soil and meteorological data, ML facilitates well-informed decision-making in irrigated agriculture, promoting sustainability and water conservation. These technologies reduce needless irrigation, ease the problems associated with water shortages, and promote effective water management techniques in agriculture by accurately distributing water where and when it is required (Younes et al., 2024).

5.5. Autonomous Harvesting and Crop Classification

Since numerous processes, including pollination, fruit set management, and harvesting, are done manually, fruit growing involves a large amount of labor. The introduction of automation and mechanization has also been limited by the variety of orchard terrains and tree architecture. Robotic harvesting methods are being developed to overcome this problem, especially for labor-intensive fruits like pears and apples. Using deep learning-based object recognition on RGB pictures, fruits are first identified, classified and located in these systems. To increase accuracy, depth data is frequently included. The fruits are subsequently harvested by robotic arms that use inverse kinematics and route planning to prevent collisions, while a customized end-effector grabs and twists the fruit to remove it (Yoshida et al., 2022).

Agricultural robots powered by AI and computer vision are growing in significance as essential elements of precision agriculture. UAVs and other agricultural robots may carry out a variety of duties that are typically performed by humans or machinery, including harvesting, weed control, and field observation. Monitoring crop development and plant health at various geographical and temporal scales is made possible by ground robots and UAVs employed in field observation. By using computer vision to identify crops and weeds, robotic weed management reduces the need for chemicals and allows for the deployment of tailored herbicides or mechanical weed removal techniques. In a similar vein, robotic harvesting systems identify the goods on the plant and instruct the robot arms and end effectors to begin harvesting (Lu and Young, 2020).

6. Data Sets and Performance Evaluation

6.1. Common Agricultural Image Datasets

For the development of computer vision models in precision agriculture, agricultural picture datasets are crucial for tasks like crop categorization, disease detection, and object recognition. They can be broadly divided into two categories: large-scale general-purpose datasets like ImageNet and MS COCO, which contain millions of annotated images but few crops, and domain-specific agricultural datasets like PlantVillage, LeafSnap, and Flowers102, which concentrate on plants but are small in size and primarily used for classification. In response, CropDeep was developed (Zheng et al., 2019), which includes more than 31,000 well-annotated photos of 30 fruit and vegetable categories that were gathered in greenhouses using smartphones, IoT cameras, and autonomous robots. The dataset captures the complexity of true agricultural situations by including many plant sections and growth phases. In order to assess classification and detection performance, several cutting-edge deep learning models were tested on CropDeep, revealing architectures that offer high accuracy and quick detection appropriate for real-world agricultural applications.

6.2. Performance Metrics

Certain criteria are needed to evaluate the detection, localization, and classification performance of deep learning-based object detection models in agriculture. Typical metrics include the following:

a) Intersection over Union (IoU): The IoU is utilized to assess item accuracy in localization by evaluating the overlap between the anticipated bounding box and the ground truth box. A higher IoU value (e.g., IoU > 0.5) indicates better localization performance.

$$IoU = \frac{\text{OVERLAP AREA}}{\text{UNION AREA}}$$

b) Precision (AP_i): The percentage of accurately recognized items among all objects identified by the model is known as precision. There are fewer false positives and more trustworthy detections when accuracy is better.

$$Precision = \frac{\text{TP}}{\text{FP} + \text{TP}}$$

In the equation, TP indicates true positives, while FP indicates false positives.

c) Mean Average Precision (*mAP*): *mAP* is a common object detection statistic that combines average precision and IoU.

$$mAP = \frac{1}{N}\sum_{i=0}^{n} AP_i$$

d) Frames Per Second (*FPS*): For real-time uses like as drone-assisted crop monitoring, the model's inference speed is crucial.

$$FPS = \frac{1}{Inference\ time\ per\ frame}$$

e) Recall: The percentage of accurately identified objects among all real objects in the picture is known as recall. There are fewer false negatives when recall is higher.

$$Recall: \frac{TP}{FN + TP}$$

In the equation, FN represents false negatives.

f) F1-Score: The F1-Score is a balance assessment of a model's detection abilities, representing accuracy and recall.

$$F1 - Score = \frac{2\ x\ Recall\ x\ Precision}{Recall + Precision}$$

Class imbalance, environmental unpredictability, and inaccurate labeling frequently limit the evaluation of AI-driven item recognition in agriculture. Even though metrics such as mAP, IoU, and F1-score as presented in (Dalal and Mittal, 2025) provide established standards, they may not fully capture the requirements of real-world agricultural scenarios, especially in smallholder and resource-constrained environments. Variable illumination, partial occlusions, low-resolution imaging, energy consumption, and computational efficiency are all critical considerations for effective assessment. Selecting metrics that reflect practical constraints and field-level needs is essential for translating AI models into dependable and sustainable agricultural tools.

7. Challenges, Limitations, and Risks

7.1. Data Quality and Labeling Issues

The quality of training data possesses a substantial influence on how well the AI model performs. Labeling errors are common in agricultural images because various specialists may classify the same disease or condition differently. Annotations that are inaccurate or lacking might have a negative impact on model training and generalization. Furthermore, coverage restrictions, environmental impediments, or sensor failures can all lead to missed data. Therefore, to guarantee robust and dependable model performance in agricultural applications, strict data cleaning, automated labeling support, and expert-supervised validation processes are crucial.

7.2. Environmental Variability and Model Durability

In agricultural settings, there is a lot of variability because things like lighting, weather, and plant shape can have a big effect on picture quality. Models trained under certain conditions may not work as well when they are shown photos taken in different lighting, with different cloud covers, or at different stages of development. Differences in plant species or developmental stages make domain shift even worse, which makes the model less robust and general. AI models could make wrong predictions in the field if they aren't tested thoroughly in a range of situations. This could lead to lost yields or wasted resources. To solve these problems and make sure that agricultural applications work reliably, we need large datasets that include biological and environmental variability, data augmentation techniques, and ongoing model evaluation.

7.3. Hardware and Cost Barriers

Farmers and small-scale agricultural businesses may not be able to afford high-resolution cameras, UAVs, specialized sensors, and advanced computer units because they are so expensive. It is even harder for people in rural areas to use digital agricultural technology because they don't have much access to energy or the internet. Agricultural robots are one of many precision agriculture tools that are still being tested and may not be widely used until production costs go down. These problems with infrastructure and the economy make it harder for new technologies to spread, which could make the gap between big and small farms even bigger. To get rid of these problems and encourage fair access, long-term use, and useful integration of digital technologies in many agricultural settings, we need low-cost, open-source solutions, government incentives, and community-based projects.

7.4. Data Security and Digitality

Agricultural data is highly valuable for both business and marketing.

Sensor data, such as soil properties, yield projections, and market forecasts, must be kept private. If this information is sent to third-party providers, it could be at risk of cyberattacks and business intelligence threats. Using platforms owned by multinational agribusinesses also raises concerns about the country's food security. Because of this, things like using open standards, keeping data on your own computer, and encrypting data are becoming more important. Ensuring data sovereignty protects sensitive information and helps create strong, independent digital agriculture systems. This builds trust among stakeholders and helps keep agriculture sustainable in the long term.

8. Future Perspectives

The future of digital agriculture will be formed by an integrated ecosystem in which autonomous systems, sophisticated image analytics, and artificial intelligence agents all work together harmoniously. Agricultural fields are changing from being passive areas where crops grow to becoming intelligent cyber-physical organisms that continuously produce enormous amounts of data via sensor networks, autonomous robotic units, and UAVs, processing this data to make decisions on their own in real time. It is anticipated that autonomous agricultural robots and UAVs with swarm intelligence would soon be able to operate continuously around-the-clock with little assistance from humans, completely changing the agricultural production paradigm. In addition to reducing personnel expenses, this technological advancement will create a long-lasting "per-plant management" philosophy through high-resolution image analytics, enabling customized interventions that maximize operational accuracy and are in line with each plant's genetic potential.

Deep learning-based prediction models and dynamic decision support systems will become crucial defenses for global food security in the face of catastrophic weather events and resource shortages caused by climate change. The early identification of plant water stress or pathogen impacts prior to their morphological manifestation will be made possible by the combination of thermal and multispectral imagery with low-latency edge computer systems. The "Blue Revolution" idea, in which water supplies are managed with gram-level accuracy, is supported by this early-detection capacity, turning scarcity into a controllable characteristic.

By carefully targeting individual plants, autonomous systems' variable rate interventions will maintain the biological integrity of the soil and methodically lessen the ecological impact of agricultural activities. A new agricultural governance paradigm that emphasizes data security, traceability, and digital sovereignty is introduced by collective intelligence shown by AI agents in MAS.

Producers will be able to transform complicated data into strategic outputs without being constrained by technical skills thanks to hierarchical structures that combine the great computational power of cloud computing with the real-time data processing speed of edge computing. Cybersecurity standards will be integrated throughout the production chain, agricultural data will be viewed as a strategic asset, and intuitive user interfaces will make technology an essential production element rather than a luxury. In the end, this technology revolution creates the groundwork for a data-driven, climate-resilient agricultural future that ensures sustainable production methods, protects environmental values, and satisfies the growing global need for food.

9. Conclusion

This chapter thoroughly studied the theoretical and scientific foundations of integrating artificial intelligence agents and image processing technologies with the digital agricultural ecosystem. The functions of IoT-based sensor networks, big data analytics, cloud computing, and edge computing infrastructures in agricultural data management were examined in agreement with the smart production paradigm presented by Agriculture 4.0. Additionally, conceptual methods were described, emphasizing their connection to agricultural decision-support systems, including the basic features of AI agents, agent kinds, and multi-agent systems.

Additionally, the integration of popular deep learning architectures in agricultural image processing such as CNN, YOLO, U-Net, and Transformer-based models with artificial intelligence agents was examined. Key use cases, including plant disease detection, pest density analysis, yield prediction, water stress monitoring, and autonomous harvesting systems, were given within the application domains. Commonly used agricultural imaging datasets, hardware and software ecosystems, performance assessment criteria, and important challenges like data quality, environmental unpredictability, and cost-related constraints were also covered.

Finally, future study possibilities including sustainability-focused smart agricultural techniques and generative artificial intelligence were taken into consideration. Artificial intelligence agents have the ability to significantly improve data-driven decision-making processes, increase the efficacy of digital agriculture applications, and help the creation of sustainable agricultural production systems. The development of smart agriculture ecosystems will be further accelerated in the future by supporting these technologies with more extensive data infrastructures, autonomous systems, and transdisciplinary methods.

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Chapter 2

INPUT- AND OUTPUT-ORIENTED EFFICIENCY IN GOOSE FARMS OF DIFFERENT SIZES: THE CASE OF KARS PROVINCE

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1. INTRODUCTION

Although goose meat production accounts for a relatively limited share of total poultry production worldwide, it holds strategic importance for certain countries in terms of both meeting domestic consumption needs and offering export potential (Rosinski, 2002). Goose meat, and particularly goose liver, is considered a high value-added product worldwide, especially in Far Eastern and European markets (TOB, 2019). Demand for these products contributes to the economic sustainability of goose farming.

According to 2023 data, the global goose population reached 700,590,000 head. China, which alone accounts for approximately 94% of global production, maintains its absolute leadership in this field. China is followed by Mozambique, Myanmar, Russia, Madagascar, Ukraine, and Egypt (FAO, 2023). Türkiye ranks eighth worldwide with a goose population of 1,328,000 head, representing 0.35% of the country's total poultry population (TurkStat, 2024). Production activities concentrated particularly in Eastern Anatolia position Türkiye as a strategic producer both traditionally and economically.

An examination of global goose meat trade statistics indicates that in 2023 a total of 56,000 tons of fresh or chilled goose meat were exported. China accounts for 59% of global exports, Poland for 25%, and Hungary for 13%; together, these three countries dominate 97% of the world market. Despite its production potential, Türkiye remains highly limited in foreign trade, ranking 45th among 52 exporting countries. On the import side, China ranks first with a 64% share, followed by Germany (21%), France (4%), and Austria (3%). Türkiye has no recorded imports in this product group (FAO, 2023).

According to TurkStat (2024), Türkiye's total goose population is 1,303,026 head, a substantial portion of which is concentrated in Eastern Anatolia. Kars province alone accounts for approximately 41% of Türkiye's total, with 533,316 head, and continues its historical leadership. Goose farming in the province is more than a traditional production model; it constitutes a principal livelihood for the local economy and a core component of regional cultural identity. In terms of production intensity, Kars is followed by Ardahan (127,534 head) and Muş (58,001 head).

In production economics, efficiency refers to the maximum output achievable with available inputs or, alternatively, the minimum input use required to obtain a given output level (Parlakay & Alemdar, 2011). This measure, which encompasses not only technical efficiency but also strategic resource management (Özden & Özer, 2019), is a key determinant of profitability and global competitiveness in agriculture (Kaçıra, 2007). The role of productivity increases in sectoral transformation is frequently emphasized in the literature; for instance, Vicente (2004) demonstrated that the rise in total factor productivity in Brazilian crop production was driven by radical improvements in labor and land productivity.

Today, agricultural efficiency is associated not only with optimizing economic output but also with environmental sustainability. As noted by Bojar et al. (2017), intensive input use increases pressure on natural resources and may lead to threats to ecosystem balance, such as soil, water, and air pollution. Therefore, the efficient use of production factors simultaneously maximizes farm profitability and minimizes environmental harm, thereby safeguarding long-term sustainability.

A review of global research on goose farming shows that the literature predominantly focuses on local and regional production activities, technical efficiency parameters, and specific poultry husbandry practices (Rosinski, 2002; Yuwanta, 2002; Vekić & Jovičić, 2025; Szabó et al., 2025). In addition to such locally oriented studies, there is also research that addresses international trade dynamics, global market shares, and countries' competitive advantages from a macroeconomic perspective (Molnár, 2016). Moreover, the economics of geese is shaped not only by direct production outputs but also by indirect interactions within agricultural systems and organic linkages with other production branches. Indeed, a study conducted at Grasmere Station calculated production losses in sheep sharing the same ecosystem due to feed consumption by wild geese, evaluating this situation as an "opportunity cost" in farm economics (Harris et al., 1987). These findings clearly indicate that goose farming should be analyzed not merely as an animal production activity but also through the lens of resource allocation and multidimensional system interactions.

Although scientific studies on goose farming in Türkiye are limited, they generally focus on production processes. The majority of these studies concentrate on slaughter and carcass characteristics, yield and fattening performance, meat quality, and economic structure. Research on slaughter and carcass characteristics has evaluated meat yield and carcass structure across different goose breeds (Tilki et al., 2004; Arslan & Tufan, 2011; Kırmızıbayrak et al., 2011; Tilki et al., 2011), while studies on yield and fattening performance have examined the effects of feeding and environmental conditions on growth (Aksu Elmalı & Kaya, 2008). Although economic studies on goose farming are few, they provide important sectoral evidence.

Key contributions include assessments of the economic potential of goose products (Aral & Aydın, 2007), analyses of production costs and profitability (Demir & Aksu Elmalı, 2012), and socio-economic examinations of producer profiles and income levels (Demir et al., 2013; Boz et al., 2014). In addition, studies on free-range systems and incubation methods (Boz et al., 2016), and structural factors affecting breeder production (Taşkın et al., 2017), inform production practices. Research addressing the current state of the sector, encountered problems, and solutions (Şengül & Yeter, 2020; Akın, 2024) is important for policy development, while studies also exist that investigate consumer expectations regarding goose meat quality and its physico-chemical characteristics (Yakan et al., 2012). Furthermore, investigations evaluating the compatibility and potential of extensive systems with organic husbandry in Eastern Anatolia (Oral & Ak, 2020) and studies focusing on consumption tendencies (Gündüz et al., 2019; Gündüz, 2020) enable a multidimensional assessment of the sector.

Despite this body of literature, no study has been identified that addresses the production efficiency of goose farms through a holistic, input–output oriented approach. In particular, there is a significant knowledge gap regarding the assessment of resource-use efficiency in Kars province, which constitutes the core of Türkiye's goose population.

The primary objective of this study is to determine the input- and output-oriented efficiency of goose farms of different sizes in Kars province, the central region of goose farming in Türkiye. Accordingly, the study first presents descriptive statistics on the socio-economic structure of the surveyed farms and then analyzes production costs and profitability. Within the analytical framework, farms' technical efficiency performance was calculated using Data Envelopment Analysis (DEA) under both input and output orientations. Based on the results, potential improvement ratios required for inefficient farms to reach the benchmark level were determined, and strategic recommendations were developed to enhance the efficiency of goose farms.

2. MATERIALS AND METHODS

2.1. Data Sources and Sampling Procedure

The primary material of this research consists of original data obtained through face-to-face surveys conducted with goose farmers in Kars province, covering the 2018 production period. The theoretical background and secondary data were compiled from records and statistical reports obtained from institutions such as the Kars Provincial and District Directorates of Agriculture and Forestry and the Chamber of Commerce and Industry, as well as from the relevant scientific literature.

The selection of the study area was based on the spatial distribution of the goose population across the province. Statistical examinations indicated that approximately 67% of total stock was clustered in the Central district (33%), Arpaçay (22%), and Susuz (12%). Accordingly, it was decided to conduct the study primarily in these three districts.

Because there is no current and comprehensive official database on goose farms in the region, the sample size was initially targeted at 100 farms using quota sampling, a purposive sampling technique. The distribution of farms across districts was designed according to the principle of proportional representation based on the existing share of goose stock. However, due to a decline in farm numbers caused by epidemic diseases observed in the region and access constraints during fieldwork, the survey was completed with a total of 90 farms: 49 from the Central district, 23 from Arpaçay, and 18 from Susuz. In total, 22 villages affiliated with these districts were visited during the field study.

To represent heterogeneity by farm size, sampled units were divided into three groups according to the number of geese owned: farms with 1–25 geese were categorized as "Group 1" (small), those with 26–50 geese as "Group 2" (medium), and those with more than 50 geese as "Group 3" (large).

2.2. Production Cost Analysis

In this study, production costs were calculated for live, fresh, and dried goose. The production cost of live goose was calculated using the simple cost method, whereas the costs of fresh and dried goose were calculated using the residual method due to the presence of by-products such as liver, offal, and feathers. Kıral et al. (1999) indicate that this method is appropriate when primary and by-products are produced jointly.

The unit cost of live goose was calculated by dividing total fixed and variable costs by 1 kg of live weight. In the case of fresh and dried goose, the remaining cost after the deduction of by-product revenues was calculated by dividing it by the weight of the respective product. In addition, opportunity costs arising from the use of capital during the production period were included in variable costs. Costs were assumed to be evenly distributed over the production period; interest was calculated for an 8-month period using half of the annual interest rate (2%) derived from the 4% annual rate applied by T.C. Ziraat Bankası for poultry production in 2018, applied to half of total variable costs. Furthermore, depreciation (wear and tear) was included using the straight-line method, at a rate of 5% for poultry houses/buildings and machinery-equipment, based on the Revenue Administration (2018). Finally, a management cost equal to 3% of variable expenses was added as a managerial charge.

2.3. Input- and Output-Oriented Efficiency Analysis

To calculate input- and output-oriented efficiency in goose farming, Data Envelopment Analysis (DEA) was employed. DEA is a mathematical, non-parametric (linear programming) method that evaluates each producer's performance comparatively against the best-performing producer under the prevailing conditions (Karsak & İşcan, 2000; Adanacıoğlu, 2009).

Efficiency analysis was conducted under the assumption of variable returns to scale (VRS) for both input and output orientations. In the input-oriented analysis, the extent to which input quantities could be reduced while maintaining the current output level was examined; in the output-oriented analysis, the extent to which output could be increased without any increase in current input levels was investigated.

In the input-oriented approach, the objective is to minimize the amount of resources used while maintaining a given production level. This model is directly related to rational resource use and cost-saving strategies. The input-oriented model under constant returns to scale (CRS) can be expressed as follows (Coelli et al., 1998):

$$\min_{\theta,\lambda} \theta,$$

$$\text{st.} -y_i + Y\lambda \geq 0$$

$$\theta xi - X\lambda \geq 0$$

$$\lambda \geq 0$$

Here, θ denotes a scalar representing the efficiency score of farm i, and λ denotes an N×1 vector of coefficients (constants). In the approach developed by Farrell (1957), θ = 1 indicates that the farm lies on the efficiency frontier, whereas values less than 1 indicate the need for improvements in resource use.

In output-oriented analyses, the basic approach is to determine the maximum attainable output level while keeping the existing input bundle fixed. Under the CRS assumption, the output-based model can be formulated as:

$$\max_{\Phi,\lambda} \Phi,$$

$$\text{st.} - \Phi y_i + Y\lambda \geq 0$$

$$xi - X\lambda \geq 0$$

$$\lambda \geq 0$$

When the convexity constraint N1′λ = 1 is added to this linear programming model, an output-oriented DEA model under the VRS assumption is obtained. In this study, the revenue maximization problem constructed to evaluate farms' economic performance is solved in the following structural form:

$$\max_{\lambda, yi} p_i y_i$$

$$\text{st.} - y_i + Y\lambda \geq 0$$

$$xi - X\lambda \geq 0$$

$$N1' \lambda = 1$$

$$\lambda \geq 0$$

Here, p_i denotes a vector of output prices for farm i, while yi, as calculated by the model, denotes the vector of optimal output quantities that maximizes revenue for the relevant farm, under the constraints of observed output quantities (p_i) and existing input levels (x_i) (Coelli et al., 2002).

To determine efficiency levels of the surveyed goose farms, the first step was to define the input and output variables included in the model. Accordingly, one output and six input variables were incorporated into the model to represent the production performance of the enterprises. The output variable was Gross Production Value (TL), reflecting farms' economic size and market performance. This value includes the total monetary value of live goose sales as well as fresh and dried goose meat and by-products such as liver, offal, and feathers. Input variables were composed of both physical and cost-based measures. Flock size (head) represented the physical scale input, while key cost components of production, including chick cost (TL), labor costs (TL), feed costs (TL), and veterinary and medicine costs (TL), were included as direct production expenditures. In addition, auxiliary cost items that ensure continuity in the production process, such as vitamin–mineral supplements, litter, heating, electricity, water, repair and maintenance, and marketing expenses, were incorporated into the model as a composite input under the heading of other costs (TL).

Moreover, based on the findings obtained from model estimations, potential improvement analyses were conducted for farms. This analysis determined the rates at which inefficient farms would need to minimize resource use (input savings) and increase their current production capacity (output maximization) in order to reach the performance levels of successful benchmark farms. Thus, both idle amounts in the input composition and target output values required for full efficiency were identified using concrete evidence.

3. RESULTS AND DISCUSSION

3.1.Demographic Profile, Production Practices, and Marketing Structure of the Surveyed Goose Farms

An examination of the demographic structure of goose farmers in the study area indicates that producers are, on average, 46 years old and possess approximately 25 years of established production experience in the sector. The average household size is six persons; the number of individuals directly participating in goose farming activities is one, while the number employed in overall agricultural activities is two. A notable characteristic of the sector is the dominant role of female labor in farm management; indeed, 89% of farm operators are women. In terms of education level, 61% of managers are primary school graduates and 12% are middle school graduates.

