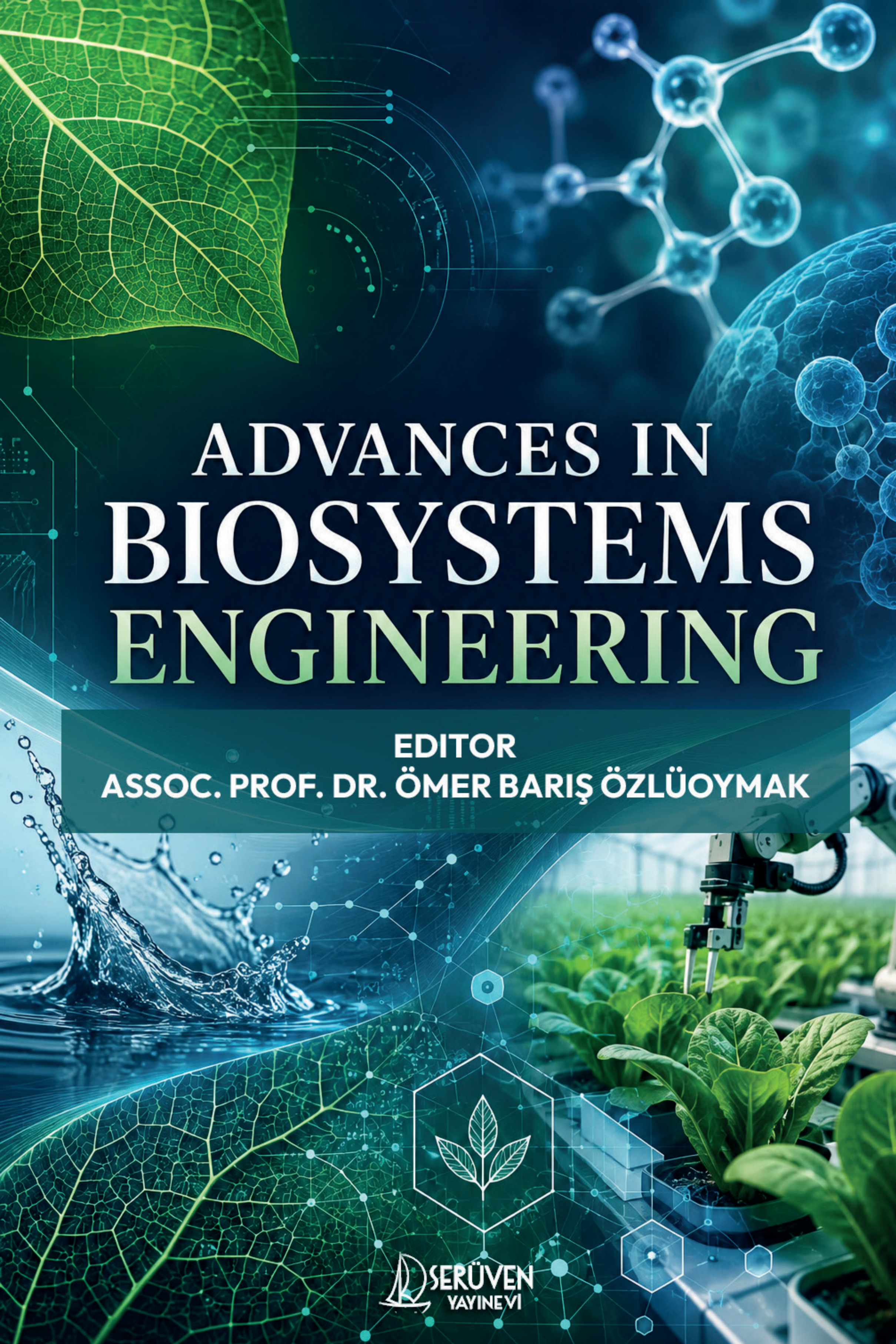


ADVANCES IN BIOSYSTEMS ENGINEERING

EDITOR

ASSOC. PROF. DR. ÖMER BARIŞ ÖZLÜOYMAK

SERÜVEN
YAYINEVİ

Genel Yayın Yönetmeni· C. Cansın Selin Temana

Kapak & İç Tasarım · Serüven Yayınevi

Birinci Basım · © Haziran 2026

ISBN · 978-625-8810-11-0

Serüven Yayınevi
Adres: Kızılay Mah. Fevzi Çakmak 1. Sokak
Ümit Apt No: 22/A Çankaya/ANKARA
Telefon / Phone: 05437675765
web: www.seruvenyayinevi.com
e-mail: seruvenyayinevi@gmail.com