Regarding diversification of farm activities, 97% of producers engage not only in goose farming but also in crop production or other livestock branches. In particular, in Group 3 (large farms), the rate of engaging in additional agricultural activities reaches 100%. Additionally, 43% of respondents are active in non-agricultural sectors, with 31% working in regular occupations such as wage labor or tradesmanship, and 15% operating in self-employment.

With respect to sourcing production material in goose farming, the most frequently used method is incubation, with a mean score of 4,78. This is followed by the procurement of goslings from outside sources (mean 1,26). Across all groups regardless of farm scale, the incubation method remains the primary preference (Group 1: 4,76; Group 2: 4,83; Group 3: 4,67). In second-choice preferences, a scale-based differentiation is observed: small and medium farms (Groups 1 and 2) tend to purchase goslings, whereas large farms (Group 3) place greater emphasis on purchasing young geese, with a mean score of 1,48 (Table 1).

Table 1. Goose production methods of the surveyed farms

Goose production method	Group 1		Group 2		Group 3		Overall	
	$\bar{x}$	SD.	$\bar{x}$	SD	$\bar{x}$	SD	$\bar{x}$	SD
Using breeder geese (natural incubation method)	4,76	,78627	4,83	,67511	4,67	,96609	4,78	,77966
Purchasing eggs	1,00	,00000	1,00	,00000	1,00	,00000	1,00	,00000
Purchasing goslings	1,31	,80638	1,23	,83166	1,24	,53896	1,26	,75790
Purchasing young geese (grower geese)	1,17	,53911	1,00	,00000	1,48	1,03049	1,17	,60429
Purchasing adult geese	1,14	,51576	1,03	,15811	1,14	,65465	1,09	,44075

Note:($\bar{x}$) mean score on a Likert scale (1)never, (2)very rarely, (3) sometimes, (4)quite often, (5) always; SD = standard deviation.

An examination of production motivation indicates that only a limited share of output is allocated to household consumption, while the primary share is marketed for commercial purposes. Producers supply their products as live geese, fresh carcasses, and dried carcasses using a traditional method. In terms of production and sales volume, fresh carcass goose ranks first, with 89,30 units produced and 76,50 units sold per farm. This is followed by dried carcasses (43,98 produced; 19,82 sold) and live geese (28,81 produced; 23,79 sold). Among by-products, offal (heart, gizzard, head, feet, etc.) holds the largest share with 42,10 kg produced and 12,01 kg sold, followed by goose feathers and liver production.

3.2. Production Costs and Relative Profitability Analysis in the Surveyed Farms

Production costs and relative profitability levels for live, fresh, and dried goose in the surveyed farms are presented in Table 2. An assessment of the cost structure in Kars province indicates an inverse relationship between farm size and unit cost. Calculations show that the average production cost per goose is 383,60 TL; however, this value varies widely by farm scale, ranging from 544,07 TL in Group 1 to 243,31 TL in Group 3. This finding demonstrates the clear functioning of economies of scale in goose farming and indicates that large-scale farms achieve a competitive advantage by reducing unit costs.

Structural analysis of production costs reflects the "traditional and family-oriented" character of goose farming in Kars. Within fixed costs, which account for approximately 58,41% of total expenses, family labor constitutes the largest share at 55,36%.

An examination of farms' financial structure indicates that the average variable cost per unit is 159,55 TL. Among these cost components, feed expenditures represent the highest share at 57,18%, followed by material (gosling) procurement at 15,58%. The remaining burden comprises heating (8,57%), litter (4,34%), and other operational expenditures (14,33%).

The dominance of feed costs (57,18%) within variable expenses is particularly noteworthy. The reduction in feed cost per goose from 114,08 TL to 69,04 TL as farm size increases suggests that large farms either adopt more rational procurement strategies or benefit from bulk purchasing advantages.

Data presented in Table 2 indicate that losses reach their highest level in the production of dried carcasses, which are a value-added product. This suggests that the labor- and time-intensive nature of traditional drying methods cannot be fully reflected in market prices. Relative profit ratios remaining below 1 across all groups (<1.00) indicate that, under current market prices, farms cannot achieve technically and economically efficient production; operations appear to persist largely because family labor is not perceived as a cash cost (i.e., it does not require direct cash outflow).

When examining the relationship between farm size and relative profit, it is observed that across all forms—live, fresh, and dried carcass—only large-capacity farms (Group 3) attain relatively higher relative profit ratios. Unlike small and medium farms (Groups 1 and 2), large farms appear to exhibit a more resilient cost structure in the face of market prices.

Table 2. Production cost of live, fresh, and dried goose in the surveyed farms

Cost İtems	Group 1	Group 2	Group 3	Overall
Material costs				
Goslings	26,00	25,00	23,00	24,86
Feed	114,08	86,31	69,04	91,23
Vitamins and Minerals	2,55	3,06	1,47	2,47
Total material costs (TL/head) (1)	142,63	114,37	93,51	118,56
Other costs				
Veterinary, medicines, vaccines, etc.	3,99	2,30	1,64	2,59
Bedding (litter) costs	14,17	6,81	4,64	6,92
Heating cost for the poultry house (wood, gas cylinder, etc.)	23,38	9,51	7,54	13,67
Electricity and water costs	5,30	2,90	2,55	3,57
Marketing costs (packaging, transportation to market)	7,96	4,48	2,34	4,57
Cost of transporting purchased feed to the farm (fuel, transportation charge, etc.)	8,28	4,80	2,33	5,32
Maintenance and repair costs of the poultry house	4,65	1,59	,82	2,26
Total other costs (TL/head) (2)	67,73	32,39	21,86	38,90
Interest charge on variable costs incurred (3) (1+2) X (1,33%)	2,80	1,95	1,53	2,09
Total variable costs (TL/head) (1+2+3) = (4)	213,16	148,71	116,90	159,55
Imputed value of family labor*	315,36	186,64	119,08	212,35
Depreciation of buildings (poultry house, etc.) and equipment	9,16	6,89	3,82	6,91
Management cost (4 X 3%)	6,39	4,46	3,51	4,79
Total fixed costs (TL/head) (5)	330,91	197,99	126,41	224,05
Total production costs (TL/head) (4+5) =(6)	544,07	346,70	243,31	383,60
Cost per kg calculations				
Average live weight (kg/head) (7)	4,54	4,61	4,86	4,65
Cost of 1 kg live goose (6/7) (8)	119,84	75,21	50,06	82,49
Average fresh carcass weight (kg/head) (9)	3,09	3,13	3,30	3,16
By-product revenue (liver, offal, feathers) (TL/head) (10)	24,42	19,36	40,96	26,07
Cost of 1 kg fresh goose ((6-10)/9) (11)	168,17	104,58	61,32	113,14
Average dried carcass weight (kg/head) (12)	2,62	2,66	2,81	2,69
Cost of 1 kg dried goose ((6-10)/12) (13)	198,34	123,06	72,01	132,91
Prices and unit profit				
Weighted average live goose price (TL/kg) (14)	30,35	30,51	30,66	30,61
Unit profit from live goose sales (TL/kg) (14-8) = (15)	-89,49	-44,69	-19,41	-51,88
Weighted average fresh goose price (TL/kg) (16)	38,83	45,64	49,49	46,65
Unit profit from fresh goose sales (TL/kg) (16-11) = (17)	-129,34	-58,94	-11,82	-66,50
Weighted average dried goose price (TL/kg) (18)	55,56	55,49	54,75	55,12
Unit profit from dried goose sales (TL/kg) (18-13) = (19)	-142,78	-67,57	-17,26	-77,79
Relative profit				
Relative profit for live goose (14/8)	0,25	0,41	0,61	0,37
Relative profit for fresh goose (16/11)	0,23	0,44	0,81	0,41
Relative profit for dried goose (18/13)	0,28	0,45	0,76	0,41

****Imputed value of family labor:** labor for feeding and care, grazing, cleaning the poultry house, labor for transporting purchased feed to the farm, slaughtering, and transportation to market.*

3.3. Input- and Output-Oriented Efficiency Analysis in the Surveyed Goose Farms

According to input- and output-based analyses, the average output-oriented efficiency score of goose farms is 81,29%. Efficiency in large farms (85,47%) is higher than in small (83,02%) and medium farms (77,84%) by 2,45 and 7,63 percentage points, respectively. The Kruskal–Wallis test indicates a statistically significant difference among farm groups at the 5% level (χ^2 = 6,159; p = 0,046) (Table 3).

When the distribution of efficiency scores is examined in 10% intervals, 25.56% of farms (23 farms) are found to be fully efficient. Regarding the distribution of fully efficient farms, 34.48% of small farms (10 farms), 12.50% of medium farms (5 farms), and 38.10% of large farms (8 farms) fall into this category. This indicates that large farms are particularly advantageous in terms of efficiency. Conversely, only one farm has an efficiency score below 50%, and this farm belongs to the small-farm group. This suggests that small farms generally exhibit greater variability in efficiency and possess higher potential for improvement (Figure 1).

Table 3. Efficiency scores obtained by farm groups

Farm groups		**Variable Returns to Scale (VRS) efficiency (output-oriented)**	**Variable Returns to Scale (VRS) efficiency (input-oriented)**
Group 1	N	29	29
	Mean	83,02	87,60
	Minimum	44,96	52,78
	Maximum	100,00	100,00
	Standard deviation	14,79148	12,78220
Group 2	N	40	40
	Mean	77,84	81,84
	Minimum	57,51	60,88
	Maximum	100,00	100,00
	Standard deviation	10,86329	11,31775
Group 3	N	21	21
	Mean	85,47	87,04
	Minimum	60,04	64,13
	Maximum	100,00	100,00
	Standard deviation	13,53607	12,95756

Overall	N	90	90
	Mean	81,29	84,91
	Minimum	44,96	52,78
	Maximum	100,00	100,00
	Standard deviation	13,12037	12,36621

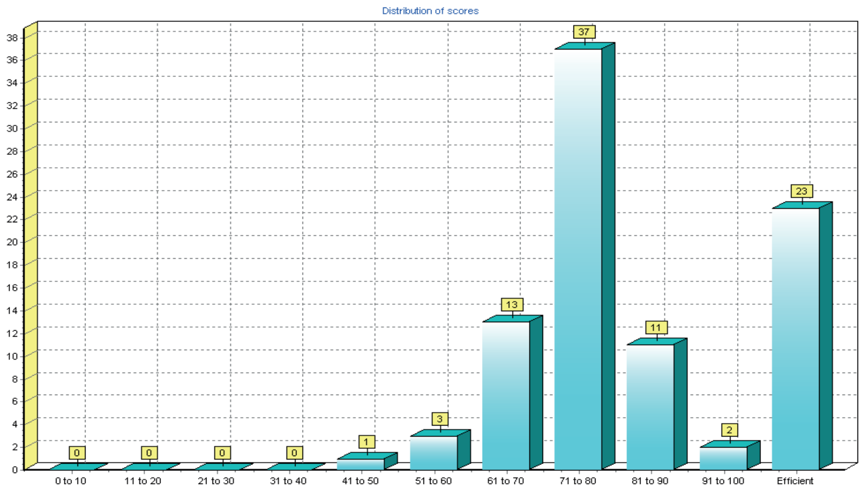

Figure 1. Distribution of farms' efficiency scores based on output-oriented efficiency.

In the input-oriented efficiency analysis, the average efficiency score of farms is calculated as 84,91%. This value is slightly higher than in the output-based analysis, and the efficiency levels of small (87,60%) and large farms (87,04%) are very close. By contrast, medium farms exhibit lower efficiency (81,84%). According to the Kruskal–Wallis test results, there is a statistically significant difference among farm groups at the 10% level (χ^2 = 5,626; p = 0,060) (Table 3).

As shown in Figure 2, the share of fully efficient farms in the input-oriented analysis is also 25,56% (23 farms). These farms also displayed full efficiency in the output-oriented analysis. The distribution of these fully efficient farms is 34,48% in small farms (10 farms), 12,50% in medium farms (5 farms), and 38,10% in large farms (8 farms). In addition, no farm exhibited an efficiency score below 50% in the input-oriented analysis, indicating a more balanced overall efficiency distribution.

When output- and input-oriented analyses are considered together, goose farms can generally be regarded as operating efficiently. While output-oriented efficiency is higher in large farms, input-oriented results indicate that small farms behave more frugally and reach similar efficiency levels. This may be explained by small farms meeting a greater share of their feed requirements from pasture.

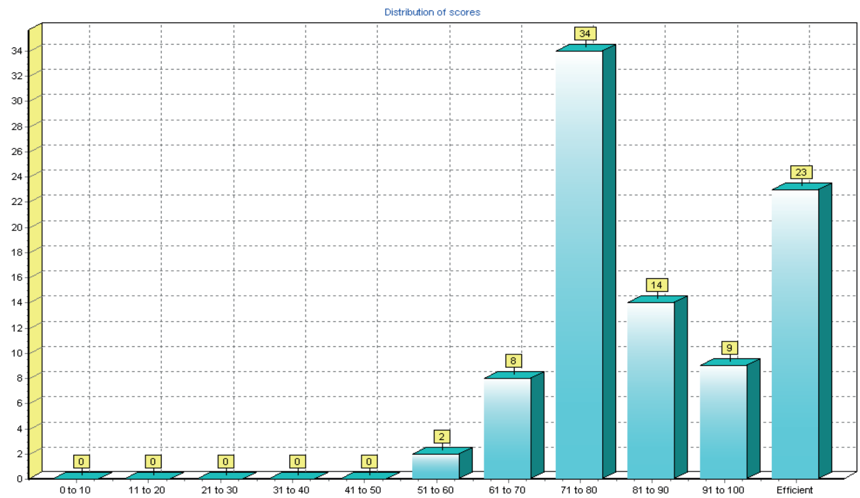

Figure 2. Distribution of farms' efficiency scores based on input-oriented efficiency.

The study also conducted potential improvement analyses for inefficient farms to achieve full efficiency. Under the VRS assumption, the output-oriented model suggests increasing gross production value by 21,86%, while reducing all other inputs. Reductions are particularly pronounced in feed (24,41%), labor (19,01%), and veterinary-medicine expenditures (21,88%). In the input-oriented analysis, holding gross production constant, reductions ranging between 10% and 23% are recommended for flock size, gosling cost, feed, labor, veterinary-medicine, and other expenditures (Table 4). Overall, farms aiming for full efficiency should particularly reduce feed, labor, and veterinary-medicine expenditures and improve the efficiency of production and marketing processes.

Table 4. Total potential improvement ratios required to make the surveyed goose farms efficient

Variables	Input-oriented potential improvement ratios	Output-oriented potential improvement ratios
	%	%
Gross Production Value (TL)	+0,09	+21,86
Flock size (head)	-9,97	-0,51
Gosling cost (TL)	-10,67	-2,74
Labor costs (TL)	-18,69	-19,01
Feed costs (TL)	-22,85	-24,41
Veterinary and medicine costs (TL)	-22,93	-21,88
Other costs (TL)	-14,80	-9,58

4. CONCLUSIONS AND RECOMMENDATIONS

This study aimed to analyze the input- and output-oriented efficiency of goose farms of different sizes in Kars province, one of the key centers of goose farming. The findings yielded important conclusions regarding both production costs and efficiency.

The results indicate that production cost per goose declines as farm scale increases, demonstrating the critical role of economies of scale in minimizing costs in the sector. However, when overall profitability indicators are considered, the fact that production costs exceed market prices across all forms—live, fresh, and dried carcasses—constitutes a fundamental challenge for the sustainability of the sector. The highest losses occurring in the production of dried carcasses, a high value-added product, suggest that the intensive labor and time costs required by traditional drying processes are not fully reflected in final sales prices. The observation that relative profit ratios improve only in large farms (Group 3) implies that economic rationality is feasible only with a certain production capacity and optimized input management.

Potential improvement projections derived from DEA indicate that inefficient farms have substantial scope to enhance performance through both input savings and output increases. Output-oriented analysis suggests that it is possible for farms to increase gross production value by 21,86% while maintaining current input levels. Conversely, input-oriented projections reveal that, holding production constant, feed expenditures could be reduced by 22,85%, veterinary-medicine costs by 22,93%, and labor costs by 18,69%. In both scenarios, the highest improvement potential is concentrated in feed and veterinary-medicine expenditures, indicating a need for professionalization in farms' technical management processes.

In conclusion, to strengthen the economic competitiveness of goose farming in Kars, a transition should be supported from micro-scale family farming toward professional farm structures that have completed modernization and can optimize input costs. To control major expense items such as feed and labor, the dissemination of rational feeding programs and cooperative organization to secure bulk purchasing advantages in input procurement are recommended. Moreover, Kars Goose Meat, which received a geographical indication (Protected Designation of Origin) registration on 03.10.2023 with registration number 1479, should be supported—particularly in dried carcass form—through an effective branding strategy. The legal protection and prestige provided by this registration should be leveraged as a catalyst for local producers, creating a market value that can cover high production costs and allow producers to realize a profit margin.

Various policy- and practice-level improvements are required to increase the sustainability and efficiency of goose farming. First, given the decisive role of feed costs in total production expenses, providing feed support particularly for small-scale farms and planning such support dynamically by production period are important. To reduce veterinary and medicine expenditures, preventive health services should be expanded and training activities focused on health and hygiene should be intensified. The family labor-based production structure creates an invisible workload and constrains efficiency; therefore, labor-sharing and joint equipment use through cooperatives should be encouraged. Furthermore, investment in regional processing facilities is needed to render by-products with high economic potential—such as goose liver and feathers—processable for industry. In particular, the export value of goose liver for European and Far Eastern markets should be evaluated.

The use of technological tools emerges as an important element for production efficiency. Low productivity of local geese makes technological equipment such as incubators decisive for flock size. Indeed, producers in regional studies have reported difficulties in storing eggs under appropriate temperature and humidity conditions, leading to increased losses during incubation. Accordingly, a growing tendency to shift toward commercial breeds (Linda, Chinese, Mast, Mamu, etc.) has been noted (Akın, 2024). Therefore, supporting producers' access to incubators, automatic feeding systems, and slaughter equipment is critical for increasing production capacity. Reflecting local consumption habits in production planning and developing alternative marketing models such as frozen goose products will also contribute to sectoral diversification. Additionally, since goose producers are not sufficiently informed about state supports and IPARD/TKDK incentives, extension activities should be intensified regionally and the promotion of these supports should be prioritized. Finally, scientific studies aimed at vaccination and treatment should be accelerated to combat epidemic diseases that threaten the sector, and compensation mechanisms that can be activated during crisis periods should be established to ensure producer security.

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Chapter 3

THE IMPACT OF DIGITALIZATION ON THE MARKETING OF AGRICULTURAL PRODUCTS IN TURKIYE

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1. INTRODUCTION

The marketing of agricultural products is not merely a complementary stage of the production process; it constitutes a strategic domain that directly affects the sustainability of producer incomes, the strengthening of rural welfare, and the assurance of food supply security. Increases in agricultural productivity alone are insufficient unless they are accompanied by efficient, transparent, and competitive marketing structures that enable producers to capture a fair share of the final value. Particularly in developing countries, the structural characteristics of value chains, the intensity of intermediaries, and information asymmetries often limit producers' share of final consumer prices (Reardon et al., 2003).

In traditional marketing systems characterized by limited access to information, producers frequently make decisions under incomplete knowledge regarding market prices and demand conditions. Digital communication technologies, however, have been shown to accelerate information flows, enhance market integration, and improve marketing efficiency (Aker, 2011). In the context of Türkiye, access to information and the level of producer organization have similarly been identified as key determinants of marketing performance (Karadaş & Bulut, 2022). These findings suggest that digitalization holds the potential to address structural inefficiencies embedded in conventional agricultural marketing systems.

In recent years, digitalization has initiated a transformative process within agricultural marketing systems. Digital platforms, online marketplaces, and e-commerce applications reduce the spatial and informational distance between producers and consumers. Data-driven marketing strategies—supported by analytics, algorithm-based targeting, and consumer behavior analysis—enhance product visibility and sales performance (Yang et al., 2022). Smart marketing models, integrating consumer data analysis and logistics optimization, can generate competitive advantages in agricultural e-commerce environments (Ma & Zhang, 2022). In this respect, digitalization extends beyond technological infrastructure, encompassing the integration of data management, digital tools, and strategic marketing practices.

Social media platforms have also emerged as influential instruments in the digital marketing landscape. These user-interactive environments enable producers to establish direct communication with consumers and shape purchasing intentions through content-based marketing strategies (Kaplan & Haenlein, 2010; Song et al., 2023; Xi, 2025). Nevertheless, online marketing performance largely depends on digital capacity. As farmers' ability to effectively utilize digital tools increases, participation in online markets and sales performance tend to improve (Song et al., 2023). Empirical evidence further highlights a positive relationship between digital competence and online sales outcomes (Xi, 2025). This underscores that digital transformation is not solely a matter of technological investment but also of human capital development.

Access to higher value-added markets can positively affect producer profitability; however, these gains are contingent upon quality standards, organizational capacity, and market access conditions (Narayanan, 2014). Institutional innovations and strengthened coordination mechanisms within value chains are also recognized as critical factors enhancing marketing performance (Holloway et al., 2000). Moreover, structural drivers such as urbanization and rising incomes, which reshape consumption patterns, further transform agricultural marketing systems (Tschirley et al., 2015).

Although digital agricultural marketing practices have gained momentum in Türkiye in recent years, the transformation remains heterogeneous. Differences in infrastructure, levels of digital literacy, and the degree of producer organization lead to uneven digital adoption across regions and production scales. Therefore, digitalization should not be viewed merely as a shift in sales channels, but rather as a multidimensional transformation process affecting market structures, competitive dynamics, value distribution, and producer income allocation.

Against this backdrop, this study aims to analyze the impact of digitalization on the marketing of agricultural products from a comprehensive Turkish perspective. To structure this analysis, the chapter proposes a conceptual framework illustrating the transformation from traditional agricultural marketing systems to digitally integrated value chains, as illustrated in Figure 1. The chapter comparatively examines traditional marketing structures and digital marketing instruments, evaluates the economic, structural, and institutional implications of digital transformation, and discusses its effects on producer incomes, price formation, competition dynamics, and value chain organization. Furthermore, it proposes policy and strategic recommendations to enhance digital agricultural marketing practices in Türkiye within a sustainable and inclusive framework.