Baskı & Cilt
Sertifika No: 47083

ADVANCES IN BIOSYSTEMS ENGINEERING

EDITOR

ASSOC. PROF. DR. ÖMER BARIŞ ÖZLÜOYMAK

CONTENTS

Chapter
1

ENGINEERING SOLUTIONS FOR PRECISION WEED CONTROL AND THE EVOLUTION OF INDIVIDUAL PLANT TREATMENT USING SMART GROUND-BASED SPRAYING SYSTEMS

Ali BAYAT[1]

---

[1] Department of Agricultural Machinery and Technologies Engineering, Faculty of Agriculture, Çukurova University, Adana 01330, Türkiye. E-mail: alibayat@cu.edu.tr ORCID: 000-0002-7104-9544

1. Introduction

The paradigm of traditional agriculture characterized by the uniform broadcast application of herbicides across entire fields is becoming both economically and ecologically unviable. This "all-or-nothing" approach ignores the inherent spatial variability of weed populations, leading to significant chemical waste and the acceleration of herbicide resistance. According to Busari et al. (2015), the transition toward sustainable soil and crop management is no longer optional; it is a critical necessity to protect the environment while simultaneously meeting the caloric demands of a surging global population.

The fundamental engineering challenge in modern crop protection is the shift from field-scale management to plant-scale intervention. While aerial platforms, such as Unmanned Aerial Vehicles (UAVs), have gained popularity for mapping, ground-based precision equipment offers a distinct mechanical and operational advantage. These machines provide superior payload capacity for high-volume sensors and tanks, mechanical stability for precision nozzles, and the robust ability to operate in diverse weather conditions where flight might be restricted. As noted by Lowenberg-DeBoer and Erickson (2019), the adoption of these ground-based precision technologies is driven by their proven capacity to enhance the efficiency of input use, thereby reconciling environmental stewardship with farm profitability.

The integration of real-time detection systems into ground sprayers represents the pinnacle of site-specific weed management (SSWM). By utilizing engineering solutions that detect weeds in real-time and actuate chemical delivery only where a target is present, farmers can achieve unprecedented levels of efficiency. Current research indicates that moving from traditional methods to smart ground equipment can reduce herbicide consumption by up to 90% in specific row-crop scenarios (Lencsés et al., 2020). This reduction is not merely a cost-saving measure but a strategic move toward "Individual Plant Treatment" (IPT), where each weed is managed as a singular unit.

Furthermore, the mechanical evolution of these systems is closely linked to soil health. Busari et al. (2015) emphasize that precision equipment supports conservation tillage practices by allowing for effective weed control without the need for intensive mechanical soil disturbance. This synergy between smart chemical application and soil conservation creates a holistic engineering framework for 21st-century agriculture. By bridging the gap between high-speed mechanical operation and millisecond-level sensor feedback, smart ground equipment serves as the cornerstone of the next green revolution, where data-driven precision replaces volume-based protection.

2. Real-Time Sensing and Identification Systems

The fundamental engineering challenge in precision weed control is the reliable, millisecond-level identification of target weeds among crops. In a dynamic field environment, sensors must account for varying lighting conditions, dust, and high operational speeds. According to Peteinatos et al. (2014), the integration of high-resolution optical sensors into ground-based platforms is the primary driver behind the transition from "blind" spraying to "see-and-spray" technology.

2.1. Spectral Reflection and Vegetation Indices

Initial engineering solutions for weed detection relied on active light sensors, such as the WeedSeeker or WEED-IT systems. These devices emit their own light (typically in the Red and Near-Infrared spectra) and measure the reflection from the surface below. By calculating the Normalized Difference Vegetation Index (NDVI), the system can distinguish between non-living surfaces (soil, stones, or residue) and living green plants. This "green-on-brown" detection is highly effective in fallow fields or pre-emergence scenarios, significantly reducing herbicide waste in non-cropped areas (Luck & Fulton, 2014).

2.2. Computer Vision and Deep Learning (CNNs)

The evolution toward "green-on-green" detection—distinguishing a weed from a crop—has required the integration of Artificial Intelligence. Modern ground equipment now employs high-speed RGB cameras coupled with Convolutional Neural Networks (CNNs). Unlike simple spectral sensors, CNNs analyze the leaf morphology, texture, and spatial patterns of plants to classify them. Berrer et al. (2023) highlight that deep learning models can now achieve over 95% accuracy in identifying specific weed species within complex crop canopies, such as sugar beets or maize.