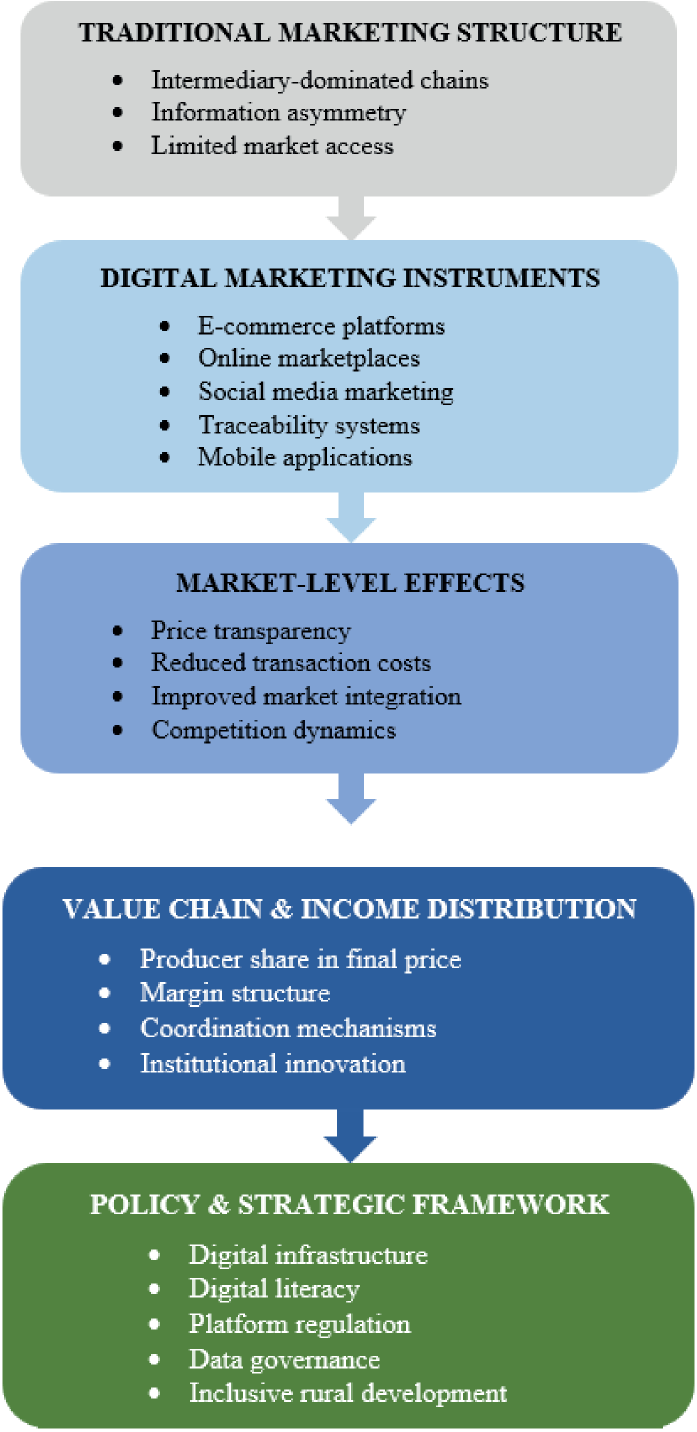

Figure 1. *Conceptual framework of digital transformation in agricultural marketing in Türkiye.*

The framework illustrates the structural transition from traditional marketing systems to digitally integrated value chains and highlights the market-level, distributional, and policy implications of digitalization.

2. TRADITIONAL STRUCTURE IN AGRICULTURAL MARKETING

Agricultural marketing encompasses a multi-stage value chain extending from the completion of production to the delivery of products to final consumers. This process involves interconnected activities such as collection, grading, storage, transportation, pricing, and retailing. Due to the biological nature of agricultural production, seasonality, and product perishability, marketing processes in agriculture are inherently more complex than in many other sectors (Shepherd, 2007).

In line with the first layer of the conceptual framework presented in Figure 1, the traditional agricultural marketing structure in Türkiye can be characterized by intermediary-dominated chains, information asymmetry, and limited market access. Particularly in fresh fruit and vegetable markets, the system typically operates through a multi-layered chain involving producers, commission agents, wholesalers, retailers, and consumers. The presence of numerous intermediaries increases transaction costs and often widens the gap between producer prices and consumer prices. The literature emphasizes that, in developing countries, value chain configurations and intermediary intensity significantly influence price formation mechanisms (Reardon et al., 2003). Empirical evidence from Türkiye similarly demonstrates that increases in the number of intermediaries can substantially expand the producer–consumer price margin (Karadaş & Bulut, 2022). Consequently, marketing margins may structurally widen, leading to a value distribution pattern that disadvantages producers within the value chain.

A further defining characteristic of this structure is the relative concentration and organization of buyers. In markets where numerous small-scale producers face a limited number of buyers, oligopsonistic market structures may emerge. Such configurations enhance the price-setting power of buyers while weakening producers' bargaining capacity. As a result, producers may be exposed to higher market risks and increased income volatility, particularly in environments where risk-sharing mechanisms are limited or underdeveloped.

Information asymmetry constitutes another fundamental weakness of traditional marketing systems. Producers frequently operate with limited knowledge of current market prices, demand trends, and consumer preferences. Similarly, consumers often lack sufficient information regarding production conditions and quality standards. This mutual information gap reduces overall market efficiency and constrains optimal decision-making (Aker, 2011). The persistence of such informational deficiencies further underscores the potential relevance of digital information systems as transformative instruments within agricultural markets.

Deficiencies in standardization and quality management also represent critical structural weaknesses. Inconsistencies in grading, packaging, and labeling practices negatively affect both price formation and consumer trust. The limited effectiveness of quality management systems and standardization mechanisms often leads to coordination failures across marketing channels, thereby reducing overall value chain performance.

In Türkiye, the predominance of small-scale agricultural enterprises further intensifies structural marketing challenges. Small producers frequently conduct storage, standardization, and marketing activities individually, limiting their ability to benefit from economies of scale. This structural constraint increases transaction costs, restricts bargaining power, and reinforces dependency on intermediaries. As a result, small-scale production structures may amplify pricing risks that operate to the disadvantage of producers.

Cooperative organization and producer associations offer potential mechanisms for strengthening collective marketing capacity and enhancing market integration. By acting collectively, small-scale producers may improve their negotiation power and achieve more favorable market conditions. However, the economic performance of cooperatives depends heavily on institutional design, governance quality, member participation, and professional management capacity (Bijman et al., 2016).

In summary, the traditional agricultural marketing structure in Türkiye exhibits several structural weaknesses, including high marketing margins, information asymmetry, insufficient standardization, and market configurations that tend to operate against producers' interests. These limitations increase the need for more transparent, data-driven, and producer-centered marketing models. In this context, digitalization should be considered not merely as a technological innovation, but as a potential structural and institutional transformation capable of reshaping value distribution, market coordination, and competitive dynamics within agricultural marketing systems.

3. DIGITAL AGRICULTURE AND DIGITAL MARKETING CONCEPT

Digital agriculture (often referred to as Agriculture 4.0) represents a data-driven approach to agricultural production and decision-making that emerges from the integration of information and communication technologies (ICT) into farming operations, management systems, and value chain processes. Core components of this transformation include sensor technologies, the Internet of Things (IoT), satellite imaging, big data analytics, and artificial intelligence–based decision-support systems (Wolfert et al., 2017). Through these technologies, agricultural production evolves from a predominantly physical set of activities into a measurable, analyzable, and optimizable system.

One of the most significant marketing-related outputs of digital agriculture is traceability. The systematic recording and processing of production data enable transparent communication regarding product origin, quality attributes, and production conditions. By reducing information asymmetry—one of the key structural weaknesses of traditional marketing systems—traceability mechanisms strengthen consumer trust and enhance the linkage between production and market stages (Treiblmaier, 2018). In this sense, digital agriculture provides the informational infrastructure upon which digitally enabled marketing systems can operate more efficiently.

Digital marketing, by contrast, refers to the systematic use of digital channels in the promotion, distribution, and sale of products and services. In the context of agricultural products, digital marketing is implemented through e-commerce platforms, online marketplaces, mobile applications, and social media channels. These instruments enable producers to overcome spatial and temporal constraints and establish direct interactions with consumers. As reflected in the second layer of the conceptual framework presented in Figure 1, digital marketing instruments function as operational mechanisms translating digital capabilities into market access.

Recent developments in agricultural e-commerce models indicate that digital marketing is not merely a new sales channel, but also an optimization process grounded in data analytics. Marketing strategies based on consumer behavior data have been shown to enhance sales performance and improve targeting efficiency (Yang et al., 2022). Similarly, smart marketing models that integrate logistics coordination and data processing systems contribute to improved supply–demand matching and enhanced marketing effectiveness (Ma & Zhang, 2022). These findings suggest that digital marketing represents an analytical and strategic function embedded within broader digital transformation processes.

Digital capacity and digital literacy constitute critical mediating factors between digital agriculture and digital marketing. As farmers' ability to utilize digital tools increases, participation in online sales channels and overall sales performance tend to improve. Empirical studies demonstrate that digital competence significantly influences online sales volumes, marketing channel choices, and strategic market positioning (Song et al., 2023; Xi, 2025; Zhang et al., 2025). These findings underscore that digital transformation is not limited to technological infrastructure investments but also requires sustained human capital development and skills enhancement.

Consumer engagement represents another essential dimension of digital marketing. Social media platforms, characterized by interactive and user-generated environments, allow producers to construct brand narratives and respond to consumer feedback in real time (Kaplan & Haenlein, 2010). Content-based marketing strategies in agricultural products can enhance consumer trust and purchasing intentions, signaling a shift from purely price-driven competition toward experience- and trust-based marketing dynamics (Song et al., 2023). This evolution reflects broader structural changes in how value is created and perceived within agricultural markets.

However, the perishable nature of agricultural products and the heterogeneity of quality standards necessitate that digital marketing strategies be designed in conjunction with logistics infrastructure and quality management systems. The effectiveness of e-commerce applications is closely linked to cold chain systems, delivery reliability, standardization practices, and physical distribution efficiency (Shepherd, 2007). Therefore, digital agriculture and digital marketing should be conceptualized as components of an integrated system in which data generation, logistics coordination, and quality assurance mechanisms operate cohesively.

In summary, digital agriculture renders production processes data-driven and technologically enhanced, while digital marketing provides the instrumental and strategic toolkit that converts this data into economic value. Together, these complementary transformation processes enable the restructuring of agricultural value chains. Nevertheless, the sustainability of this transformation depends on the coordinated development of digital infrastructure, human capital, institutional regulation, and logistics integration. Digitalization should therefore be understood not as a standalone technological shift, but as a systemic transformation reshaping production–market linkages and value creation mechanisms in agricultural marketing systems.

4. DIGITAL MARKETING TOOLS IN AGRICULTURAL PRODUCT MARKETING

Digitalization has diversified the tools and methods used in agricultural product marketing, leading to the restructuring of marketing processes. Digital tools accelerate information flow, increase market transparency, and reduce the distance between producers and consumers. However, the effectiveness of these tools is closely related to producers' digital capacity and institutional infrastructure (Song et al., 2023).

4.1. E-Commerce and Online Sales Channels

E-commerce is one of the most common digital marketing tools, enabling producers to offer their products directly to consumers or institutional buyers. Online sales channels shorten the marketing chain, reduce information asymmetry, and positively impact producer income performance (Aker, 2011; Xi, 2025). Big data–supported smart e-commerce models optimize demand forecasting and inventory management, thereby improving sales performance (Ma & Zhang, 2022; Yang et al., 2022). However, due to the perishable nature of agricultural products, the success of e-commerce is directly linked to logistics organization and cold chain capacity (Shepherd, 2007).

Agricultural e-commerce applications not only transform distribution channels but also introduce new models in pricing and sales strategies. Pre-sale applications, in particular, have been shown to reduce demand uncertainty and contribute to price optimization, helping producers manage marketing risks (Xiao et al., 2025).

4.2. Digital Marketplaces and Platform Economy

Digital marketplaces are online trading environments where multiple producers and buyers meet on the same platform. These platforms increase price transparency and facilitate easier access to product information (Varian, 2018). However, the platform economy also creates new cost elements, such as commissions and service fees. Access to these platforms for small-scale producers is often limited due to technical and financial constraints, highlighting the importance of cooperative-based collective marketing models (Bijman et al., 2016).

4.3. Social Media and Digital Promotion

Social media allows producers to share product stories and receive real-time consumer feedback (Kaplan & Haenlein, 2010). Content marketing, particularly in strengthening trust and quality perception, plays a critical role (Song et al., 2023). In Türkiye, studies have shown that Instagram stands out in promoting organic agricultural products (Kara, 2018). However, the effective use of social media tools depends on producers' digital literacy and content production capacity (Xi, 2025).

4.4. Traceability and Digital Information Systems

Traceability systems allow the digital recording of all processes from production to consumption. These systems enhance consumer trust and strengthen market transparency (Treiblmaier, 2018). In particular, traceability in high-value and organic products creates a significant competitive advantage. Moreover, traceability systems facilitate monitoring and food safety processes for public authorities (Klerkx et al., 2019).

4.5. Mobile Applications and Digital Information Sharing

Mobile applications facilitate producers' access to market prices, weather data, and demand conditions, thereby easing decision-making processes (Aker, 2011). These systems strengthen market integration, though their effectiveness is dependent on digital literacy and infrastructure (Song et al., 2023).

4.6. Holistic Digital Integration

When used not in isolation but as an integrated system, digital marketing tools produce stronger outcomes. Data-driven production, digital platforms, logistics integration, and consumer feedback collectively enhance the efficiency of the marketing chain (Wolfert et al., 2017). However, the realization of this potential depends on simultaneous development in infrastructure investments, education, and institutional regulations (Klerkx et al., 2019).

5. THE IMPACT OF DIGITALIZATION ON AGRICULTURAL MARKETING

Digitalization is transforming not only the tools used in agricultural marketing but also the market structure, price formation mechanisms, competition dynamics, and the functioning of value chains. Digital platforms accelerate information flow, strengthen producer–consumer interactions, and facilitate more data-driven marketing processes (Wolfert et al., 2017; Varian, 2018).

5.1. Producer Incomes

Digital marketing channels allow producers to sell through shorter marketing chains, reducing information asymmetry and potentially increasing income performance (Aker, 2011). Empirical studies show that producers with higher digital capacity achieve higher online sales volumes and income levels (Xi, 2025; Song et al., 2023). Digitalization also affects the distribution of economic value within the value chain. Digital empowerment has been shown to transform value-sharing mechanisms during the commercialization process, strengthening producers' positions within the value chain (Zhan & Jin, 2024).

However, income growth is not automatic for all producers. Producers with lower digital literacy and access to infrastructure benefit less from this process, while organized and technology-equipped producers tend to be in more advantageous positions (Bijman et al., 2016). Therefore, digitalization presents both opportunities and risks in terms of income inequality among producers.

5.2. Marketing Margins

Digital platforms have the potential to reduce the number of intermediaries by increasing direct interactions between producers and consumers (Reardon et al., 2003). However, platform commissions, logistics, and digital service costs create new expenditure items. It has been shown that data-driven e-commerce models can reduce total marketing costs, although platform fees remain an important cost component (Ma & Zhang, 2022). Thus, rather than eliminating marketing margins, digitalization is restructuring them.

5.3. Price Formation and Transparency

Digital platforms and mobile applications enable the instantaneous sharing of price information, increasing market transparency (Aker, 2011). This contributes to more rational production and sales decisions by producers and more informed consumer choices. However, increased transparency may also exacerbate short-term price volatility. In particular, sudden demand changes in perishable products can amplify price fluctuations (Shepherd, 2007). Therefore, the effects of digitalization on price mechanisms should be assessed alongside regulatory frameworks.

5.4. Competition and Platform Concentration

Digitalization reduces barriers to market entry, facilitating access for more producers to markets (Reardon et al., 2003). However, the dominance of large digital platforms may lead to weakened competition and the concentration of market power in certain actors (Porter, 2008). In the context of Türkiye, cooperative-based and government-supported digital marketplaces have the potential to mitigate platform concentration risks (Bijman et al., 2016).

5.5. Consumer Behavior

Digital marketing tools enable consumers to access more and more detailed information about products. Transparent and verifiable information presentation increases consumer trust, thereby positively influencing purchasing intentions (Mangold & Faulds, 2009). Experience-based digital environments and social media content can especially influence perception and trust levels in organic and value-added products (Dertli & Dertli, 2023). Moreover, it has been shown that digital marketing applications also play a role in the formation of sustainable consumption behaviors (Zia & Alzahrani, 2022).

These developments contribute to the evolution of agricultural product demand from a price-focused to a multifaceted structure centered on quality, trust, and sustainability.

5.6. Value Chain and Sustainability

Traceability systems and data analytics have the potential to improve production planning, enhance resource-use efficiency, and reduce waste (Klerkx et al., 2019). Big data-supported e-commerce models can strengthen demand forecasting and reduce overproduction and stock losses (Ma & Zhang, 2022). The effects of digitalization are not limited to economic efficiency.

Empirical studies have demonstrated that agricultural digitalization has significant and positive effects on green development indicators (Meng & Li, 2025). Therefore, digitalization is a strategic tool capable of transforming both economic and environmental performance within agricultural value chains.

Digitalization has not only diversified the tools used in agricultural marketing but has also transformed the market structure, price formation mechanisms, competition dynamics, and the operation of value chains. Digital platforms accelerate information flow, strengthen producer–consumer interactions, and enable more data-driven marketing processes (Wolfert et al., 2017; Varian, 2018).

Therefore, digitalization must be viewed as a comprehensive transformation process, affecting both technological innovations and the economic and institutional dimensions of agricultural marketing. As discussed in this chapter, digitalization creates new opportunities for producer incomes, but also introduces risks related to digital inequality. It restructures marketing margins, enhances market transparency, and reduces the number of intermediaries, while also increasing short-term price volatility. Furthermore, digitalization expands competition but may lead to platform concentration risks, particularly for smaller-scale producers. Finally, digital marketing tools have shifted consumer behavior towards a trust- and quality-based decision-making process, moving beyond a price-focused structure.

Thus, digitalization is not merely a technological innovation but represents a multi-dimensional transformation that spans economic, institutional, and market changes.

6. DIGITAL AGRICULTURAL MARKETING APPLICATIONS IN TURKIYE

Digitalization in the marketing of agricultural products has gained momentum in recent years in Türkiye. Public policies, producer organizations, and private sector initiatives have contributed to the development of digital marketing infrastructure. However, the impacts of digital transformation exhibit a heterogeneous pattern due to regional infrastructure disparities, digital capacity, and organizational levels (Klerkx et al., 2019).

6.1. Digital Marketplaces and E-Commerce

In Türkiye, online sales platforms enable producers to offer their products directly to consumers or institutional buyers, shortening the marketing chain (Reardon et al., 2003). The use of digital sales channels has increased, particularly for organic, local, and geographically indicated products in major cities. However, platform commissions and logistics costs can limit producer profitability. In rural areas, inadequate internet infrastructure and distribution capacity are significant factors limiting the widespread adoption of digital marketing (Song et al., 2023).

6.2. Public-Sector Supported Digital Information Systems

Public institutions have developed digital information systems for market prices and production data, supporting producers' decision-making processes. These systems facilitate price tracking and increase market transparency (Aker, 2011). However, the effective use of this data depends on the digital literacy levels of producers. Digital capacity disparities may limit the equitable use of these systems among producers (Xi, 2025).

6.3. Digitalization of Cooperatives

Cooperatives and producer associations play a significant role in the integration of small-scale producers into digital markets. Collective marketing practices facilitate the exploitation of economies of scale, enhancing producers' bargaining power (Bijman et al., 2016). However, the lack of digital infrastructure and qualified human resources limits the widespread adoption of digital cooperative models (Klerkx et al., 2019).

6.4. Social Media-Based Marketing

In Türkiye, social media has become an essential marketing tool, especially in promoting organic and local products. Content analyses show that visual-oriented posts increase consumer trust, with Instagram emerging as a leading platform for agricultural product promotion (Kara, 2018). However, the effectiveness of social media marketing depends on producers' digital literacy and content production capacity (Xi, 2025).

6.5. Traceability and Digital Certification

QR-coded labels and digital certification systems have become increasingly common, particularly for organic and geographically indicated products. These applications facilitate consumers' access to information regarding product origin and production conditions, thereby enhancing trust (Treiblmaier, 2018). Moreover, traceability systems have the potential to enhance the effectiveness of public sector oversight processes (Klerkx et al., 2019).

6.6. Value Chain and Sustainability

Although still in its early stages, experience-based digital environments such as the metaverse are being explored as a new avenue in agricultural marketing in Türkiye. Digital experiences, particularly for organic products, are noted to positively influence consumer trust and purchase intentions (Dertli & Dertli, 2023). However, these applications have yet to reach widespread adoption.

General Assessment

While significant progress has been made in digital agricultural marketing applications in Türkiye, a homogeneous and inclusive structure has not yet been achieved. The current situation can be summarized as follows:

- E-commerce is widespread in large cities but limited in rural areas.
- Public information systems are available, but usage capacity varies.
- Cooperative digitalization is developing but insufficient.
- Social media marketing is effective.
- Traceability applications are on the rise.
- Digital literacy and logistics infrastructure are key limiting factors.

Therefore, for digitalization to become sustainable and inclusive, it is essential to strengthen infrastructure investments, educational programs, and institutional coordination.

7. CHALLENGES AND LIMITATIONS IN DIGITAL AGRICULTURAL MARKETING

While digitalization offers significant opportunities in agricultural marketing, the successful and inclusive implementation of this transformation depends on various structural and institutional limitations. These limitations are not limited to technical infrastructure; they span multiple dimensions, including human capital, production scale, logistics capacity, market regulations, and data management (Klerkx et al., 2019).

7.1. Digital Infrastructure and Access Issues

The fundamental prerequisite for digital marketing is a reliable and widespread internet infrastructure. In Türkiye, especially in rural areas, the quality and continuity of internet access vary regionally, which can limit producers' participation in online markets (Song et al., 2023). The infrastructure problem is not only about internet access but also about access to appropriate devices and software. Small-scale and low-income producers, in particular, may find themselves at a disadvantage in accessing digital systems (Xi, 2025).

7.2. Digital Literacy and Human Capital

Effective use of digital tools requires skills not only to access information but also to evaluate and apply it. Research has shown that internet access alone is not sufficient; digital literacy is one of the key factors determining sales performance (Song et al., 2023). In Türkiye, the limited digital skill levels among older producers slow the widespread adoption of digital marketing.

Furthermore, the lack of qualified digital experts in cooperatives represents a significant structural limitation (Bijman et al., 2016).

7.3. Scale Issues and Disadvantages of Small Producers

The small scale of agricultural enterprises in Türkiye makes it difficult to integrate them into digital marketing systems. Packaging, standardization, logistics organization, and platform commissions create additional cost burdens for small producers (Reardon et al., 2003). While digital platforms become more accessible and profitable for producers who can take advantage of economies of scale, small producers risk being excluded from the system. This highlights the potential of digitalization to deepen existing inequalities (Klerkx et al., 2019).