2.3. Latency and Real-Time Data Processing

The technical bottleneck in sensor-based identification is system latency. As a ground sprayer moves at 12–18 km/h, the time elapsed between image capture, AI processing, and nozzle activation must be minimal. Reiser et al. (2022) emphasize that a total system lag of even 50 milliseconds can cause the herbicide burst to land centimeters away from the intended target. To mitigate this, engineers utilize Edge Computing—processing data directly on the machine's hardware rather than in the cloud—and predictive algorithms that "fire" the nozzles slightly ahead of the machine's forward motion based on real-time ground speed data.

2.4. Environmental Resilience in Sensing

Field conditions pose significant physical constraints on sensing hardware. To maintain accuracy, modern equipment incorporates:

· **Active Lighting Bars (Fig. 1):** High-intensity LEDs that normalize the light environment, allowing the cameras to function consistently during cloudy days or at night.

· **Ultrasonic Height Sensors (Fig. 2):** These sensors ensure the boom—and thus the cameras—remains at a constant distance from the canopy, preventing image distortion and ensuring a consistent field of view for the AI (Partel et al., 2019).

· **Protective Air Curtains (Fig. 3):** Using pressurized air to create a "shield" around lens openings, preventing dust accumulation which would otherwise degrade image quality.

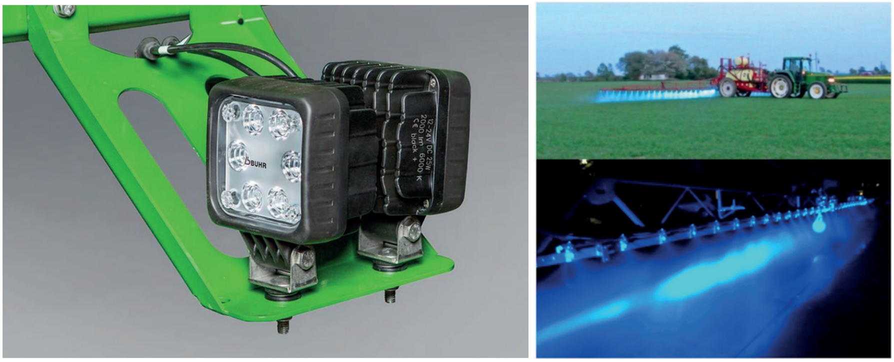


*Figure1. Active lighting bars (*https://amazone.net/en/products-digital-solutions/agricultural-technology/crop-protection/trailed-sprayer/led-boom-lighting-for-super-s-booms)

Figure 2. Sprayer boom height detection system architecture and Distribution map of boom height variation in a wheat stubble field (Dou et all.,2021).

*Figure 3. Lens Cleaning with compressed air. (*https://www.samcon.eu/en/products/equipment/air-blade/*)*

3. Advanced Actuation: Pulse Width Modulation (PWM)

Once a weed is identified, the sprayer must deliver a precise dose without altering the spray pattern or droplet size. Beyond simple "on-off" spot spraying, VRA allows the system to adjust the herbicide dose based on the weed density or the specific species detected

3.1. Operational Mechanisms: Map-Based vs. Sensor-Based

VRA systems are engineered using two distinct logic frameworks:

- **Map-Based VRA (Fig. 4):** Relies on a "look-ahead" logic where the controller cross-references the machine's RTK-GPS coordinates with a pre-loaded prescription map. This method is highly effective for managing perennial weed patches identified through satellite or UAV imagery (Lowenberg-DeBoer & Erickson, 2019).

- **Sensor-Based VRA (Fig 5):** Utilizes a "detect-and-act" logic. Real-time sensors (optical or vision-based) identify the target, and the controller triggers the actuator instantaneously. This is the primary method for **Individual Plant Treatment (IPT)**, where the specific location of weeds is not known until the moment of encounter.

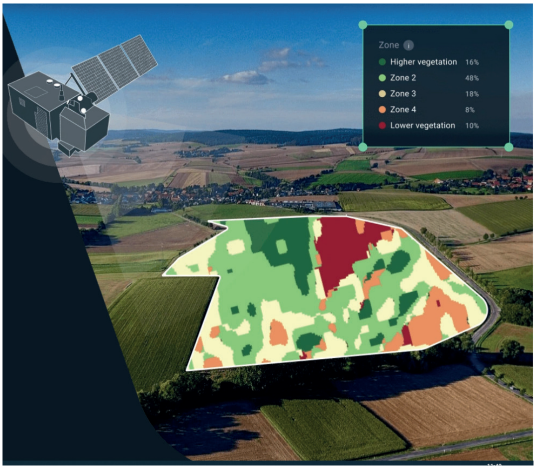


Figure 4. Map-based VRA (https://eos.com/products/crop-monitoring/vra-maps/)

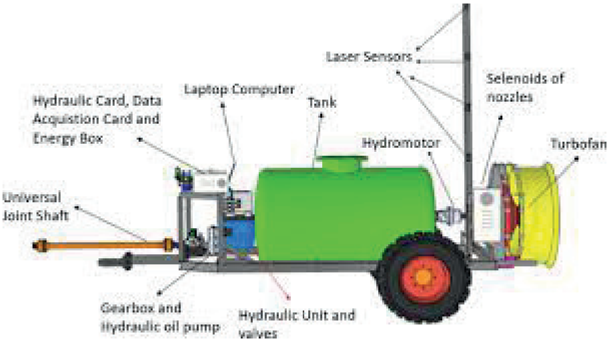


Figure 5. Sensor-Based VRA (İtmeç & Bayat, 2026)

The comparative advantages and engineering challenges of Map-Based VRA and Sensor-Based VRA are summarized in **Table 1** (Lowenberg-DeBoer & Erickson, 2019; Subeesh & Mehta, 2021).

Table 1. *Comparative Advantages and Engineering Challenges*

Feature	**Conventional VRA (Pressure-based)**	**PWM-driven VRA**
Droplet Size Consistency	Poor (changes with flow rate)	Excellent (remains constant)
Response Time	Slow (due to pump/line pressure lag)	Instantaneous (ms response)
Precision Level	Section-based	Individual Nozzle/Plant
Complexity	Low	High (requires high-speed controllers)

The data presented in **Table 1** highlights the fundamental engineering trade-off between system simplicity and application precision. While conventional pressure-based VRA systems offer a lower barrier to entry due to their mechanical simplicity, they are physically limited by the direct correlation between flow rate and pressure; any attempt to adjust the dosage inevitably compromises droplet size and spray pattern integrity. In contrast, PWM-driven VRA serves as the superior technical solution for Individual Plant Treatment (IPT). By utilizing high-frequency digital pulsing, it achieves the near-instantaneous response times (measured in milliseconds) required to target weeds at high field speeds, all while maintaining a consistent droplet spectrum to mitigate environmental drift (Giles & Money, 2015; Reiser et al., 2022).

3.2. The Role of Pulse Width Modulation (PWM) in Precision Actuation

In conventional sprayers, flow rate (Q) is linked to pressure (P) by the formula $Q = k\sqrt{P}$. This presents a significant engineering conflict: increasing the flow rate for a dense weed patch requires increasing the pressure, which reduces droplet size and increases the risk of drift.

Pulse Width Modulation (PWM) solves this by decoupling flow rate from pressure. By using high-frequency solenoid valves (10–50 Hz), the system manages the "duty cycle"—the ratio of time the valve is open.

Constant Pressure**:** PWM allows the sprayer to maintain optimal pressure for a specific nozzle type, ensuring consistent droplet size and spray pattern regardless of the application rate (Giles & Money, 2015).

Turn Compensation: One of the most critical engineering advantages of PWM is its ability to adjust flow rates across the boom during turns. Luck and Fulton (2014) demonstrated that PWM prevents over-application at the inner boom and under-application at the outer boom by adjusting individual nozzle duty cycles in real-time. Carreira & Silva (2022) illustrated that PWM theoretically provides a solution for achieving uniform spraying during turns; however, as the boom width increases, the required duty cycle range exceeds the system limits, making this a significant engineering constraint in practice (Fig. 6).