7.4. Logistics and Physical Distribution Constraints

The online marketing of agricultural products requires a robust logistics infrastructure. Especially for perishable products, inadequate cold chain capacity, delayed delivery times, and high transportation costs limit the effectiveness of digital marketing (Shepherd, 2007). Logistics constraints not only increase costs but also affect consumer satisfaction and trust in platforms. Therefore, digital marketing strategies must be considered alongside physical distribution planning.

7.5. Market Regulations and Institutional Framework

For digital agricultural marketing to operate effectively, a suitable legal and institutional framework is required. Uncertainties regarding platform transparency, data security, consumer rights, and competition regulations can undermine market trust (Porter, 2008). Moreover, the dominance of large digital platforms can lead to reduced competition and the concentration of market power in specific actors. This makes it necessary to regulate digital platforms within the framework of competition and transparency principles.

7.6. Data Management and Privacy Issues

Digital agricultural and marketing systems rely on intensive data generation. However, uncertainties about who collects the data, how it is used, and who it is shared with can create distrust among producers (Treiblmaier, 2018). Additionally, insufficient data standardization makes it difficult to integrate different platforms and limits inter-system coordination. Therefore, developing national data standards is critical (Klerkx et al., 2019).

General Assessment

Digital agricultural marketing is not a tool that can independently solve existing marketing problems. For an effective digital transformation, the following are essential:

- Strengthening rural digital infrastructure,
- Improving digital literacy levels among producers,
- Supporting the integration of small producers into digital platforms,
- Expanding investments in logistics and cold chain systems,
- Regulating digital platforms within competition and transparency frameworks,
- Ensuring data security and standardization.

In this regard, digitalization should be considered not only as a technological innovation but as a comprehensive transformation process that involves economic, institutional, and social dimensions.

8. POLICY AND STRATEGY RECOMMENDATIONS FOR DIGITAL AGRICULTURAL MARKETING DEVELOPMENT

In order for digital agricultural marketing in Türkiye to develop sustainably and inclusively, comprehensive and multi-stakeholder policy approaches are required. Digital transformation should be addressed in conjunction with rural development, income stability, and food supply security objectives (Klerkx et al., 2019). Accordingly, policy recommendations are concentrated in the following key areas.

8.1. Strengthening Rural Digital Infrastructure

Reliable internet access is a fundamental prerequisite for the widespread adoption of digital marketing. In rural areas of Türkiye, infrastructure deficiencies limit producers' access to online markets (Song et al., 2023). Therefore, the following actions should be prioritized:

- Expansion of rural fiber and mobile internet infrastructure,
- Establishment of agriculture-focused digital access centers,
- Support for affordable access to hardware and software.

Digital infrastructure investments should not be seen merely as a technical necessity, but as a critical component of modernizing agricultural marketing systems (Varian, 2018).

8.2. Digital Literacy and Capacity Building

Effective use of digital tools requires more than just access; it necessitates the ability to acquire, evaluate, and apply information. Research indicates that internet access alone is insufficient; digital literacy is one of the key factors determining sales performance (Song et al., 2023). In Türkiye, the limited digital skill levels among older producers slow the adoption of digital marketing. Additionally, the lack of qualified digital experts in cooperatives represents a significant structural limitation (Bijman et al., 2016). To address this, the following measures should be taken:

- Implementation of practical farmer training programs,
- Introduction of digital management modules for cooperatives,
- Expansion of e-commerce support for young farmers.

Furthermore, integrating agricultural consultancy services with digital marketing processes will accelerate adoption (Xi, 2025).

8.3. Cooperative-Based Collective Digital Marketing

Cooperatives play a critical role in integrating small-scale producers into digital markets. Collective marketing practices facilitate the exploitation of economies of scale, thereby enhancing producers' bargaining power (Bijman et al., 2016). In this context:

- Establishment of shared e-commerce platforms,
- Provision of digital infrastructure grants to cooperatives,
- Operation of digital logistics centers through cooperatives can help reduce the cost disadvantages faced by small producers.

8.4. Regulation of Digital Platforms and Competition Policies

For digital agricultural marketing to function effectively, it requires a suitable legal and institutional framework. Platform transparency, data security, consumer rights, and competition regulations are crucial to ensuring market trust (Porter, 2008). However, the dominance of large digital platforms can reduce competition and lead to the concentration of market power in certain actors. Therefore, the following actions should be taken:

- Transparent disclosure of platform commissions,
- Strengthening competition oversight to prevent monopolization,
- Updating consumer protection regulations covering the digital market.

8.5. Strengthening Logistics and Cold Chain Infrastructure

The success of digital marketing relies heavily on physical distribution infrastructure. Cold chain deficiencies and high transportation costs limit the effectiveness of online sales, particularly for perishable products (Shepherd, 2007). Therefore, the following steps are necessary:

- Increasing the number of regional cold storage facilities,
- Developing integrated logistics solutions with digital platforms,

- Strengthening public-private sector cooperation.

8.6. Expanding Traceability and Digital Certification

Traceability systems enhance consumer trust by providing transparent information about product origin and production conditions (Treiblmaier, 2018). Digital certification, particularly for organic and geographically indicated products, provides a significant competitive advantage. Therefore:

- National traceability standards should be established,
- Digital certification should be encouraged,
- Publicly supported data platforms should be developed (Klerkx et al., 2019).

8.7. Clarifying Data Management and Security Frameworks

Digital agriculture is data-driven. Therefore, transparent regulations regarding data ownership and usage are essential (Treiblmaier, 2018). In this regard:

- National data standards should be established,
- Legal regulations to protect producers' data should be strengthened,
- Data sharing protocols between platforms should be created (Klerkx et al., 2019).

General Strategic Framework

Digital agricultural marketing should be approached within a long-term and integrated strategy rather than as short-term projects. Infrastructure, education, cooperativism, logistics, and regulatory policies should be designed as complementary components. This transformation must be carried out in alignment with:

- Rural development,
- Income stability,
- Food supply security,
- Sustainable production objectives.

In conclusion, digitalization is not merely a technological innovation but a comprehensive transformation process that involves the economic, institutional, and social reorganization of agricultural marketing systems.

9. CONCLUSION

This study has provided a comprehensive analysis of the impact of digitalization on agricultural product marketing within the context of

Türkiye. The structural issues of traditional agricultural marketing systems—such as intermediary intensity, information asymmetry, and high marketing margins—have been highlighted, and the ways in which digital transformation reshapes these structures have been analyzed (Reardon et al., 2003).

Digital agriculture applications have rendered production processes data-driven, while digital marketing tools have created new value chain structures that convert this data into economic value. Traceability systems, e-commerce platforms, and digital content marketing are reducing information asymmetry, increasing market transparency, and redefining producer-consumer interactions (Wolfert et al., 2017; Treiblmaier, 2018).

However, the findings show that digitalization does not automatically guarantee equitable income growth. Digital capacity, infrastructure access, and organizational level are the primary determinants of the benefits producers derive from digital markets (Song et al., 2023; Xi, 2025). This indicates that digitalization is a dual transformation process, offering both opportunities and risks of inequality.

In terms of marketing margins and price formation, digitalization partially reduces dependency on intermediaries; however, it introduces new cost factors such as platform commissions and logistics costs (Ma & Zhang, 2022). While increased market transparency rationalizes decision-making processes, new risks, such as increased price volatility—particularly for perishable products—may arise (Aker, 2011; Shepherd, 2007).

Although digital agricultural marketing applications in Türkiye have shown significant progress, regional infrastructure disparities, inequalities in digital literacy levels, and the small-scale nature of many businesses limit the inclusiveness of the transformation (Klerkx et al., 2019; Bijman et al., 2016).

In this context, the policy approach recommended in this study requires simultaneous progress in the following key areas:

- Strengthening rural digital infrastructure,
- Developing digital literacy and producer capacity,
- Supporting cooperative-based collective marketing models,
- Regulating digital platforms according to competition and transparency principles,
- Strengthening logistics and cold chain infrastructure.

Furthermore, traceability systems and data management are strategically important not only for marketing effectiveness but also for food safety and sustainable production goals (Treiblmaier, 2018; Klerkx et al., 2019).

In conclusion, digital agricultural marketing is a powerful tool with the potential to transform Türkiye's agricultural value chain. However, realizing this potential requires not only technological investments but also institutional coordination, an organized production structure, and inclusive policy designs. Therefore, digitalization should be viewed not merely as an innovation that increases economic efficiency but as a strategic transformation area integrated with rural development, income stability, and sustainable production goals.

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Chapter 4

THE ROLE OF OSMOPROTECTANTS IN PLANTS UNDER ABIOTIC STRESS CONDITIONS

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1. Introduction

Fossil fuel consumption, land use changes (deforestation), and the concentration of greenhouse gases such as carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) in the atmosphere have resulted in an increase of approximately 1.0 °C increase in global surface temperatures, and current projections predict that this warming trend will intensify in the coming decades (IPCC, 2021).

Climate change caused by global warming is associated with irregularities in temperature regimes, changes in precipitation patterns, and an increase in extreme weather events. These changes have negative effects on plant growth and crop yields (Janni et al., 2024). Furthermore, climatic anomalies are reported to cause temporal shifts in the phenological stages of plants (flowering, fruit setting, etc.), disrupting the balance of crop production (İkinci, 2025).

Plants are exposed to unfavorable and stressful environments that are constantly changing during their growth and development periods. Conditions that negatively affect plant growth and development, reducing product quality, quantity, and yield, are defined as stress (Wang et al., 2000) and are divided into two main categories: biotic and abiotic (Suzuki et al., 2014).

Abiotic Stress Factors: Non-living environmental factors such as temperature (high/low), drought, salinity, heavy metal pollution, radiation waves, soil pH level, flooding, and gaseous pollutants (ozone (O_3), sulfur dioxide (SO_2)).

Biotic Stress Factors: Living organisms such as pathogens (viruses, bacteria, fungi), pests, human damage, and herbivorous animals.

Drought, salinity, and high temperature stresses, which are among the most important environmental factors limiting agricultural productivity and directly threatening food security, are fundamental parameters that determine the geographical distribution and ecological function of plants. The effects of these stress factors are increasing due to the impact of climate change (Fedoroff et al., 2010).

Drought is defined as a situation where there is insufficient water in the soil due to rainfall amounts falling below normal levels, resulting in a slowdown or stopping of plant growth and development processes (Yüksel & Aksoy, 2017). It is reported that more than 45% of the world's agricultural land is affected by continuous or repetitive drought events, and this rate is increasing every year (Ashraf & Foolad, 2007). The uneven distribution of rainfall caused by global climate change and the wrong use of water resources increase the frequency and severity of drought in many regions (Bacon 2004). The severity of global drought is predicted to increase in the coming years, affecting more than 50% of cultivable land by 2050 and posing significant challenges, particularly for crop production (Gu et al., 2024; Kasim et al., 2012).

In addition to geological processes, soil salinity resulting from anthropogenic processes such as inappropriate irrigation strategies, inadequate drainage systems, industrial activities, accumulation of organic waste, fossil fuel consumption, and energy production is becoming increasingly noticeable each year due to factors such as drought and temperature, threatening food security by reducing agricultural production. (Singh et al., 2015). Soil salinity occurs in approximately 30% of irrigated agricultural production areas due to excessive fertilizer use, poorly managed agricultural practices, and the application of intensive farming techniques. However, soil salinity primarily results from the accumulation of water-soluble salts (sodium (Na^+), potassium (K^+), chloride (Cl^-), and sulfate (SO_4^{2-})) in the plant's root zone (Balasubramaniam et al., 2023).

Soil salinity, which has been increasing in recent years due to the effects of climate change, is estimated to reduce agricultural production yields by 30% and, if effective preventive measures are not taken, this rate of degeneration could exceed 50% by 2050 (Yan et al., 2003; Wang et al., 2008).

Plant cellular functions undergo significant changes due to the effects of various abiotic stress factors to which they are exposed. Among these changes are organic compounds defined in the literature as osmolytes or osmoprotectants, which are highly soluble, low molecular weight, electrically neutral, and non-toxic. These compounds are naturally synthesized and accumulated in plant cells and play an important role in plant development by providing adaptation under various adverse environmental conditions by maintaining cell turgor pressure and redox balance and reducing reactive oxygen species (ROS) (Zulfiqar et al., 2020).

This section focuses on the effects of drought and salinity stress on plants, evaluating the morphological, characteristic, and biochemical changes that occur in plants under stress conditions, as well as the roles of osmolytes such as proline, glycine betaine, and mannitol in plant defense properties.

2. The Effects of Drought and Salinity Stress on Plants

Drought, especially in arid and semi-arid ecosystems, ranks among the most important environmental stress factors limiting global agricultural production. It is generally related to rainfall duration and intensity, but is also influenced by climatic factors such as temperature, low relative humidity, and winds. Water shortage is considered a major problem in agricultural production, and the negative effects of drought stress generally appear throughout all stages of plant development, from planting to harvest (Iwuala et al. 2019).

In the first stage of drought stress, plants tend to accelerate root development to increase access to limited water resources and nutrients, while simultaneously slowing down stem growth (Yüksel & Aksoy, 2017). However, a suberinization (mushrooming)-like tissue layer is observed on plant root surfaces to protect the underlying living cells from the destructive effects of drought (Çırak & Esendal, 2006).

Drought negatively affects plant root development and nutrient uptake by limiting the mobility of nutrients in the soil structure; this situation requires the reorganization of mineral element accumulation in plant tissues (Luo et al., 2011).

In plants under water stress, water loss through transpiration on leaf surfaces exceeds the amount of water absorbed by the plant, leading to the onset of drought stress effects. As a result, there is a decrease in turgor pressure, closure of stomata, and reductions in photosynthesis rate, stomatal conductance, and growth and development parameters (Anjum et al., 2011).

In advanced stages of drought, leaves curl, chlorosis (yellowing) occurs, and permanent wilting points are reached (Seleiman et al., 2021), leading to a complete halt in photosynthesis, disruption of metabolic balance, and plant death (İpek, 2015).

Along with drought, there is a slowdown in transpiration rate and in the diffusion rate of plant nutrients between the soil matrix and root surface, and consequently, a decrease in the efficiency of nutrient uptake by the roots (Aroca 2012). As a result, photosynthesis rate decreases, leading to yield and quality losses in the crop (Kaçar et al., 2006; Özen & Onay, 2007; Sahin et al., 2016).

Salt stress occurs when soluble salts such as Na^+ or Cl^-, which are present in high amounts in the soil, are absorbed by salt-sensitive plants (glycophytes) and accumulate in a toxic manner in plant tissues and/or organs (Shahzad et al., 2019). and creates osmotic stress that reduces the amount of water available to plants in the short term, causing damage at the cellular, organ, and whole plant levels (Muchate et al., 2016).

Two main problems occur in plants under salt stress. First, the plant's water uptake from the soil becomes difficult due to low (negative) osmotic potential (physiological drought). Second, ion toxicity occurs due to the accumulation of excessive amounts of sodium (Na^+), carbonate (CO_3^{2-}), and chloride (Cl^-) ions in the cytoplasm (Korkmaz & Durmaz, 2017).

Salt stress disrupts the cellular ion balance in plants and, as a result, negatively affects many metabolic processes such as photosynthesis, cell division, and growth, thereby limiting the plant's growth and development.

Furthermore, it causes photosynthetic pigments such as chlorophyll and carotenoids, thylakoid membrane proteins, membrane lipids, and various enzymes involved in the photosynthetic processes of plants to lose their functionality (Hao et al., 2021).

Toxic salt ions such as Na^+ and Cl^-, which cause salinity, disrupt the permeability and selectivity of cell membranes in plant roots or compete with nutrient elements, thereby preventing the plant from absorbing the water and essential nutrients it needs from the soil, leading to water and nutrient deficiency or imbalance in the plant (Muchate et al., 2016; Parihar et al., 2015). As a result, dehydration and turgor loss occur in plant leaves, leading to death in leaf cells and tissues (Isayenkov, 2012). In addition, osmotic stress and ion toxicity delay the germination of plant seeds, causing reductions in germination rate, germination speed, and root and shoot elongation (Ibrahim, 2016).

Salt stress triggers the formation of ROS such as superoxide radical (O_2^-), singlet oxygen ($^1O_2$), hydrogen peroxide (H_2O_2), and hydroxyl radical (OH^-), which are reactively present in the normal metabolic process of plants (Shahzad et al., 2019). An increase in ROS is observed with salinity, causing oxidative damage to the structure of various cellular components such as proteins, lipids, and nucleic acids, threatening plant life (Singh et al., 2015).

In plants growing in saline soils, leaf water potential, osmotic potential, turgor pressure, and transpiration rate decrease. Due to this osmotic stress, plant stomata close, inhibiting CO_2 diffusion and leading to disruption of photosynthetic processes and an increase in ROS (Munns, 2002; Shahzad et al., 2019).

3. Physiological and Biochemical Changes in Plants Caused by Drought and Salinity Stress

Abiotic stress factors such as drought and salinity trigger a series of complex signal transduction mechanisms in plants at the physiological, biochemical, and molecular levels. In response to these stress conditions, plants develop various adaptation strategies to survive under changing environmental conditions and maintain homeostasis. Under drought stress, plants adapt by regulating their morphological structure, growth rates, and osmotic potentials. This adaptation process also involves critical physicochemical changes, such as the improvement of the plant's defense systems (Duan et al., 2007).

When drought is sensed, the adaptation mechanism in plants is activated, and first, stomatal narrowing or closure occurs to prevent water loss through transpiration from open stomata (Osakabe et al., 2014). As a result, CO_2 uptake decreases and photosynthesis rates decline (Chavez et al., 2003). Additionally, plants form dense feather on their leaves, lowering the temperature of the underlying cells by 1-2 °C and thereby reducing transpiration rates (İpek, 2015; Göksoy & Turan, 1991).

Plants develop an osmotic regulation mechanism against drought and salinity stress, increasing the amount of soluble particles within the cell to maintain intracellular osmotic potential and turgor balance (Bartels & Souer, 2004). During this process, plants increase the synthesis and accumulation of soluble compounds known as osmolytes, such as proline, glycine betaine, sucrose, and mannitol, which have low molecular weights (Ashraf & Foolad, 2007; Mahajan & Tuteja, 2005). These osmolytes increase stomatal conductance by balancing leaf water pressure and, in this process, ensure the continuity of photosynthesis and metabolic activities, providing plants with short-term resilience under arid conditions and helping the plant to grow (Öztürk, 2015).

The degree to which plants are affected by drought stress varies depending on the genotype, and the degree of impact is related to the physiological and biochemical responses and changes that the genotype develops under stress conditions (Kayabaşı, 2011).

The abscisic acid (ABA) hormone, which is effective in regulating the response of plants under stress conditions, is produced in large quantities in plant roots, where it is first synthesized, and is then transported to the stem and leaves, causing stomata to close and thereby preventing transpiration, thus preventing water loss in plants during drought (Vishwakarma et al. 2017). It also slows down the development of the plant's apical organs, such as leaves and branches, allowing the roots to grow deeper and access more water and nutrients (Kaçar et al., 2006).

The accumulation of ROS, which causes cellular damage in the vegetative tissues of plants due to the effects of stress factors, has been observed. The level of this oxidative accumulation varies depending on environmental factors such as light intensity, extreme temperatures, drought, and salinity, as well as the duration and severity of exposure to these stress factors (Miller et al., 2010). At the cellular level, ROS compounds react with vital macromolecules such as biological membranes, proteins, lipids, carbohydrates, and nucleic acids, causing disruption of cellular metabolism. These biochemical interactions form the basis of irreversible cellular damage and oxidative stress under severe stress conditions (Smirnoff, 1993).

Plants have developed enzymatic (superoxide dismutase (SOD), catalase (CAT), peroxidase (APX), ascorbate peroxidase (AP), glutathione reductase (GR), glutathione peroxidase (GPX)) and non-enzymatic (ascorbate (AsA), glutathione (GSH), proline, flavonoids, phenolic compounds, alkaloids, α-tocopherol, and carotenoids) antioxidant defense systems to reduce or completely eliminate the damage caused by ROS (Halliwell, 2006; Kusvuran et al., 2007).

Non-enzymatic antioxidant defense molecules are particularly effective in protecting photosynthetic membranes (Farooq et al., 2009; Anjum et al., 2011). They are present at low levels in leaves and chloroplasts during normal development. However, under stress conditions, their concentrations increase and they enhance tolerance to oxidative stress by ensuring the complete elimination of O_2^- and OH^- from the cell (Büyük et al., 2012). Enzymatic antioxidant defense systems increase the resistance level of plants against oxidative damage and enable plants to be resistant under stress conditions by eliminating ROS and reducing their harmful effects (Yaşar, 2003).

Plants exhibit more selective permeability in their root systems against salinity stress, minimizing the uptake of excess Na^+ ions and preventing their absorption into the plant. Additionally, plants remove excess salt ions from the cytosol and transport them to the vacuole, where they are either partitioned or stored in older tissues (Gupta & Huang, 2014). This prevents ion toxicity caused by salinity, maintains ion balance (K^+/Na^+), and ensures continued growth or prevents cell death. Increasing the amount of K^+ in the cytoplasm prevents cellular damage and nutrient deficiency in plants and creates a suitable environment for plant growth (Yamaguchi & Blumwald, 2005).

4. Definitions of Some Osmoprotektants

Plants synthesize and accumulate various dissolved organic compounds in their tissues to ensure growth and development under abiotic stress conditions, maintain homeostasis, and sustain cellular turgor (Bohnert & Jensen, 1996; Burg & Ferraris, 2008). The accumulation, concentration, structure, and distribution of osmoprotectants at the cellular level in plants under abiotic stress depend on factors such as growth conditions, stress type, stress intensity, and plant species (Zulfiqar et al., 2023).

These organic compounds, also known as osmoprotectants or osmolytes, are classified according to their functional groups as amino acids, sugars, quaternary ammonium compounds, polyamines, and polyols (Table 1) (Singh et al., 2022).

Osmolytes, which are synthesized and accumulated under stress conditions, have essential functions in plants. The primary role of osmoprotectant accumulation in plants under stress conditions is to maintain osmotic balance by regulating turgor pressure in plant cells. They also alleviate ion toxicity, improve photosynthetic activity, protect cell membranes, stabilize protein structure and cellular structures, detoxify ROS, and improve stress tolerance by maintaining cellular redox balance (Suprasanna et al., 2016).

Table 1. *Classification of some osmoprotectants according to their functional groups*

Main Group	Amino Acids	Quaternary Ammonium Compounds	Polyols (Sugar Alcohols)	Sugars	Polyamines
Subgroup	Proline	Glycine betaine	Mannitol	Trehalose	Putrescine
	Alanine	Proline betaine	Sorbitol	Maltose	Spermidine
	Arginine	Choline-O-Sulfate	D-ononitol	Sucrose	Spermine
	Glycine	TMAO (Trimethylamine N-oxide)	D-pinitol	Fructose	
	Glutamine	β-Alanine Betaine	Myo-inositol	Galactinol	
	Asparagine				
	γ-Amino-Butyric Acid				

Given the strong correlation between osmoprotectants and abiotic stress tolerance, it is important to research the role of osmoprotectants under changing climate conditions. Therefore, this section focuses on the synthesis, accumulation, and effects of exogenous applications of proline, glycine betaine, and mannitol, which are important osmoprotectants, on plants.