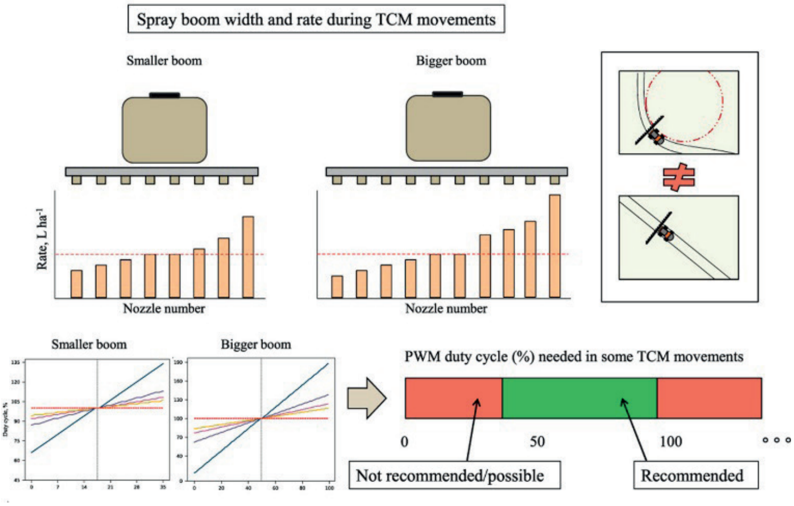


Figure 6. Turning and circular movements (TCM) generate rate errors

3.3. Engineering Challenges and System Latency

The primary constraint in VRA is system latency. For an IPT system to be effective, the sensor, controller, and PWM valve must communicate within milliseconds. Reiser et al. (2022) noted that at a standard field speed of 12 km/h, a total system lag of 100 ms would result in a 33 cm displacement, effectively missing the target. Engineering solutions to this include:

- Predictive Algorithms: Using machine speed data to "pre-trigger" valves.
- High-Speed Solenoids: Utilizing industrial-grade actuators capable of operating at frequencies higher than 30 Hz to minimize the physical response lag.

The technical trade-offs between these high-speed engineering solutions and traditional systems, specifically regarding response time and droplet stability, are systematically compared in **Table 2** (Reiser et al., 2022; Giles & Money, 2015)

Table 2. *Performance Comparison of VRA Actuation Methods*

Feature	Pressure-Based VRA	**PWM-Based VRA**
Droplet Size Stability	Poor (Varies with flow rate)	Excellent (Remains constant)
Response Time	Slow (>1000 ms due to line lag)	Instantaneous (<50 ms response)
Precision Unit	Boom Section	Individual Nozzle / Plant
Spray Pattern Integrity	Moderate (Collapses at low pressure)	High (Constant pattern width)
Turn Compensation	Not possible	Full individual nozzle adjustment

Feature	Pressure-Based VRA	**PWM-Based VRA**
Drift Risk	High (at high pressure/flow)	Low (Controlled droplet size)
Literature	Luck & Fulton (2014)	Giles & Money (2015); Reiser (2022)

As shown in the table 2, PWM-based VRA is the superior engineering solution for individual plant treatment. While conventional pressure-based systems are limited by the physical constraints of fluid dynamics—where increasing flow necessitates increasing pressure—PWM systems utilize high-frequency solenoids to manage dosage without compromising the quality of the spray application. This is particularly critical in precision weed control to ensure that the chemical reaches the target weed with the correct droplet size to prevent drift and maximize efficacy (Giles & Money, 2015).

4. Individual Plant Treatment (IPT) and Robotic Evolution

The most advanced stage of precision weed control is Individual Plant Treatment (IPT). In this model, every single plant in the field is treated as a unique management unit.

· RTK-GPS Integration**(Fig. 7):** To achieve IPT, the equipment must know its location with centimeter-level accuracy. Real-Time Kinematic (RTK) GPS provides the 1–2 cm precision required to correlate a camera's "find" with a nozzle's "hit."

· **Autonomous Platforms (Fig. 8):** The future of IPT lies in small, autonomous ground robots. Unlike heavy tractors, these robots cause minimal soil compaction. Slaughter et al. (2008) highlight that the robotic evolution involves not just chemical application, but also mechanical and thermal (laser) weeding as alternatives to herbicides.

Figure 7. RTK-GPS Integration

Figure 8. Autonomous Platforms

5. Technical Comparison of Equipment Generations

The evolution of agricultural spraying technologies demonstrates a direct correlation between hardware complexity and herbicide efficiency. As detailed in Table 3, the progression from "Generation 1" to "Next-Gen" autonomous systems increases input savings from roughly 15% to over 95% (Lowenberg-DeBoer & Erickson, 2019; Pathak et al., 2020).