4.1. Proline

Plants exposed to various stress conditions such as drought and salinity accumulate amino acids such as proline, alanine, arginine, and cysteine in their bodies to develop physiological responses to these conditions. Prolin, the first osmoprotectant synthesized in chloroplasts and cytoplasm, especially under abiotic stress, acts as a fundamental protective molecule through its functions of preventing and regulating protein denaturation, ensuring the continuity of enzymatic activities, neutralizing free radicals that can cause cellular damage, and balancing the intracellular osmotic potential (Biedermannova et al., 2008; Kishor et al., 2005).

Osmotic adjustment, which regulates cell expansion, stomatal and photosynthetic mechanisms under drought stress conditions, maintains plant viability, and increases yield, is defined as an important tolerance mechanism, and proline is one of the compounds contributing to osmotic adjustment (Heuer, 1999). Numerous studies have indicated that proline accumulation mitigates the effects of both drought and heat stress, increases salt and flooding tolerance, and enhances drought resistance (Ghosh et al., 2021).

Numerous studies have reported increased proline accumulation in plant tissues in response to drought stress. It has been reported that drought increased the proline content in the Yalova variety of sugar beet by 42.9% (Yalçın et al., 2022), and another study conducted on different wheat varieties showed that drought increased the endogenous proline content by 13-20 times compared to the control (Ural et al., 2024). Similarly, drought has been reported to increase endogenous proline levels in different rice varieties (Lum et al., 2014) and wheat (Naz & Perveen, 2021).

Furthermore, proline accumulation in plants acts as a signaling molecule that regulates gene expression in response to drought stress, particularly by increasing the levels of key transcription factors such as DREB (dehydration-responsive element-binding) and AREB/ABF (abscisic acid-responsive element-binding) transcription factors, thereby activating stress-tolerance-related genes and regulating the defense system of plants under adverse conditions (Kishor et al., 2005).

Under salt stress, proline accumulation increases, helping to maintain cellular integrity in plants by stabilizing cell membranes, preventing increased membrane permeability and ion imbalance. Furthermore, proline accumulation prevents cell dehydration in plants, retaining water within the cell and maintaining osmotic balance and cell turgor pressure (Ashraf & Foolad, 2007).

Studies have shown that salt stress increases proline accumulation in bean plants, which leads to the preservation of turgor and supports salt tolerance (Misra & Gupta, 2005). Similarly, it has been reported that salt stress applied to triticale plants significantly increases proline content in the plant (Akgün et al., 2011) and that an increase in salt levels in spinach plants leads to an increase in the amount of proline synthesized in the plant (Di Martino et al., 2003).

Exogenous proline applications have both positive and negative effects on plants, depending on the applied dose. Many studies have shown that low doses of exogenously applied proline reduce the damage caused by ROSs and mitigate the adverse effects of salinity, drought stress, heavy metal, and cold stress conditions (Spormann et al., 2023).

It has been reported that proline applied at high concentrations to tomato (*Solanum lycopersicum* L.) plants inhibits plant growth and causes an imbalance in inorganic ion content (Heuer, 2003). It has been observed that proline applied at low concentrations (20-30 mM) to rice (*Oryza sativa* L.) plants reduces the adverse effects of salinity stress, whereas proline applied at high concentrations (40-50 mM) shows toxicity in plants and negatively affects growth (Roy et al., 2014). It has been stated that low-concentration proline (1 mM) applied to two types of rice (*Oryza sativa* L.) seeds before sowing under salinity stress has a positive effect, but high-concentration proline (10 mM) has a harmful effect (Deivanai et al., 2011).

It has been stated that proline applied to sugar beet (*Beta vulgaris* L.) grown under drought conditions reduces the negative effects of drought (ROS production, electrolyte leakage, and lipid peroxidation) by increasing the endogenous proline content, total phenolic compounds, and antioxidant enzyme activity (AlKahtani et al., 2021). It has been reported that water stress reduces the nutrient content in the above-ground organs and roots of maize (*Zea mays* L.) plants, and that foliar application of proline significantly alleviates the adverse effects of water stress by increasing the plant's uptake of K^+, Ca^{2+}, N, and P elements (Ali et al., 2008).

4.2. Glycine Betaine

Among quaternary ammonium compounds, glycine betaine (GB) is important as it is synthesized and accumulated in microorganisms such as bacteria, algae, and fungi, as well as in animals and many plants (Chen & Murata, 2011). During their normal development, plants such as sugar beet (*Beta vulgaris* L.), spinach (*Spinacia oleracea* L.), barley (*Hordeum vulgare* L.), wheat (*Triticum aestivum* L.), and sorghum (*Sorghum bicolor* L.) accumulate GB, even at low levels. However, under different stress conditions, they synthesize and accumulate higher amounts of GB in their tissues (Küçük, 2013). Many physiological studies indicate that the level of GB accumulation in plants is related to the tolerance level of the plants (Saneoka et al., 1995). The GB accumulation capacity of plants varies even among different plant species. For example, while some maize and sorghum genotypes have a high GB accumulation capacity, rice cannot accumulate GB (Niu et al., 2023).

GB is trimethylglycine, which interacts with the genetic structures of plants through proteins, causing changes in the gene expression and activity of many enzymes, thereby enabling plant growth and development under different abiotic stress conditions. It has been reported that plants that synthesize GB or cannot synthesize GB but are treated with exogenous GB show increased expression of SOD, CAT, POD, APX, GR, GPX, monodehydroascorbate reductase (MDHAR), and dehydroascorbate reductase (DHAR) under stress conditions (Hernandez-Leon & Valenzuela-Soto, 2023).

GB accumulation or exogenous application in plants plays a strategic role in maintaining biomolecular integrity by stabilizing cell membranes, DNA structure, and proteins, or by participating in metabolic processes (Chen & Murata, 2011). High GB accumulation in plants under stress conditions increases seed germination rates and grain growth, promotes healthier root development, increases biomass in wheat seedlings (Yıldırım et al., 2015), and improves the photosynthetic system in plants, thereby increasing yield (Chen & Murata, 2008).

It has been stated that endogenous GB content in cotton (*Gossypium hirsitum* L.) plants varies significantly among varieties, that water scarcity causes a significant increase in GB content in all varieties, and that there is a positive correlation between the degree of drought tolerance and endogenous GB content (Naidu et al., 1998).

It has been stated that GB and proline contents increase in tomato (*Solanum lycopersicum* L.) plants under salinity stress as osmoregulators produced in response to stress to mitigate the adverse effects of salt stress (Umar et al., 2018). It has been reported that GB accumulation increases in different red beet (*Beta vulgaris* L.) varieties under saline growing conditions and that this is related to high Na+ levels in the tissues (Subbarao et al., 2001).

It has been stated that applying GB exogenously to cultivated plants that accumulate GB or do not accumulate GB under adverse environmental and stress conditions contributes to reducing the negative effects of stress factors (Mickelbart et al., 2006). GB can be applied to plants through different methods (seed, leaf, and root), is efficiently and easily absorbed and transported within the plant body, and when applied to the leaves, is easily taken up by leaf tissues (Chen & Murata, 2008).

GB applied to lettuce (*Lactuca sativa* L.) grown under limited irrigation conditions has been shown to increase yield and quality in lettuce, as well as to be effective in improving water use efficiency (Ibrahim et al., 2023). GB was applied to alfalfa (*Medicago sativa* L.) plants at different irrigation levels, and significant improvements were observed in the plant's growth parameters, biochemical contents, and mineral nutrient concentrations. It has been reported that GB application significantly improves plant performance, especially under water-limited conditions (Khadouri et al., 2020).

It has been stated that GB applied to pepper (*Capsicum annuum* L.) seeds during the germination stage reduces the negative effects of salinity on morphological parameters (Khafagy et al., 2009). It has been stated that GB application to maize (*Zea mays* L.) plants under saline soil conditions has a significant effect on plant growth, leaf water content, net photosynthesis rate, stomatal conductance, and water use efficiency (Yang & Lu, 2005). GB was applied to tomato (*Solanum lycopersicum* L.) plants exposed to low temperature stress, and it was observed that cold tolerance increased, antioxidant enzyme activities increased, and the photosynthetic system was better protected (Dai et al., 2024).

4.3. Mannitol

Mannitol, also known as manna ($C_6H_8(OH)_6$), is a white, crystalline solid belonging to the polyols (sugar alcohols) group of osmolyte compounds. It is synthesized and accumulated in microorganisms such as fungi, yeasts, and bacteria, as well as in many plants. Although it is found in varying amounts in each plant, an increase in mannitol synthesis is observed in plants, especially under stress conditions. Mannitol is primarily produced in plants as a photosynthetic product (Dawood et al., 2022). It plays important roles in regulating metabolic processes and maintaining cellular water balance, primarily for carbon and energy storage (Mitoi et al., 2009).

Under stress conditions, mannitol is reported to be a compound compatible with cellular mechanisms and to play an important role in reducing the effects of stress factors such as heat, salinity, and drought (Bhauso et al., 2014). Furthermore, it protects plants by acting as an osmoprotectant in processes such as maintaining membrane integrity, stabilizing protein structures, scavenging ROSs that cause cellular damage, and preserving photosynthetic activity under various abiotic stress conditions (Chan et al., 2011). Studies have shown that endogenous mannitol accumulation and exogenous mannitol applications protect plants under different stress conditions.

In vitro and in vivo studies have shown that mannitol osmolytes remove ROS and that mannitol accumulation increases salt tolerance in plants (Dawood et al., 2022).

Tobacco (*Nicotiana tabacum L.)* plants that synthesize and accumulate mannitol were obtained by adding a bacterial gene encoding mannitol 1-phosphate dehydrogenase, and it was reported that these plants showed increased tolerance to salinity stress (Tarczynski et al., 1993). Similarly, it has been reported that genes added to the chloroplast of tobacco plants increase chlorophyll stability in leaf tissue, increase the rate of CO_2 fixation, and reduce the oxidative damage caused by hydroxyl radicals to cells by supporting endogenous ROS scavenging mechanisms (Shen et al., 1997).

Under water restriction, the mannitol concentration in the leaves of the ash tree (*Fraxinus excelsior* L.) was reported to be twice as high as in sufficiently watered tree leaves, which was attributed to mannitol accumulation in the tree's osmotic and tolerance adjustments in response to water stress (Guicherd et al., 1997).

Many studies have reported that applying mannitol to plants under stress conditions alleviates the negative effects of stress and promotes plant growth and yield increases. Foliar application of mannitol has been reported to increase drought stress tolerance in apple (*Malus domestica* L.) trees and improve plant growth, chlorophyll content, macro- and micro-mineral content, and fruit set compared to control plants (Mahmoud et al., 2024).

Mannitol applied to different varieties of faba bean (*Vicia faba* L.) plants has been reported to maintain water potential in cells in sandy soils and under drought conditions, reducing oxidative damage in cells by preserving and stabilizing membrane integrity (Dawood et al., 2022).

It has been reported that mannitol applied to tomato (*Solanum lycopersicum* L.) plants under severe drought stress maintains high chlorophyll content in the plant, and that the combined application of melatonin and mannitol reduces water loss in leaves, increases soluble sugar content, and increases membrane stability levels under moderate drought (Decutt et al., 2025).

Mannitol applied to water-stressed cress (*Lepidium sativum* L.) plants has been reported to increase physiological parameters, secondary metabolites, and antioxidant activity, and to play an important role in cellular osmotic regulation (Singh et al., 2020).

Mannitol applied to different maize genotypes under saline growing conditions improved osmotic balance in the cell and protected cellular structures by scavenging ROS, alleviating salt stress and increasing plant growth (Afzal et al. 2023).

It has been observed that mannitol applied to the leaves of maize plants (*Zea mays* L.) under salt stress increases photosynthetic pigments, biomass levels, and K^+, Ca^{2+}, and P content. Additionally, it has been stated that mannitol is more effective than thiourea in improving salt tolerance (Kaya et al., 2013).

5. The Application Potential of Osmoprotectants in Sustainable Agriculture and the Perspective of Climate Change

Among the effects of global climate change, abiotic stress sources such as drought, soil salinity, and extreme temperatures are among the problems that limit the sustainability of agricultural production, particularly in semi-arid and arid climate regions, due to the decrease in water resources and increased salinity in the soil. These stress factors cause disruption of the water balance in plants, ion toxicity, oxidation in cells, and slowdowns in metabolic activities, resulting in serious losses in plant growth and yield.

Plants develop different physiological and biochemical defense strategies against stress conditions. Osmoprotectants, which are among these strategies, are biochemical compounds that support adaptation to stress conditions and play an important role in sustainable agricultural practices.

These organic compounds, which are naturally synthesized and accumulated in plants but can also be applied exogenously (via foliar application, seed treatment, and root zone application), can reduce growth and yield losses by increasing plant resistance to stress conditions and regulating metabolic activities within the plant. Osmoprotectants, also known as osmolyte compounds, reduce water loss by maintaining intracellular osmotic balance, stabilize protein and cell membrane structures, store carbon and energy to sustain photosynthetic activity, support nutrient uptake, and play a protective role against the harmful effects caused by ROS. With these properties, osmolyte accumulation within plants or exogenous application enables plants to maintain metabolic activities and support growth under stress conditions such as drought and salinity. The most widely known and studied osmolytes in plants are proline, glycine betaine, and mannitol, with ongoing research in this field gaining increasing importance.

Efforts to increase the resistance of plants to stress conditions are becoming increasingly important in order to meet the food demands of the growing global population. Among the strategies to reduce the effects of these stress conditions, the exogenous application of osmoprotectants has significant potential.

The foliar application of osmolyte compounds has been reported to improve plant water use efficiency by regulating osmotic balance in plant cells, reduce oxidative damage in cells by maintaining membrane integrity, increase total phenolic compounds and antioxidant enzyme activity, enhance mineral nutrient uptake, improve plant growth by increasing photosynthesis, and increase yield.

While the use of osmolyte in agricultural production is important, studies continue on the synthesis and accumulation of osmoprotectants in plant breeding and biotechnological fields for different plant species. In order to ensure the continuity of sustainable agricultural practices under climate change conditions, genes associated with the synthesis of these osmolyte compounds are being identified, and these genes are being transferred to different plants to develop plant genotypes resistant to stress conditions. These applications are particularly important for ensuring the continuity of plant production and increasing yields in agricultural areas where water resources are limited and soil salinity is high.

6. Conclusions and Recommendations

Organic compounds such as proline, glycine betaine, and mannitol, which are naturally synthesized in plants or applied exogenously, play an important role in adaptation to abiotic stresses such as drought and salinity stress caused by global warming.

The areas of application and potential of osmoprotectants in agriculture are quite broad. In addition to exogenous applications, it is possible to develop plant varieties with high stress tolerance by studying the synthesis mechanisms in plants in more detail at the molecular level through biotechnological applications, identifying the genes associated with osmoprotectant biosynthesis, and regulating these genes. In this sense, transgenic and genome editing techniques offer significant research opportunities in this field.

In addition, numerous studies have been conducted on osmoprotectant applications; however, there is a need for studies to determine the effectiveness of osmolyte application at different doses under different environmental conditions, on different plant species, and during different growth stages.

Furthermore, it is essential to prioritize studies on reducing the negative effects of climate change on agricultural production and improving crop production by combining osmolyte applications with biostimulants, beneficial microorganisms, and other sustainable agricultural practices.

Such integrated studies can contribute to improving sustainable production, especially in agricultural production areas affected by drought and salinity. More comprehensive research on the physiological, biochemical, and molecular levels of these compounds is of great importance for the widespread adoption of sustainable agricultural practices, particularly because they are environmentally friendly products.

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Chapter 5

NUTRITIONAL CONTENT AND FUNCTIONAL PROPERTIES OF LEEK (*Allium ampeloprasum*)

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Introduction

Leek (*Allium ampeloprasum*) is a member of the Alliaceae family and is a species of significant economic importance. (Alan et al. 2016). Among the Alliums, it is the largest monocot genus, containing over 800 species (Stearn 1992; Veiskarami et al. 2019). Alliums belong to the Alliaceae family, which is closely related to the Amaryllidaceae family (Fritsch and Friesen 2002). It has a wide distribution across the temperate, warm, and northern regions of the Northern Hemisphere (Brewster 1994). The distribution areas of the genus, which has high species diversity, extend from the Mediterranean basin to Central Asia and Pakistan (Fritsch and Friesen 2002). In Turkey, it is commonly found in the Mediterranean Region. At least 20 Allium species (such as leek (*A. ampeloprasum* L.*),* onion *(A. cepa* L.), garlic (*A. sativum* L.), bunch onion (A. *fistulosum* L.), chives (*A. schoenoprasm* L.)) hold an economically significant place (Wheeler et al. 2013). Among the edible Allium species, the oldest cultivated crops include onion, garlic, leek, and Japanese bunching onion (Brewster 2008). The principal cultivated varieties have developed from wild ancestors found in the mountainous areas of Central Asia (Brewster 2008).

Leek (*A. ampeloprasum*) is used extensively as a spice, food, and medicinal herb. A. ampeloprasum is a plant that is grown and eaten throughout the world, and new cultivars and traits have emerged over time. Open-pollinated standard lines make up the majority of varieties grown globally. F1 hybrid varieties are used in developed nations to produce homogenous plants and high harvests (Bernaert et al. 2012). Leeks, an economically significant crop, are primarily cultivated in countries bordering the Mediterranean Sea, including Türkiye, the Mediterranean islands, Africa's north, the southwest of Asia, and southern England (Hanci, 2022).

The production and consumption of leeks are quite widespread worldwide. This circumstance has allowed for the gradual emergence of new cultivars (Hanci et al., 2024).

The Nutritional Content of Leeks

Leeks are generally sold fresh and used in cooking, but in recent years, they are also available as frozen and dried products (Hanci et al., 2018).

The chemical composition of leeks may prove affected by a number of variables, particularly temperature, rainfall amount and duration, exposure to sunlight, soil composition, the plant's growth stage, and interactions with other plants or animals in the ecosystem. Changes in carbohydrate content can be attributed to minor differences in the plant's growth stage, while mineral elements are largely influenced by soil composition and other environmental factors (García-Herrera et al., 2014).

Leek is a vegetable commonly consumed fresh during the winter months and is preferred for its high levels of vitamins, carbohydrates, minerals, and secondary metabolites. It is known that leeks contain high amounts of β-carotene, lutein, vitamin E, and vitamin C (Vancoillie et al., 2024a). Endogenous enzymes like alliinase and lachrymatory factor synthase catalyze chemical reactions that break down S-alk(en)yl-L-cysteine sulfoxides to create distinctive taste and aroma elements during the occurrence of tissue destruction in Allium species. In these plants, 10 different S-alk(en)yl-L-cysteine sulfoxides compounds have been identified. Among these, the most common in leeks are S-methyl-L-cysteine sulfoxide (metin) and trans-S-1-propenyl-L-cysteine sulfoxide (isoalliin) (Bernaert et al., 2013b). In addition; S-(2-pyrrolyl)-L-cysteine sulfoxide, S-ethyl-L-cysteine sulfoxide (ethin), S-methyl-L-cysteine sulfoxide, S-(1-butenyl)-L-cysteine sulfoxide (homoisoalliin), S-(3-pentenyl)-L-cysteine sulfoxide, trans-S-1-propenyl-L-cysteine sulfoxide (isoalliin), S-propyl-L-cysteine sulfoxide (propiin), S-(methylthio)methyl-L-cysteine sulfoxide (marasmin), S-butyl-L-cysteine sulfoxide (butin), and S-(2-propenyl)-L-cysteine sulfoxide (alliin) have also been identified (Bernaert et al., 2013a).

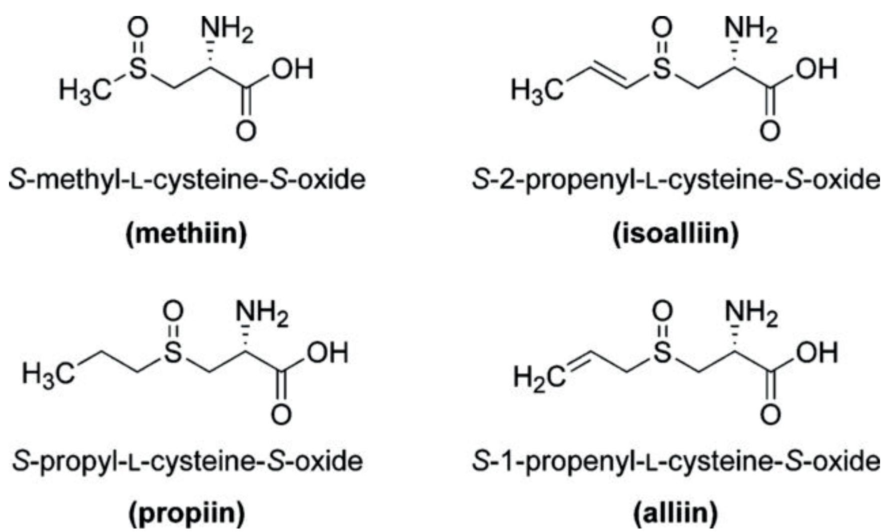

Figure 1. Configurations of the four cysteine sulfoxides found in Allium species (Storsberg et al., 2004)

Flavonoids and phenolic acids are the main substances found in leeks. Leek leaves have been shown to have more antioxidant activity, sulfur, and polyphenols than the pseudo stem and leaf portions. In a investigation, it was determined that the winter leek variety "de carentan 2" had a high total phenolic content in its leaf sections, with 5477 mg.kg-1 in dry matter, 1580 mg.kg-1 in white sections, and 2172 mg.kg-1 in green sections. The autumn leek variety "elephant" had 4803 mg.kg-1 in its leaf sections, 1550 mg.kg-1 in green sections, and 1122 mg.kg-1 in white sections. The antioxidant activity was determined to be 106 mmol.kg-1 in the leaf parts of the "de carentan 2" variety and 49.53 mmol.kg-1 in the leaf parts of the "october" variety, which is a fall leek (Čeryová et al., 2024). Additionally, it is known that the green parts of leeks contain levels of ascorbic acid 2.1-4.5 times higher than those in the white parts (Anisimova et al., 2021).

In addition to their high carbohydrate content, leeks are a rich source of dietary fiber. In a investigation by Eppendorfer and Eggum (1996) examining the structure of leeks on a dry matter basis, the protein, total dietary fiber, soluble, and insoluble dietary fiber contents were reported as 7.4-17.4%, 17.4-28.3%, 8.2-12.2%, and 9.2-16.1%, respectively. The lipid-soluble volatile constituents of leek roots comprise a substantial amount of unsaturated fatty acids (4). The concentrations of n-hexadecanoic acid (12.81%) and (Z,Z)-9,12-octadecadien-1-ol (11.72%) are notably elevated. The existence of unsaturated oils could provide effects such as lowering blood lipids, preventing atherosclerosis, alleviating arrhythmia, and fostering cognitive growth in infants (Ma, 2012).

The presence of organosulfur compounds, particularly allyl chemicals, that inhibit carcinogenesis in the test animals' forestomach, oesophagus, colon, mammary gland, and lung appears to be responsible for the positive effect. In order to avoid DNA compound production in various tissues of interest, as well as to stop carcinogen activation (cytochrome P450s) or detoxification (glutathione S-transferases), substances containing organosulfur regulate the activity of various metabolizing enzymes (Bianchini and Vainio, 2001).

Allium species can synthesize sulfur-containing substances. In specific instances, S-alk (en) yl-L-cysteine sulfoxides, which are non-protein sulfur amino acids, may constitute a minor fraction of the dry weight. The associated γ-glutamyl-S-alk (en) ylcysteine storage dipeptides are enzymatically hydrolyzed to yield such amino acids (Lancaster and Shaw, 1989). Approximately 75% of the sulfur in Allium species is believed to exist as ACSOs or their storage form, γ-glutamyl-ACSOs. These odorless, non-volatile ACSOs serve as the fundamental components of propanethial sulfoxide, the lachrymatory factor (LF), and numerous flavors and aromas (Jones et al., 2004).

To produce unstable alk(en)yl sulfenic acids, pyruvic acid, and ammonia, the endogenous enzymes alliinase and lachrymatory factor synthase cleave ACSOs in damaged Allium species. The flavor is enhanced by thiosulfinates, which are formed through the non-enzymatic rearrangement of alk(en)yl sulfenic acids. The byproducts of the enzymatic reaction that do not possess any flavor are pyruvic acid and ammonia (Lancaster and Kelly, 1983).

Kaempferol is shown to be the primary flavonoid aglycone that can be found in leeks, as indicated by study held by Hertog et al. (1992a). Utilizing on the aglycone kaempferol, Fattorusso et al. (2001) successfully identified flavonoid glycosides in leek. These flavonoid glycosides include kaempferol 3-O-glucoside, kaempferol-3-Oneohesperidoside, kaempferol 3-O-[2-O-(trans-3-methoxy-4-hydroxycinnamoyl) – β - dgalactopyranosyl]- (1→4) – O – β -d glucopyranoside, and kaempferol 3-O-[2-O-(trans-3-methoxy-4-hydroxycinnamoyl)-β-d-glucopyranosyl]-(1→6)-O-β-d glucopyranoside.It is d-glucopyranoside.

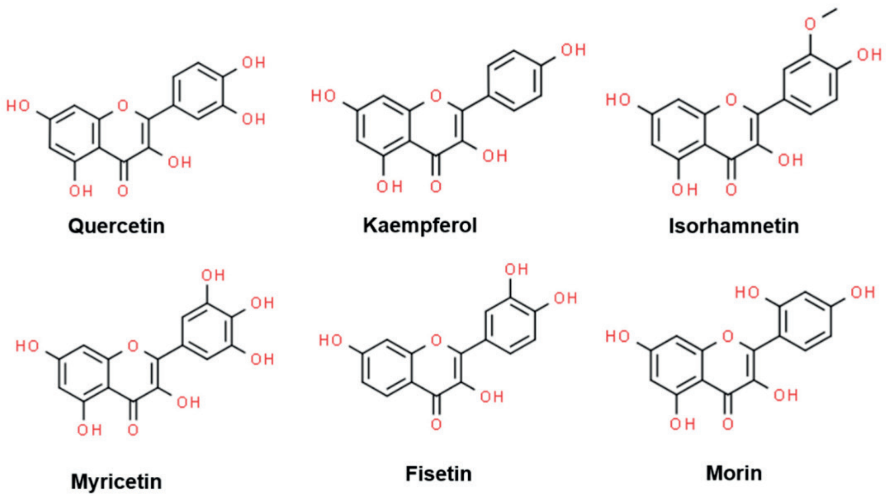

Figure 2. *Chemical compositions of the principal flavanol aglycone representatives in Allium species (Kothari et al., 2020)*

The Impact of Leeks on Human Health

Leeks are widely cultivated vegetables known for their numerous health benefits (Kiremit and Arslan, 2016). There have been a great number of investigations that have investigated the connection between allium vegetables and cancer. Study by Putnik et al. (2019) indicates that intake of these plants is associated with a diminished risk of developing cancers of the stomach, colon, breast, and esophageal. The organosulfur compounds and polyphenols in these vegetables impart various bioactive properties, which in turn confer numerous health benefits. It is known to have antimicrobial, antiviral, antioxidant, anticarcinogenic, anti-mutagenic, anti-inflammatory, liver-protective, and neuroprotective effects. At the same time, it can reduce the risk of cardiovascular diseases due to its antithrombotic, antihypertensive, hypolipidemic, hypocholesterolemic, and anti-hyperhomocysteinemic properties. Additionally, these vegetables exhibit antidiabetic, antiprotozoal, antispasmodic, antiasthmatic, anti-amnesic, hypotensive, hypoglycemic, and immunomodulatory effects. The positive effects of these vegetables on human health have been the subject of many studies over the years (Putnik et al., 2019).

Among the leading pharmacological benefits of leeks are their antiseptic, asthma-preventive, diuretic, antibacterial, antifungal, and antioxidant properties. Thanks to these properties, leeks offer a natural treatment option, with their skin-damage-preventive and gastrointestinal disease risk-reducing effects (Shahrajabian et al., 2023). Leeks are rich in essential minerals for human health, including potassium, phosphorus, iron, and zinc. Leeks additionally include minerals including copper, sodium, manganese, and magnesium (Aljuhaimi et al., 2024).

Leeks are a low-calorie food source. They also contain moderate levels of important nutrients, including folate, copper, fiber, and vitamin B6. Among the main antioxidants contained in leeks are kaempferol and allicin, and it is thot that these compounds may have a protective effect against diseases in the body. Kaempferol has been scientifically associated with a diminished risk of acquiring chronic diseases such as malignancy. According to Mumtaz et al. (2024), kaempferol's anti-inflammatory effects allow it to be effective in reducing inflammation, eliminating cancer cells, and assisting in the prevention of the proliferation of cancer cells. It has been suggested that modifications to diet may decrease the risk of developing cancer through lowering the consumption of processed foods and increasing the number of vegetables. A growing number of people are interested in conducting studies to determine the dietary patterns, bioactive foods, and components that can lower the risk of developing cancer. According to investigate conducted by Zamri and Hamid (2019), it has been demonstrated that around thirty to forty percent of cancers can be avoided by following a healthy diet and nutrition, engaging in regular physical activity, and keeping the body in good condition.

Leek substance has the ability to demonstrate anti-allergic benefits due to the antioxidant and anti-inflammatory properties that it possesses. In addition to phenolic acids and their derivatives, leeks are regarded as abundant suppliers of secondary metabolites. These metabolites encompass a wide range of flavonoids, such as flavans, flavanones, flavones, flavonols, dihydroflavonols, flavan-3-ols, flavan-4-ols, and flavan-3,4-diols, as well as flavonoid polymers (Ìeryová et al., 2024). It is known that consuming leeks improves stomach and intestinal health, accelerates metabolic processes, and has a protective effect against stomach and breast cancer (Bianchini and Vainio, 2001). Additionally, heated leeks have been shown to act as an antigen (Takamatsu et al., 2024).

Studies on the Nutritional Content of Leeks

In accordance with the findings of Wang and Feng (2002), the volatile oil extracted from leeks includes a considerable quantity of sulfur-based substances. The disulfide and trisulfide constituents make up the majority of volatile oil, while the tetra sulfide ingredient is present in less quantity. allyl methyl trisulfide (%35,19), diallyl disulfide (%28.31), diallyl trisulfide (%20,91), and dimethyl trisulfide (%12.33) were found to be the main elements of the volatile oil that was derived from leek roots, as stated by the results discovered by Liu et al. (2015). Each and every one of them demonstrated that the roots of the leek contained an extremely high concentration of sulfur compounds.

In a study aimed at reducing the use of chemical nitrates in the production of fermented sausages, freeze-dried leek powder was added at rates of 0.84% and 1.68%. As a result of the study, the addition of 0.84% freeze-dried leek powder and 75 ppm sodium nitrite provided color stability, texture profile, redness, TBA values, and sensory characteristics similar to other fermented sausage products containing 150 ppm $NaNO_2$. Thus, it has been noted that a 50% reduction in sodium nitrite usage can be achieved, allowing for the production of healthier fermented sausages (Tsoukalas et al., 2011).

Radovanovic et al. (2015) aimed to determine the overall phenolic and total flavonoid amounts and antioxidant effect of extracts (ethanol used) from the green parts and stems of the "Varna" leek variety grown in Central Serbia (Balkans). In this study, the overall phenolic quantity of the leaf ethanolic extract was reported as 45.39±2.52 mg/g DE, the total phenolic content of the stem ethanolic extract was 69.46±165 (mg/g DE); the overall flavonoid amount of the leaf ethanolic extract was 10.24±284 (mg/g DE), the total flavonoid content of the stem ethanolic extract was 33.53±2.51 (mg/g DE); the DPPH activity of the leaf ethanolic extract was 98.91±0.18 IC50 (µg/mL), and the DPPH capacity of the stem ethanolic extract was 61.05±0.12 (µg/mL). Based on the findings of a microbiological research carried out in Serbia on leeks, it has been found that leeks exhibited antimicrobial properties in vitro with many gram-positive and gram-negative bacteria, including Staphylococcus aureus and Bacillus subtilis (Radovanović et al., 2015).

Strari et al. (2018) determined the the overall quantity of phenol of green leek leaves in 30 leek varieties to be 22.114 mg GAE/100 g WW; the overall the amount of phenol of white leek stalks to be 17.620 mg GAE/100 g WW; the FRAP value of white leek stems to be 9 µmol Fe_2SO_4 g^{-1} DW; the FRAP value of leaf tissues to be 27 µmol Fe_2SO_4 g-1 DW; the antioxidant activity (DPPH) of white leek stems to be 6 µmol TE g^{-1} DW; and the DPPH antioxidant activity of green parts to be 9 µmol TE g^{-1} DW.

Golubkina et al. (2018) reported that the dry matter content of 9 leek varieties ranged from 12.4% to 24.3%; the ash content ranged from 2.5% to 13.7%; the ascorbic acid content ranged from 19.2 to 136.8 mg/100 g FW; and the overall quantity ranged from 284 to 740 mg GAE/100 g DW.

Feghhi-Najafabadi et al. (2019) determined the overall quantity of leaf extracts of A. ampeloprasum subsp. persicum to be in the range of 2.46±0.55 – 8.12±0.41 mg GAE/g; antioxidant (DPPH) activity to be IC50= 315-554 µg/mL; and H_2O_2 activity to be IC_{50}= 100-810 µg/mL.

Guizellini et al. (2020) indicated that the entirety phenolic quantity in leeks varying from 1 to 3±0.4 mg GAE/g FW; Orhan and Orhan (2016) found that the general phenolic concentration of leek leaf extracts was 163.33 mg GAE/g, with a flavonoid level of 27.26 mg QE/g; Kovarovic et al. (2019) determined that the overall quantity of leek genotypes collected from the Zohor district of Slovakia varied from 504.22±48.28 mg GAE kg^{-1} DW to 4,767.71±80.55 mg GAE kg^{-1} DW.

Biernacka et al. (2021) reported the DPPH activity of the dried white and green parts of leeks, finding 332.4±8.91 EC_{50}; mg dm/mL in the white part and 126.8±3.61 EC_{50}; mg DM/mL in the green part.

Biernacka et al. (2022) sliced the green parts of leeks grown in the Lublin region of Poland, freeze-dried them, and produced enriched pasta by adding the obtained leek powder to semolina. In the pasta samples, they found that antioxidant activity and total phenolic content were higher than in the control group. Considering the product's color, taste, and aroma, they recommended an optimal leek powder amount of 3 g/100 g (Biernacka et al., 2022).

Salata et al. (2022) examined the impact of Egyptian clover live mulch on the overall phenolic content and antioxidant capacity of leeks. The research revealed an overall maximum phenolic amount of 655±1.87 mg GAE 100 g^{-1} DW and a minimum of 616±1.85 mg GAE 100 g^{-1} DW. The maximum FRAP measurement was 8.01±0.11 µmol Fe^{2+} g^{-1}, while the minimum was 5.51±0.08 µmol Fe^{2+} g^{-1}. The maximum DPPH measurement recorded was 1.01±0.11 µmol Trolox g^{-1}, and the lowest was 0.80±0.08 µmol Trolox g^{-1}.

Al-Mousswi and Jameel (2022) determined the total chlorophyll content of local leeks in Iraq to be 1.426 mg/g^{-1} FW and the total chlorophyll content of imported leeks to be 1.294 mg/g^{-1}. The average carotenoid content has decreased significantly, to 0.509 mg/g $^{-1}$ FW for the local variety and 0.464 mg/g $^{-1}$ FW for the imported variety.

A study reported that essential oils and extracts obtained from leek roots exhibit antibacterial properties. It has been determined that the essential oil obtained from leek roots exhibits strong inhibitory effects against foodborne pathogenic microorganisms, including *E. coli*, *S. enterica*, *S. dysenteriae, P.*

aeruginosa, S. aureus, and *S. suis*. Additionally, several studies have observed that it inhibits certain fungal species, including *A. niger, A. flavus, P. citrinum*, and *R. nigricans*. Synergistic interactions among the active components in leek roots further enhance the plant's antimicrobial activity (Wang et al., 2023).

Gülal and Koyuncu (2023) reported that the SSC content of the Lincoln leek variety ranged between 6.50% and 7.56%, while the titratable acidity ranged between 0.096 and 0.075 g 100 ml^{-1}.

Hanci et al. (2024) performed an investigation to assess the biochemical variability of local leek genotypes in Turkey. The research utilized 50 indigenous leek variants representing various parts of Turkey, along with 2 open-pollinated commercial varieties and 1 hybrid commercial cultivar. A total of twenty biochemical analyses were carried out. At the conclusion of the research, the levels of soluble solids were recorded at an average of 4.808 across the entire gene pool, with genotype 10-AP-19 exhibiting the greatest score and genotype 04-AP-71 displaying the lowest. The maximum pH level recorded was 6.68 in the 04-AP-58 genotype. Genotype 02-AP-58 achieved an overall dry matter percentage of 24.6%, exceeding twice the mean of the entire gene pool. The maximum chlorophyll concentration was recorded in genotype 03-AP-40 (2.586 mg/g), whereas the minimum was found in genotype 03-AP-38 (0.031 mg/g). The analysis of H_2O_2 removal activities in the samples that were examined indicates that genotypes 02-AP-50 and 16-AP-99 exhibit the highest percentages, at 92.053% and 88.96%, accordingly.

Vancoillie et al. (2024b) examined the biochemical transformations during the cold storage of pasteurized Brussels sprouts and leeks. In the study, the fresh weight of the leek was found to contain total vitamin C 26.49 mg/100g, vitamin K1 0.20 mg/100g, violaxanthin 0.65 mg/100g, lutein 1.72 mg/100g, β-carotene 0.70 mg/100g, neoxanthin 0.39 mg/100g, and isoallin 275.08 mg/100g, with a methionine content of 18.32 mg/100g. Additionally, they recorded that the total vitamin C content of the cooled and incubated pureed leek samples decreased by approximately 37% and 80%, respectively, compared to the leek pieces. After pasteurization, dehydroascorbic acid was lost, while ascorbic acid remained stable. In pasteurized samples, 56% of isoalliin and 11% of methionine were reduced.

Stari et al. (2024) sought to ascertain the biochemical characteristics of the aqueous and alcoholic extracts of the Allium porrum plant. The investigation revealed that the total phenolic content in the aqueous extract was 86.985 μg/ml GAE/100 g, whereas in the alcoholic extract it was 23.4 μg/ml GAE/100 g. The total flavonoid concentration in the aqueous extract was 42.81 μg/ml QE/100 g, while in the alcoholic extract it was 345.54±81 μg/ml QE/100 g. The CUPRAC activity of the aqueous extract was 0.074, while the CUPRAC activity of the alcoholic extract was 0.199; the FRAP activity of the aqueous extract was 0.104, and the FRAP activity of the alcoholic extract was 0.024; the DPPH activity of the aqueous extract was 73.318, and the DPPH radical scavenging activity of the alcoholic extract was 72.950.

Conclusion

In conclusion, leek (*Allium ampeloprasum* L.) is an important functional food that stands out with its rich phenolic and sulfur-containing compounds, vitamins, and minerals. Thanks to its strong antioxidant capacity, it contributes to the reduction of oxidative stress, and in this regard, it can play a protective role against various chronic diseases, especially cardiovascular diseases. Additionally, its ability to support gut health thru the prebiotic components it contains makes leeks even more valuable from a nutritional perspective. However, current studies are mostly supported by in vitro and limited in vivo data, and advanced research is needed to more clearly elucidate bioavailability, dose-response relationships, and mechanisms of action. Comprehensive and multidisciplinary studies conducted in the future will significantly help a deeper comprehension of the potential effects of leeks on human health and the widespread use of leeks as functional food.

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Chapter 6

AN ANALYSIS ON OCCUPATIONAL HEALTH AND SAFETY IN FISHING ACTIVITIES IN EDREMIT DISTRICT (VAN, TÜRKIYE) WITH HEALTHCARE MANAGEMENT PERSPECTIVE

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Introduction

Occupational health and safety (OHS) is an area of public health that aims to ensure a high level of physical, psychological and social well-being of workers in all occupations (World Health Organisation, 2019). This notion must be prioritized since worker health and safety are closely related to economic, social, and productivity development. Workplace accidents, injuries, and illness prevention are other areas of OHS's concentration, and in order to prevent workplace accidents, risk assessment and management are essential components of Occupational Health and Safety.

The fishing entails a perilous and demanding occupation. During their voyages at sea, fishermen use fishing vessels as living and working spaces. These maritime settings present extremely difficult working conditions due to harsh natural factors like big waves, strong winds, and subpar working conditions. It is important to remember that fishing usually lasts two to three weeks, and the workers experience loneliness, isolation, and separation from the mainland (Nguyen et al., 2024).

Behavioral, political, social, and economic factors all have an impact on health (World Health Organisation, 2017). The various goals of sustainable fisheries, including food production and revenue generation, which can promote food security and the provision of basic necessities, are made possible in large part by human health (Narayan, 2000). Fishing and human health outcomes are directly related in the case of fishing communities since seafood is essential for nutrition and food security (Béné et al., 2016). Although people's capacity to support a sustainable fishery depends on their health, fishermen frequently suffer from poor health and are subjected to a range of occupational risks (Grimsmo- Powney et al., 2009).

For these reasons, the purpose of this study in the Edremit district is to identify the dangers that fishing boat workers may encounter when fishing and the types of hazards that these risks provide.

Materials and Methods

One of Van Province's thirteen districts is Edremit District. One of the regions in the Van Lake basin where significant fishing operations are conducted is this district (Figure 1). 30 questions were posed to commercial fishermen in the Edremit district through in-person surveys conducted between April and September of 2022.

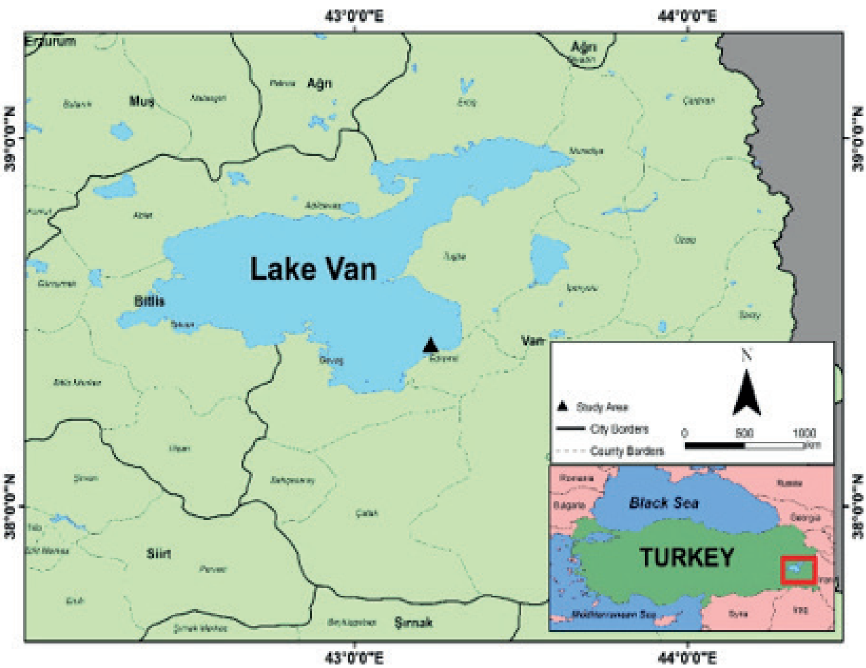

Figure1: Edremit (Van, Türkiye)

Because it is straightforward to apply to all sectors and practical in the field, the “L Type Matrix” method was used to examine the risk aspects of fishing activities in Edremit district. One technique for analyzing the cause-and-effect relationship is the “L-Type Matrix” method (Özkılıç, 2005). According to this approach, the possibility that a risk/dangerous event will occur (Table 1) and the severity of that risk/dangerous event, should it occur (Table 2) are represented by numerical values ranging from 1 to 5. The risk score is then calculated by multiplying the likelihood that the risk/dangerous event will occur by the probability’s degree of severity (Table 3). So, decisions are made regarding the necessary activities (control measures).

Table 1. The likelihood of the risk becoming realized

Possibility		Risk Realization Frequency
Too small	(1)	Hardly ever
Small	(2)	Very little (once a year)
Medium	(3)	Few (several times a year)
High	(4)	Frequently (once in a month)
Very high	(5)	Very often (once a week / every day)

Table 2. Risk severity, if actualized

Severity	Possible Outcome
Very light (1)	No loss of working hours, needing first aid
Light (2)	No loss of working hours, no lasting effect and requiring outpatient treatment
Medium (3)	Condition that causes minor injury and requires inpatient treatment
Serious (4)	Condition that causes serious injury and requires long-term treatment, occupational disease
Very serious (5)	Condition causing death or permanent incapacity for work

Table 3. Deciding what should be done based on the risk score.

Risk Score	Meaning	Action
1	Minor risks	There is no need to take measures to eliminate the identified risks.
2-3-4-5-6	Low risks	There is no need for additional measures to eliminate the identified risks. Existing measures need to be maintained and their sustainability monitored.
8-9-10-12	Medium risks	Although not urgent, measures should be taken to reduce the identified risks.
15-16-20	High risk	Work should not be started until the risk has been reduced. Considerable resource allocation may be required to mitigate risk. If business is to continue despite this risk, urgent measures must be taken.
25	Intolerable risks	Work is not started until the identified risk is reduced to an acceptable level. Ongoing activities are stopped.

The "L Type Matrix" approach was used to generate a risk assessment table for the fisherman in the Edremit district. Tantoğlu (2016) and Soykan (2018) developed the example table based on their own observations and experiences. Table 4 lists 30 significant risks along with their potential outcomes. The fishermen were questioned as part of the study:

a) The existing safety precautions against these risks and their potential repercussions,

b) The likelihood that these risks will materialize and the severity of those risks should they materialize,

c) Whether the safety precautions in place are adequate by calculating a risk score,

d) It has been determined that extra safety precautions should be taken even if it is adequate.

Results and Discussion

Ten commercial fishermen in the Edremit district participated in in-person interviews, and the results of their responses are shown in Table 4. The average of the fishermen's provided numerical numbers represents the risk's likelihood and severity.

Table 4. Findings from the Edremit district's risk analysis of fishing operations.

Risk/Dangerous Event	**Possible Outcome**	**Current Safety Measure**	**Risk Level**			**Additional Safety Measure**
			Likelihood of Risk	**Severity of Risk**	**Risk Score**	
1) Not checking the weather before sailing	Boat sinking, loss of life	Weather is checked, regularly	2	1	2	Current safety measure are sufficient
2) The occurrence of unpredictable weather conditions	Boat sinking, loss of life	Boats return to fishing coastal structure	1	3	3	Current safety measure are sufficient
3) Not using the pier during boarding and disembarking.	Falling overboard, injury	The scaffold is in continuous use	1	2	2	Current safety measure are sufficient
4) Boats are not equipped with fenders	Damage/ material loss caused by boats rubbing against each other	There are fenders, but not enough	2	1	2	The number of fenders should be increased
5) Unevenness of the working area on the deck	Injuries resulting from falls, loss of life	Working area is kept tidy	2	1	2	Current safety measure are sufficient
6) Working hanging from the deck	Falling overboard, loss of life	Not working by hanging	1	2	2	Current safety measure are sufficient
7) Netting not neatly stacked on deck	Injury from tripping and falling	Network is regularly stacked continuously	1	2	2	Current safety measure are sufficient

8) Fishermen's inexperience	Injuries, decreased in work efficiency	Newly hired fisherman is being informed	3	3	9	This information should be provided by specialized institutions
9) Working in wet and cold conditions	Employee cold, decrease in work efficiency	Fishermen wear underwear and overalls	1	1	1	Current safety measure are sufficient
10) Letting go of the rudder	Boat sinking, loss of life	The captain is always at the helm.	1	1	1	Current safety measure are sufficient
11) Falling overboard	Death by drowning	All fishermen can swim	1	1	1	Current safety measure are sufficient
12) Noise	Not hearing instructions	Sign language is used when necessary	1	2	2	Current safety measure are sufficient
13) Transport of catch/fishing gear	Injuries to the hands, back and lumbar	Fishermen help each other	2	4	8	Current safety measure are sufficient
14) Slippery deck	Injuries resulting from falls	Fishermen wear non-slip boots	1	1	1	Current safety measure are sufficient
15) Fatigue from irregular and long working hours	Injuries, decreased in work efficiency	No current safety measures	4	4	16	Fishermen must work in shifts
16) Getting tangled in the net while the net is being laid	Falling overboard, loss of life	The net is thrown into the sea by experienced people	1	1	1	Current safety measure are sufficient
17) Fire	Boat sinking, loss of life	Such a situation has never happened	1	1	1	Fire extinguishers should be available on the boats.
18) Insufficient number of life-saving equipment	Loss of life	Sufficient life-saving equipment is available and placed in a visible place.	1	1	1	Current safety measure are sufficient
19) Fishermen do not know how to swim	Death by drowning	All fishermen can swim	1	1	1	Current safety measure are sufficient
20)Absence/control of litter boxes	Environmental problems, risk of infectious disease, hygienic problems	There are trash cans and they are emptied at every return to port.	1	1	1	Current safety measure are sufficient
21) Lack of hygiene in the boat galley	Food poisoning	Foodstuffs and kitchen are cleaned regularly	1	1	1	Current safety measure are sufficient
22) Lack of hygiene in common areas such as WC	Hygienic problems	Common areas are cleaned daily	1	1	1	Current safety measure are sufficient

23) The shelves are not fixed	Injury from tipping	Shelves are fixed	1	1	1	Current safety measure are sufficient
24) Problems with freshwater requirement	Infectious disease risk, hygienic problems	There is no problem with the freshwater requirement.	1	1	1	Current safety measure are sufficient
25) Lack of first aid cabinet on the boat	Injury	There is a first aid cabinet according to the first aid regulations	1	1	1	Current safety measure are sufficient
26) Lack of first aid training	Injury	Fishermen have the information they need	2	2	4	Current safety measure are sufficient
27) Having no training in occupational health and safety (OHS)	Injury, loss of life, occupational disease, material damage	No informing about OHS	4	4	16	Fishermen should be given training in OHS as soon as possible
28) Trying to land before the boat docks fully at the pier	Falling overboard, injury	No current safety measures	3	3	9	Do not go ashore before the boat is moored to the port and the engines are turned off.
29) Insufficient communication in case the boat is moored to the pier	Falling overboard, injury	It is stated that the communication is made by a single expert.	1	1	1	Current safety measure are sufficient
30) Electric leakage	Injuries due to electric shock, loss of life, fire	It is stated that the sockets are solid	2	4	8	Plugs should be checked periodically.

Table 4. Findings from the Edremit district's risk analysis of fishing operations.

According to the fishermen's responses, 16 of the 30 risks were in the insignificant risk group (53.3%), 9 were in the low risk group (30.0%), 3 were in the medium risk group (10.0%), and 2 were in the high risk group (6.7%) (Figure 2). According to this study, the high risk group includes "Fatigue due to irregular and long working hours" and "Having no training in occupational health and safety. Several investigations carried out in the Çitören (Atay and Cengiz, 2022) and Lake Erçek (Cengiz, 2022) from the Van Lake Basin yielded same findings.

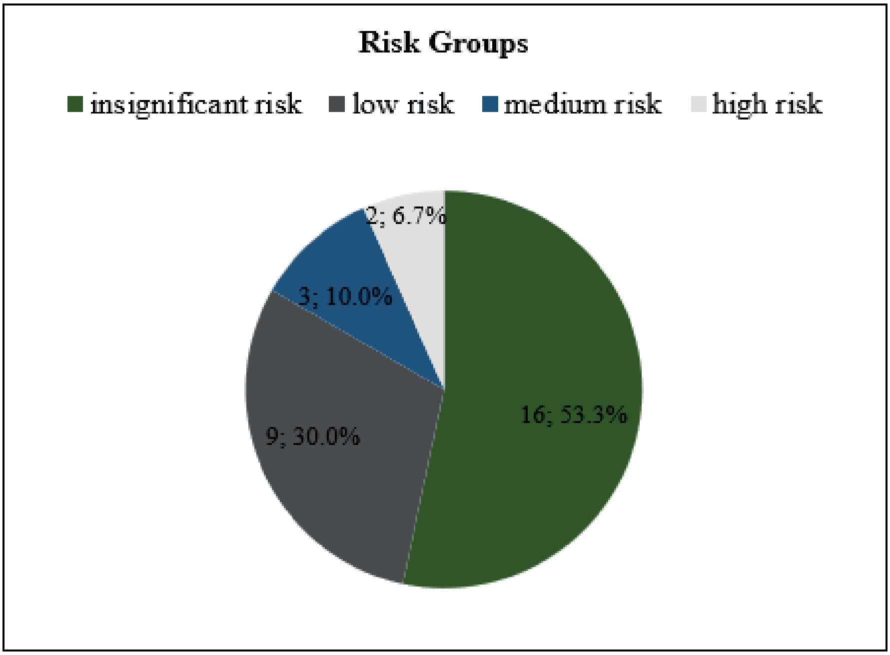

Figure 2. Distribution of risk groups proportionately

Conclusion

Management has been required to coordinate individual efforts ever since people started to organize into groups to accomplish goals that they were unable to accomplish alone. Planning, organizing, directing, controlling, and coordinating resources and processes to improve the health of people and society is the goal of the multidisciplinary field of health management within management science. In this context, occupational health and safety must be recognized as a core component of strategic health management. effective health management systems should incorporate risk assessment, preventive health programs, continuous monitoring of working conditions, and evidence-based policy development to reduce occupational injuries and diseases. furthermore, interdisciplinary collaboration between health professionals, policymakers, industry stakeholders, and workers is essential to ensure sustainable workforce well-being, economic stability, and long-term public health improvement. Fishermen may have work-related injuries and illnesses, a sense of uncertainty and worry, income loss, and mental and psychological issues. A different issue is the expense of occupational illnesses and accidents to the nation, companies, and employees. Experts should constantly educate and train fishermen about their employment, occupational health and safety, potential work accidents, and occupational diseases in relation to healthcare management in order to lessen these circumstances.

Acknowledgments

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Chapter 7

ARTIFICIAL INTELLIGENCE IN BIOSYSTEMS ENGINEERING FOR CLIMATE RESILIENT AGRICULTURE

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1. Introduction

One of the most important issues affecting agricultural systems worldwide is climate change. Crop productivity, resource efficiency, and ecosystem stability are all greatly impacted by rising temperatures, erratic precipitation patterns, and an increase in the frequency of extreme weather events. From the standpoint of biosystems engineering, agricultural production is a complex interplay between environmental factors, engineered systems, and management techniques in addition to being a biological process. Therefore, a comprehensive and data-driven strategy is needed to address climate-induced variability.

1.1 Climate Change and Agricultural Systems

After humanity transitioned to a settled life, global climates may appear not to have changed; however, scientific evidence obtained from the past to the present indicates otherwise. The Earth's climate can change due to natural causes, and today anthropogenic effects also contribute significantly to this change (Demirbaş and Aydın, 2020). Since the industrial revolution, the burning of fossil fuels, cutting down trees, changing how land is used, and industrial processes have all released a lot more greenhouse gases into the air (Türkeş et al., 2000). Through alterations in the climate system, this increase has a direct impact on plant physiological reactions, soil moisture dynamics, and nutrient cycling processes. While high temperatures lower photosynthetic efficiency and adversely impact growth and development processes, increasing drought frequency decreases water availability and puts significant strain on crop production. Additionally, erratic and unpredictable precipitation patterns complicate irrigation planning and raise questions about how nutrients are transported through the soil and absorbed by plants.

Re-designing agricultural systems with management strategies that are more adaptive, data-driven, and resilient to environmental variability is required due to all these multifaceted effects. In fact, because of the inputs used, land management techniques, and production procedures, agricultural production and thus the agri-food industry is one of the major sources of greenhouse gas emissions and greatly contributes to the greenhouse effect. Due to this circumstance, it is imperative to assess not only how agriculture is affected by climate change but also how agriculture contributes to the climate system. Smart Agriculture approaches minimize greenhouse gas emissions and reduce resource consumption through data-driven decision support systems, precision input management, and optimized production strategies (Ginigaddara et al., 2025).

1.2 Limits of Conventional Agricultural Management

In order to achieve high yields, conventional agriculture relies on inputs like synthetic fertilizers, pesticides, and genetically modified organisms; however, these techniques have limitations with regard to environmental sustainability. By using methods based on ecological cycles and devoid of agrochemicals and artificial additives, organic agriculture, on the other hand, seeks to improve soil fertility, safeguard water resources, and promote biodiversity (Gomiero, et al., 2011). Meta-analyses indicate that organic yields average approximately 80% of conventional yields, although notable variability exists among crop groups and regions (De Ponti et al., 2012). It is harder for organic farming to reach the same yield levels as conventional farming, especially when the conventional yields are high. This is because there is less nutrient stress and better pest and disease control. Also, conventional systems' limits on crop rotation and nutrient availability make it harder to produce food in a sustainable way, especially on farms and in regions. In this context, the potential of organic agriculture to mitigate environmental impacts underscores the constraints of conventional agriculture in concurrently managing productivity and environmental equilibrium (Gomiero et al., 2011). So, to compare how well both systems works, we need to create sustainable agricultural policies and make nutrient management strategies better.

1.3 From Traditional to Intelligent Biosystems Engineering

The progress of biosystems engineering has necessitated the perception of biological systems not merely as physical entities but as adaptive, intricate, and dynamic frameworks. According to the literature, biosystems are systems that are whole and have some "living" traits. They can respond to feedback from their surroundings and change based on how they work (Clark and Kok, 1998). This definition characterizes biosystems not as fixed entities but as dynamic systems that engage in ongoing interactions and evolve in conjunction with their environment. This method has allowed for the combination of ecosystem engineering with AI-driven control networks, advancing the creation of biosystems with increased autonomy potential. The design of natural, altered, and wholly synthetic biosystems is a substantial departure from classical farming toward smart and self-regulating systems that utilize observation, predictive, and adaptive control systems. This change embodies not only a technological change, but also an increased systematic and holistic perspective in the governance of biological systems.

In agri-food systems, the AI-based algorithms can analyze data from various sources, including sensors, remote sensing, and meteorological data, to provide detection of stresses before they happen, prediction of yields, improve irrigation, and manage inputs. AI can also improve energy efficiency in data centers and increase the production efficiency of renewable energy sources. AI also forecasts energy demand, balances loads, and improves the overall system efficiency, and thus, decreases energy's carbon intensity for the reduction of greenhouse gases. AI is a resource-optimizing and energy-efficient technology for the reduction of emissions (Watts et al., 2024). In climate-resilient agriculture and sustainable biosystems engineering applications, artificial intelligence is not only an analysis tool but also a critical building block that supports the transition to low-carbon production systems. The evolving focus of biosystems engineering towards intelligent and data-centric systems is analyzed, and the roles of AI in stress detection, yield forecasting, predictions, decision support systems, and production systems control are analyzed. Furthermore, under the umbrella of sustainable development, the possible benefits of these technologies on the sustainability of climate change agricultural production systems and the balance of the environment, the economy, and the ecosystem are evaluated.

2. Conceptual Framework

2.1. Fundamental Principles of Biosystems Engineering

Biosystems engineering is an interdisciplinary engineering field that encompasses the analysis, design, and control of biologically based systems within the framework of sustainable production and resource management. In literature, biosystems engineering is defined as an engineering field that involves the analysis, design, and control of biologically based systems for the sustainable production and processing of food and biological materials, as well as the effective use of natural and renewable resources in harmony with the environment in order to improve human health (Alocilja, 2002). This definition shows that the field is not limited only to agricultural production processes; it also addresses the efficient use of natural and renewable resources, environmental sustainability, and the protection of human health from a holistic perspective. Biosystems Engineering is based on the practice of systems thinking, the optimization of energy and material flows, efficiency of resources, minimization of negative impacts on the environment, and sustainability. This discipline encompasses many domains, ranging from the modeling of soil-plant-water relationships and controlled environment agricultural systems to utilization of biomass and precision agriculture. Particularly in the face of climate change and rising food demand, the discipline of biosystems engineering applies data-based monitoring, modeling and adaptive control to transform traditional production systems to become smarter, more flexible and environmentally friendly structures.

2.2. Climate-resilient agriculture

The Operationalizing Framework for Climate Resilient Agriculture defines climate-resilient agriculture as the ability for agricultural production systems to sustain continuity, productivity, and environmental protection during and after the impacts of changing climate conditions. This definition is explored through the associated perspective of resilience, adaptation, and performance of the system. In the face of climate stress factors such as drought, extreme temperatures, and irregular precipitation, resilience is the ability of agricultural systems to maintain functionality, while adaptation is the execution of structural, biological, and managerial changes to respond to such environmental changes.

The body of work that has emerged regarding the climate crisis prioritizes the Climate-Smart Agriculture (CSA) method CSA denotes a collection of practices and technologies that simultaneously improve adaptability, mitigate GHG emissions, and advance food security (Hellin et al., 2023). In this regard, the priorities include efficient water management, enhancement of organic soil matter, low-carbon production, the use of digital technologies for precision agriculture and digital agriculture. The evaluation of climate-resilient agriculture as the stabilization of production, efficient use of resources, optimization of energy, reduction of GHG emissions, and enhancement of ecosystem services (Hellin et al., 2023). Such indicators evaluate the sustainability of a system in the long term, in addition to the increased production.

From a biosystems engineering perspective, climate-resilient agriculture is not just about applying a few technical solutions; it involves transforming the entire agricultural system. This transformation comes from integrating biological processes, environmental conditions, and engineering technologies in a holistic way. By using data-driven decision support systems, modeling tools, and adaptive control technologies, agricultural production can become more flexible, predictable, and environmentally sustainable. As a result, farming systems can better respond to climate challenges while also reducing their environmental impact. In the long term, this balanced approach supports both climate adaptation and mitigation efforts and helps strengthen global food security.

2.3. AI approaches in biosystems engineering

AI, machine learning, and deep learning-based models have become crucial technologies that are changing the way modeling, optimization, and decision support systems are done in biosystems engineering (Vallejo et al., 2026). The production processes in the agriculture, livestock, food systems, and environmental management sectors can now be managed using big data and predictive algorithms in more precise, efficient, and adaptable ways. Among the many sectors of biotechnology, artificial intelligence is very valuable in advanced production systems. In plant molecular farming systems, for example, AI-based multi-approach frameworks strategically reduce limitations within the systems and significantly enhance yield and production stability (Parthiban et al., 2023). Such systems also facilitate the automation of both physical and informational routine tasks, thus freeing researchers and engineers to concentrate on higher-order scientific and strategic design tasks (Beal et al., 2016). As a result, AI is emerging as a key technology that not only facilitates the monitoring of biological systems but also empowers predictive and adaptive control.

2.4. Systems approach

The systems approach in biosystems engineering is a discipline that requires a person to think about the biological, the environmental, and the engineering elements of a system, how each interrelates, and the entire system as a whole. With the biosystems engineering system approach, all the elements involved in the engineering of a biological system, where the aim is to design a system for the sustainable production and processing of food and other biological materials, along with the effective use of natural and renewable resources, and the system designed be in harmony with the biological system of the planet that responds to the needs of the human population (Alocilja, 2002). This definition shows that the production process is evaluated not only from a technical aspect but also takes into consideration the other environmental and social factors that affect the process. Sustainable agricultural production is a holistic approach that treats a production system as a complex set of interdependent systems that include the social dimension, along with the physical and biological. This is a system where the elements are in a dynamic relationship with each other (Ikerd, 1993). This is where the emphasis is on integrated approaches from modeling, optimizing, and adaptive control, instead of the reductionist approach. The holistic application of artificial intelligence–based techniques to a production process yields the desired result of increasing the availability of food, and at the same time, maintaining environmental sustainability. These technologies are designed to effectively control and reduce outputs of greenhouse gases, which are a significant environmental concern. Analyses in the literature that use natural language processing (NLP) tools also indicate that artificial intelligence applications can play an important role in addressing structural challenges in the agricultural sector. These technologies help the sector deal with the effects of climate change by making it more productive (Usigbe et al., 2024). In this context, a systems-based approach supported by digital technologies allows the development of agricultural production models that are easier to monitor, manage, and sustain over the long term.

3.Data Collection in AI-Based Agricultural Systems

3.1. Field sensors

Micro and nanotechnology are enhancing various fields of science and improving everyday life. In particular, the agricultural sector has benefited by increasing the sensitivity of miniaturized data collection and improved the cost and efficiency of AI-based monitoring systems (Murzin et al., 2020). Field sensors are the first part of the data collection chain in AI-based agricultural systems. Soil and plant sensors help collect important data for the decision-making systems used in irrigation, fertilization, and stress detection. Sensors help collect data on soil moisture, temperature, pH, electrical conductivity, nutrients, leaf wetness, sap flow, and chlorophyll. Magnetic field sensors, on the other hand, have a wide range of applications from agricultural robotics to space and military systems. Induction coil sensors (also called search coil sensors) measure the magnetic flux density B. Rogowski coils that have been specially designed are used to measure the magnetic field intensity H. Fluxgate magnetometers are known for being very sensitive and Resolution is especially important for military and space applications because they are relatively cheap and easy to make. Additionally, Hall sensors, discovered in 1879, remain among the most widely used magnetic sensors today because of their simple design, manufacturability in small sizes, and non-invasive magnetic field measurement capability (Tumanski, 2013).

These sensors are very important for systems that collect and monitor agricultural data because they use different measurement methods, have different levels of sensitivity, and can be used in different ways. Proper sensor placement, regular calibration, and appropriate maintenance strategies are essential for ensuring the reliability of collected data and the accuracy of AI models.

3.2. Remote sensing

In agricultural monitoring systems, remote sensing (RS) is one of the most important technologies that makes it possible to quickly, without contact, and with high accuracy assess large areas. Through satellite- and unmanned aerial vehicle (UAV)-based imaging systems, parameters such as crop health, biomass development, water stress, nutrient deficiencies, and disease spread can be monitored across different spatial and temporal scales.

Due to improvements in Global Positioning Systems (GPS), advanced machinery, hardware and software, cloud computing infrastructures, and the Internet of Things (IoT), RS technologies can now be used effectively at both regional and much smaller, within-field scales. (Khanal et al., 2020). High positional accuracy and strong data transmission capabilities enable site-specific interventions in precision agriculture, making resource use more efficient.

While satellite systems offer wide-area coverage advantageous for regional crop monitoring and yield estimation, UAV-based systems provide higher spatial and temporal resolution, enabling detailed field-level analyses. Multirotor UAVs are particularly preferred due to the operational flexibility they offer. These systems, which can be designed in four-, six-, and eight-rotor configurations, allow vertical take-off and landing, ensuring high safety and eliminating the need for large runways. They also enable focused data collection on specific problematic areas within the field. However, limited battery life remains a key disadvantage, restricting flight duration and coverage area.

Multispectral and thermal imaging techniques play a crucial role in remote sensing applications. The difference in reflectance between the visible (VIS) and near-infrared (NIR) bands is directly linked to how healthy a plant is and how much it can grow (Slonecker et al., 2001). Healthy plants, due to chlorophyll content, absorb more light in the visible spectrum, especially in the red band, while reflecting strongly in the near-infrared band. Stressed plants show a reduced reflectance difference. Vegetation indices developed based on this principle (e.g., NDVI) are widely used for determining plant vitality, detecting water and nutrient stress, and estimating yields.

But atmospheric conditions, cloud cover, sensor noise, and calibration errors can all affect remote sensing data.Therefore, acquired images undergo various preprocessing steps before integration into AI models. RS systems integrated with field sensors provide both wide-area coverage and high-resolution detailed analysis, enhancing the accuracy and effectiveness of AI-based agricultural decision support systems.

3.3. Image-based monitoring

Image-based monitoring systems play a critical role in smart agriculture applications for assessing plant health and detecting stress factors at an early stage. RGB, multispectral, and thermal imaging techniques enable rapid and contactless analysis of plants' morphological, physiological, and thermal characteristics. This allows potential issues in production areas to be identified early, providing opportunities for timely interventions.

RGB images contain rich information and are becoming increasingly important across different smart agriculture applications. Image detection, data transmission, and related processes rely on agricultural Internet of Things (IoT) infrastructures (Li et al., 2023). Multispectral imaging systems are particularly critical in large-scale agricultural operations for remotely monitoring plant health and evaluating phenotypic traits through vegetation indices.

These systems exhibit a wide range of configurations, from low-cost manual solutions to single-camera automated systems, multispectral composite imaging, and integrated imaging systems created with specialized mounting of separate cameras (Huang et al., 2010). When integrated with multirotor UAVs, they provide high safety during take-off and landing and enable detailed data collection by focusing on specific areas; however, limited battery life can restrict flight duration. The reflectance difference between visible and near-infrared (NIR) light provides valuable information on plant health and growth potential. However, environmental factors such as lighting conditions, atmospheric effects, and cloud cover can affect reflectance data and introduce errors in vegetation indices; therefore, calibration and correction steps are essential to ensure the reliability of the data collected (Haque et al., 2024).

3.4. Climate Data Integration

In agriculture, combining weather data is very important for making AI-based monitoring and prediction systems more accurate. For plant growth models, stress tests, and yield prediction algorithms, climate variables like temperature, humidity, precipitation, wind speed, and solar radiation are essential inputs. As computers get more powerful, climate modelers can make bigger and bigger simulation datasets. At the same time, satellite operations and other advanced observation methods keep adding to the amount of climate-related data. Nonetheless, discerning patterns and statistical correlations among variables in extensive datasets can engender considerable impediments in the analytical process (Nocke et al., 2008).

While meteorological station data offer significant insights at the local level, they are constrained in spatial coverage and may include absent or inaccurate measurements. Combining station data with climate model outputs and satellite-based observations makes it possible to make data structures that are more consistent and can be used on a larger scale (Economou et al., 2023). AI and machine learning techniques are essential for processing these multi-source climate datasets, identifying significant features, and incorporating them into agricultural decision support systems.

3.5. Data Integration Challenges

Digitalization has changed agriculture into smart farming by bringing together technologies like IoT, sensor networks, DSS, and FMIS. However, these technologies operate best when they are used together (Ahoa et al., 2025). For systems to perform well, they need frameworks that work together and can communicate with each other. However, there are still problems with data quality, standardization, and interoperability across different sources. To build smart agricultural systems that can grow and last, we need to use technologies like AI, blockchain, and edge computing, as well as strong data governance and security (Manik et al., 2024).

4. AI for Climate Stress Detection and Prediction

4.1. Stress Classification

It is becoming more necessary to categorize kinds of stress such as drought, heat, and biotic stress using machine learning algorithms (Geyer et al., 2011). Supervised techniques like SVM, Random Forest, and k-NN are good at looking at multidimensional data. Random Forest is especially good at handling huge and complicated datasets (Zhu, 2020). Hybrid methods like KMeans-SVM improve classification accuracy (≈96%) even more and make it possible to monitor in real time, which helps find stress early and make decisions (Karthikeyan et al., 2025).

4.2. Deep Learning in Phenotyping

Deep learning methods, especially Convolutional Neural Networks (CNNs), have helped a lot with studies of plant phenotyping. High-resolution RGB, multispectral, and thermal images can automatically extract phenotypic traits like leaf area, biomass, plant height, and disease symptoms.

The plant science community is using these methods more and more to make sense of the large amounts of data that are regularly collected through high-throughput phenotyping and genotyping (Singh et al., 2018). Deep learning, which is becoming more popular for analyzing large and complicated datasets, not only improves data analysis but also makes it easier to recognize, profile, and predict visual phenotypes. This helps answer important biological questions (Pratapa et al., 2021). This method shows how important deep learning is for finding new things in plant biology. Deep learning offers computational solutions to uncover previously unexamined cellular phenotypes as the complexity and scale of imaging experiments expand. This gives researchers a big edge when it comes to finding climate-resilient varieties and quickly figuring out their genetic potential.

4.3. Early Warning Systems

The rise in climate change and environmental stress is making agricultural production and food security even less certain. With new technology, it is now possible to monitor most pollutants and environmental damage in real time, find bad trends, and make accurate predictions about possible effects using Early Warning Systems (Reichstein, et al., 2025). This shows that AI-based systems can give you an early warning and that this is their main benefit when it comes to reducing risk. An EWS is a system that brings together the processes of monitoring, collecting, analyzing, interpreting, and sharing observed data (Reichstein et al., 2025). With this structure, you can combine agricultural data, weather data, and climate indicators to do thorough and systematic analyses. These systems keep an eye on, evaluate, and report risks to help with resilience and long-term growth (Quansah et al., 2010). AI algorithms use this information to predict climate stresses like drought, extreme heat, and disease, which makes it possible to act quickly. AI-based EWS not only make it easier to predict risks, but they also turn into all-in-one decision support tools that make the best use of resources, protect the environment, and make farming more resilient.

4.4. Yield Prediction

To guess how climate change might affect crop yields, we need a model of how plants react to different weather conditions (Lobell et al., 2010). This requirement is the basis for making accurate and dependable predictions for managing resources and planning for farming. AI and statistical models can predict how plants will grow and how much they will yield by looking at things like temperature, precipitation, and other climate factors.

But because predictions from different models don't always agree, it's important to figure out why they don't agree in order to get a better idea of what climate change will likely do (Lobell et al., 2010). As a result, process-based models are used in addition to AI-based ones. For example, the CERES-Maize model has been used in Sub-Saharan Africa to simulate historical changes in maize yield across about 200 sites and to predict what would happen if the temperature rose by 2 °C and rainfall fell by 20%. These kinds of examples are important for figuring out what different models can and can't do and for making AI predictions more accurate (Iqbal et al., 2024). Integrating AI-supported and process-oriented models diminishes uncertainty and facilitates more precise forecasts of yield variations caused by climate change. These methods help farmers and policymakers take steps to avoid problems and improve crop yields. AI-based yield prediction models are essential tools for sustainable agriculture and food security.

4.5. Model Reliability

Reliability and explainability are very important for AI models to be widely used in farming. It is not enough for a model to be very accurate; it is also important that the variables it uses to make decisions are clear. In this context, Explainable AI (XAI) methods make it easier to understand the results of models and build trust in them. To check how reliable a model is, people also use methods like cross-validation, testing with separate datasets, and uncertainty analysis. AI systems made to find and predict climate stress must be fast, clear, and reliable. This is the basis for smart agriculture apps that are both long-lasting and reliable.

5. Intelligent Decision Support Systems

5.1. DSS Structure

AI-based Decision Support Systems (DSS) help farmers and agricultural managers make smart choices by letting them work with complicated data. These systems have a single structure that includes data collection, analysis, modeling, and making recommendations. Sensors, satellite images, and climate data are all put together on a central platform and processed by algorithms. DSS cuts down on uncertainty, boosts productivity, and makes the best use of resources through this framework.

Farmers can also figure out how to make themselves less vulnerable to climate change and put those plans into action in the most cost-effective way possible, based on their own economic, soil, and weather conditions (Wenkel et al., 2013). An interactive DSS is very important for looking at climate change impact assessments and possible ways to adapt agricultural land use (Power, 1997). DSS enhances farm-specific decision-making processes by providing data-driven recommendations and simulations.

5.2. Smart Irrigation

Climate change and water shortages are major threats to agricultural production. AI-powered smart irrigation systems figure out the best times and amounts of water to give plants based on the weather, soil moisture, and how much water the plants need. This method stops overwatering and saves water, which helps with sustainable production. Technological progress makes it possible to lower risks and make irrigation easier (Darshna et al., 2015). In this situation, embedded microcontroller systems can help with a lot of problems. For example, microcontroller systems with sensors can control irrigation in gardens and fields very accurately. Sensors in the field send information about the temperature and moisture of the soil to the microcontroller, which then uses that information to figure out how much water the plants need. This means that irrigation is only done when it's needed, which makes smart irrigation systems possible that can save about 80% of water (Darshna et al., 2015).

Moreover, the incorporation of wireless communication systems, monitoring devices, and sophisticated control techniques can significantly augment the efficacy of smart irrigation methods (Gamal et al., 2023). This all-around approach not only boosts productivity but also makes sure that water resources are used in a way that is good for the environment.

5.3. Nutrient Management

AI-assisted soil and nutrient management techniques seek to deliver essential nutrients to plants in appropriate quantities and at optimal times.

Improving soil fertility and fighting nutrient depletion are two strategies that work together to protect the environment and support sustainable crop production (Singh et al., 2001). In this context, system-based methodologies are utilized to advance integrated nutrient management practices and avert reductions in soil fertility (Singh et al., 2001). Additionally, to speed up the transfer of technology and make it easier to get inputs, make decisions, and use integrated nutrient management practices, system-based methods are tested and developed on eco-regional and system-wide levels (Singh et al., 2001). Also, nitrogen and phosphorus are important for human life, but putting too much of these nutrients into the Earth system can pollute the air and water in some places and make climate change worse around the world (Zhang et al., 2020). This century's biggest problem is how to manage nutrients in a way that doesn't hurt the environment or the climate while still being able to feed the world's growing population. Thus, AI-based and data-driven integrated nutrient management is an important tool for both boosting productivity and lowering environmental damage.

5.4. Disease and Pest Prediction

Pests and diseases cause big drops in the quality and quantity of crops. This not only lowers productivity and product quality, but it also pollutes the environment more because pesticides or fungicides are needed to keep pests and diseases at bay. AI- and IoT-based systems are now the best way to predict and control pests and diseases. IoT systems are made to cut down on the unnecessary use of insecticides and fungicides and to give good control by predicting when pests will show up (Lee et al., 2017). For instance, air stations were put up near orchards to look at the link between pest outbreaks and weather data, and predictive models were made (Lee et al., 2017).

Machine learning algorithms are useful for predicting plant diseases and pest outbreaks thanks to advances in technology. Reviews have shown that accurate early warning systems are very important for controlling the damage caused by pests and diseases and for making sure that the right management practices are put in place on time (David, 2023). Farmers can get real-time updates on disease and pest forecasts and act quickly when they need to. This method helps keep productivity and product quality high while lowering environmental impacts.

5.5. Farm and Regional Integration

The effectiveness of DSS is significantly enhanced when data integration extends beyond individual farms to regional and national levels. Combining data collection and analysis methods across different scales provides a holistic perspective for agricultural policies, resource management, and crisis intervention. AI-based systems support this integration by enabling information sharing between farms, optimization, and sustainable planning.

This approach strengthens decision-making processes by integrating sensor data from multiple farms, climate and soil information, pest and disease forecasts, and irrigation and nutrient management data.

At the regional level, it optimizes resource use, reduces environmental impacts, and enhances overall agricultural productivity. Regional cooperation between farms such as material exchange, coordinated crop livestock systems, and shared land or resource management can improve input use efficiency and contribute to reducing environmental pressures in agricultural production systems (Letermeet al., 2019). Additionally, regional early warning systems and coordinated management plans allow for rapid and effective responses during crises. This holistic approach increases interoperability among local and regional farms, forming the foundation for sustainable, data-driven smart agriculture.

6. Controlled Agricultural Systems

6.1. AI in Greenhouses

More and more controlled agricultural environments are using AI-assisted greenhouse systems to make production more efficient and make the best use of resources. Sensors, automation systems, and data analytics tools can keep an eye on and control the greenhouse's environmental conditions all the time. AI in greenhouses has led to better crop yields, more efficient use of water and fertilizer, fewer pests and diseases, and more sustainable farming (Maraveas, 2022). The application results also have big economic benefits. In fact, AI-based irrigation and soil fertilization apps have helped farmers get better returns on their investments, bigger crops, and better use of their resources (Maraveas, 2022). When you think about what these changes mean for the bigger picture, it's clear that sustainable production models are strategically important. Sustainable greenhouse agriculture has been demonstrated to reconcile the disparity between food supply and demand (Hoseinzadeh and Garcia, 2024). In this context, AI-assisted smart greenhouse systems not only make food production more efficient, but they also offer a new and long-lasting way to grow food that helps keep the world's food supply safe.

6.2. Climate Optimization

To control the climate in a modern greenhouse, you need to use advanced climate control models (Rytter et al., 2012). These models help you get the best temperature, humidity, CO_2, and light levels in the greenhouse so that plants can grow and produce the most. A nonlinear model predictive control framework can effectively manage the nonlinear dynamics of greenhouse climates and the variability across different production scenarios. It keeps temperature, humidity, and light levels within target ranges while keeping energy costs low (Chen et al., 2022). This approach is new because it uses genetic algorithms to solve the multi-objective optimization problem that comes up when you add climate control models on their own (Rytter et al., 2012). By combining NMPC and genetic algorithms, producers can make their plants more energy-efficient, improve their quality and yield, and lower the risk of getting sick from climate-related diseases. These methods provide adaptable and expandable solutions for managing the climate in greenhouses, which is a big step toward creating production systems that are long-lasting and strong.

6.3. Energy Efficiency

Energy efficiency and conservation are seen as important ways to cut down on greenhouse gas emissions and reach other energy policy goals (Gillingham et al., 2009). To protect the environment and lower costs, smart greenhouse systems need to use energy in the most efficient way possible. In terms of energy efficiency, market barriers, market failures, and behavioral shortcomings are all important reasons for policy changes (Gillingham et al., 2009). Thus, AI-based control strategies that aim to lower energy use do this by changing environmental factors like temperature, humidity, CO_2, and light intensity. This saves energy and makes better use of resources without harming plant growth or crop yield. AI-assisted energy management is an important tool for improving the long-term economic and environmental performance of greenhouse systems.

7. Sustainability and Environmental Impact

7.1. Water-use efficiency (WUE)

WUE is a key idea for managing water resources well in sustainable farming. WUE is not just a way to measure how much water is used; it is also a key performance indicator that shows how well water is used during the production process (Pereira, 2012). From a hydrological point of view, WUE is the amount of water used efficiently compared to the total amount of water used. When water is the main thing that stops crops from growing, cutting down on non-productive water use can raise WUE, which can lead to more transpiration and a higher yield (Stanhill, 1986).

To make irrigation systems more efficient with water use, you need to cut down on losses during transportation and application. Water is used more efficiently when irrigation is done at the right time and in the right way for the plants. Sensors, remote sensing data, and AI-based decision support systems make it possible to plan irrigation very accurately and quickly. WUE is not only about managing irrigation; it is also about the weather, how rain falls, and the soil's physical (texture, porosity, water-holding capacity) and chemical (organic matter, nutrient balance) properties that affect how much water is available. WUE is a whole idea that needs to look at climate, soil, and management practices all at once.

7.2. Energy Optimization

Energy use in farming and food production is a big problem for both the economy and the environment. This is because it comes from a lot of different processes, like irrigation pumps, greenhouse climate control systems, farming machines, and post-harvest operations. This is why making the most of energy is so important for reaching goals of efficiency and sustainability. AI-based energy management systems look at data from sensors, climate data, and usage patterns to better plan how to use energy. These systems help cut down on unnecessary energy use by making it easier to predict how much energy people will need. Smart grid technologies also help a lot with optimizing energy use. Demand response strategies give users incentives and money for using their devices in a flexible way (Zhang et al., 2024). This way, energy demand is balanced, and it's easier to use renewable energy sources. For instance, using solar energy helps the environment by reducing the need for fossil fuels. Energy optimization has become more important as part of the goals for sustainable development (Sadollah, 2020). In this context, optimization algorithms are made to use less energy, make better use of resources, and make systems work better. Machine learning and other optimization algorithms look at patterns of energy use, cut costs, and move energy use to the best times based on changes in demand structure. In conclusion, even though energy costs go down, energy systems can still work in a balanced and long-lasting way.

7.3. Carbon Monitoring

Carbon monitoring is becoming more and more important for policies on sustainable agriculture and environmental management. Monitoring greenhouse gas emissions and calculating the carbon footprint (CFP) are two of the most important things we can do to fight climate change. They are also two of the most important things that sustainability policies focus on (Laurent et al., 2012). Regularly measuring and analyzing carbon emissions helps us get a better idea of how they affect the environment. Yet there are some problems with only using the carbon footprint to measure environmental sustainability. The carbon footprint may not accurately represent the environmental burden of products, and environmental management that solely emphasizes CFP may inadvertently transfer impacts to alternative domains (Laurent et al., 2012). So, when looking at how things affect the environment, it's important to use more thorough monitoring methods.

New technologies for monitoring the environment have made it possible to keep track of carbon emissions more accurately and in real time. Monitoring has become more important as cities grow and industries expand, putting more stress on the environment (Ng, 2014). In this context, advanced sensor technologies, remote sensing systems, and data analytics methods are effectively employed to monitor carbon emissions. Nanotechnology-based sensors have recently appeared in efforts to monitor the environment. Analytical probes made with carbon nanoparticles are very sensitive, not very toxic, and could be made from renewable resources. This makes them a sustainable option for monitoring carbon and assessing the environment (Ng, 2014). These technologies make it easier to keep track of carbon emissions, which help create sustainable production systems and make strategies to reduce environmental impacts more effectively.

8. Challenges and Barriers

8.1. Data and Scalability Issues

Data quality and scalability present considerable obstacles in extensive data integration and data mining endeavors. These processes are expensive to set up and keep running (Rosenthal and Seligman, 2001). Hundreds of millions of records, different kinds of data (text, images, video, and contextual data), and data streams that never stop make it harder and harder to do data mining and integration reliably and quickly. So, systems that use applications that don't take into account scale, cost, and reliability in data integration and mining processes can't provide reliable and long-lasting performance. To make big data systems work well and reliably, they need phased integration, correct assumptions, and infrastructure that can grow.

8.2. Economic and technological constraints

Farmers' access to technology and sustainable practices is affected by economic and institutional factors, thus policies need to be in place to encourage their use (Weiss, 2019). Technological considerations are also important for separating CO_2 emissions from economic development by using low-carbon and efficient solutions (Apeaning, 2021). In general, overcoming economic, regulatory, and implementation constraints is necessary for sustainable development and the use of new technologies.

8.3. Ethical considerations

In research, ethical principles, data privacy, and algorithmic accountability are essential for safeguarding participants and ensuring the study's reliability. Ethical principles are essential to safeguard the dignity and rights of research participants (Arifin, 2018). In all qualitative or quantitative research processes, including data collection, analysis, and reporting of results, accuracy, correct reporting of data, confidentiality, and honest presentation of findings are fundamental components of the research methodology. It is important to follow ethical standards at every step of the research process (Hasan et al., 2021). This method lowers the chances of problems while making sure the results are trustworthy and clear. It is thought to be a basic duty to keep participants safe, protect their privacy, and make sure that results are correct.

8.4. Capacity building

Capacity building is a key part of making health systems stronger in low-income countries. Experiences demonstrate that improved health outcomes necessitate not only augmented financial investment but also adequate local capacity to effectively utilize these resources. Local capacity is also thought to be very important for keeping health outcomes stable and lowering the need for long-term outside help (Brown et al., 2001). Because of this, international donors, non-governmental organizations, and health ministries are putting more and more effort into building capacity. Their goal is to improve the overall performance of the health sector by making local capabilities stronger. Capacity building is important for both short-term and long-term success in health, as well as for reducing the need for outside help.

9. Future Directions

9.1. Digital Twins

Digital twins are a key technology for real-time monitoring, analysis, and decision support because they let you model physical systems in a virtual space. These systems use sensors and data integration to mimic how physical assets behave, which lets you test out different situations. Urban Digital Twins can change how cities are planned and run in a big way (Iranshahi et al., 2025). This method shows how useful digital twins can be for managing and planning complicated systems. Building local capacity is also very important for the long-term use of technology. Local capacity is thought to be very important for keeping health outcomes stable and lowering the need for outside help in the long run (Mazzetto, 2024).

9.2. Hybrid AI–Mechanistic Models

By combining artificial intelligence with physics-based models, we can better understand and forecast complex systems because we can use data-driven precision and mechanistic dependability. Hybrid techniques use AI to make predictions and physical models to make sense of the results (Lin et al., 2025). Integrating neural networks with classical simulations also improves optimization in engineering systems. This makes it possible to represent complicated processes like finite element analysis and fluid dynamics more efficiently (Li et al., 2026).

9.3. Autonomous Systems

Deep reinforcement learning (DRL) is changing how data is collected, decisions are made, and operations are run in fields including robots, automobiles, and drones (Govinda et al., 2025). These systems use input from the environment to become better, and dependable network infrastructures are needed to make sure that things keep working and don't break down (Rai et al., 2005). In general, DRL-based autonomous systems have a lot of promises to make things more efficient and help with climate change in areas like farming, transportation, and keeping an eye on the environment.

9.4. Policy and Governance

AI is becoming more and more important for making public services more efficient and open. Digital governance models that focus on AI offer good answers to many problems, from making policies to providing services to citizens (Damgacı, 2025). When AI is used well, with the help of strong digital infrastructure, ethical rules, and citizen involvement, it makes public administration more efficient and accountable.

10. Conclusion

10.1. Key Insights

This study emphasized the transformative capacity of AI in biosystems engineering for climate-resilient agriculture. AI applications, such as phenotyping based on deep learning and integrated decision support systems, make it possible to accurately track, predict, and adaptively manage agricultural production. Field sensors, remote sensing technologies, and climate data integration have all worked together to make stress detection, yield prediction, and resource optimization more accurate. AI also makes it easier to manage water and nutrients, plan for diseases and pests, control the climate in greenhouses, and smart irrigation, all of which boost productivity and sustainability.

10.2. Implications for Resilient Agriculture

The use of AI in farming systems makes them more resistant to changes in the weather by allowing decisions to be made based on data. Early warning systems and predictive models help people respond quickly to environmental stresses, which can help prevent yielding losses. Using AI to optimize the use of water, energy, and nutrients cuts down on waste and damage to the environment, which helps support sustainable production methods. Also, the regional integration of AI-based systems helps farms work together, which makes food security and ecosystem health better overall. These improvements show that AI-based biosystems engineering is not only a new technology, but also an important part of making farming strategies that can withstand climate change.

10.3. Final Remarks

The future of smart farming depends on how well AI, biosystems engineering, and environmental monitoring work together. Agricultural systems can be more productive and have less effect on the environment by using advanced data analytics, adaptive control mechanisms, and predictive modeling. Climate change is making it harder for food systems around the world to work. AI-assisted methods will be very important for making sure that farming is sustainable, resilient, and productive. To fully realize AI's potential to promote climate-resilient agriculture, we need to keep investing in technology, infrastructure, and working together across disciplines.

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