Table 3. *Technical Comparison and Efficiency Analysis of Pesticide Application Generations*

Technology Level	**Engineering Component**	**Herbicide Savings**	**Operational Speed**	**Supporting Literature**
Generation 1	Section Control & GNSS Guidance	%10 - %15	High	Lowenberg-DeBoer & Erickson (2019); Lencsés et al. (2020)
Generation 2	Real-time Spot Spraying (See & Spray)	%40 - %70	Medium-High	Giles & Money (2015); Partel et al. (2019), Özlüoymak (2022)
Generation 3	AI-Based Plant Specific Treatment	%80 - %95	Medium	Reiser et al. (2022); Berrer et al. (2023)
Next Gen	Autonomous Robotic Swarms	>%95	Variable	Pathak et al. (2020); Subeesh & Mehta (2021)

6. Engineering Constraints and Field Solutions

While the theoretical potential of Individual Plant Treatment (IPT) is significant, translating these technologies into reliable field operations presents several complex engineering challenges. The transition from a controlled laboratory environment to a dynamic agricultural field requires robust mechanical and electronic solutions to maintain accuracy and durability.

6.1. Dynamic Lighting and Spectral Variability

The reliability of computer vision systems is heavily dependent on consistent lighting. Changing sunlight angles, cloud shadows, and the "golden hour" effect can drastically alter the spectral signature and morphological appearance of plants, leading to false positives or missed targets.

Engineering Solution**:** Modern smart sprayers utilize shrouded or shielded booms to isolate the camera's field of view from ambient light. Within these enclosures, high-intensity LED lighting arrays provide a normalized, constant light source. This ensures that the AI model receives images with consistent contrast and color balance regardless of the time of day, effectively enabling 24-hour operation (Berrer et al., 2023).

6.2. Mechanical Stability and Boom Kinematics

High-speed ground travel over uneven terrain induces significant boom sway, both vertically and horizontally (yaw and roll). These vibrations can cause motion blur in camera sensors and lead to significant misplacement of the herbicide burst.

Engineering Solution**:** Active boom suspension systems, coupled with ultrasonic height sensors, are employed to maintain a constant distance between the nozzle and the target canopy. Luck and Fulton (2014) emphasize that maintaining a stable boom height is critical not only for sensor focus but also for ensuring the spray pattern remains within its designed overlap parameters. Advanced systems now use inertial measurement units (IMUs) to predict boom movement and compensate for nozzle triggering timing in real-time.

6.3. Latency and "Speed-of-Travel" Synchronization

The "Sense-Decide-Act" loop must occur within milliseconds. As tractor speeds increase to improve field capacity, the margin for error shrinks. For instance, at a speed of 18 km/h, the machine covers 5 meters per second.

Engineering Solution**:** To handle this, engineers utilize Edge Computing architectures where the image processing occurs on GPUs mounted directly on the boom. This eliminates the latency involved in sending data to a central vehicle controller. Furthermore, "look-ahead" predictive algorithms adjust the firing time of the PWM valves based on real-time encoder data from the wheels, ensuring that the chemical hits the weed precisely as the nozzle passes over it (Reiser et al., 2022).

6.4. Environmental Hardening: Dust and Chemical Exposure

Agricultural environments are notoriously harsh for delicate electronics. Dust accumulation on lenses can degrade image quality, while corrosive chemical mists can damage sensor housings.

Engineering Solution: Industrial-grade IP69K-rated housings are standard for all field sensors. Additionally, many systems incorporate "air-shroud" technology—a continuous stream of pressurized air directed across the camera lens to create a physical barrier against dust and droplets.

The multifaceted engineering challenges discussed above, ranging from optical interference to mechanical instability, are summarized in **Table 4**, highlighting the specific technological mitigations required for robust field performance (Partel et al., 2019; Reiser et al., 2022).

Table 4. *Summary of Field Challenges and Engineering Mitigations*

Constraint	**Impact on Precision**	**Engineering Solution**	**Supporting Literature**
Ambient Light Change	Misidentification and False Positives	Shrouded Booms & LED Normalization	Berrer et al. (2023)
Tractor Vibration	Motion Blur and Targeting Error	Active Suspension & IMU-based Compensation	Luck & Fulton (2014)
High Travel Speed	Spatial Displacement (Latency Lag)	Edge Computing & Predictive Triggering	Reiser et al. (2022)
Dust and Debris	Sensor Blindness and Lens Fouling	Pressurized Air Curtains & IP69K Housings	Partel et al. (2019)

The integration of these solutions ensures that the transition from a laboratory prototype to a commercial field machine is successful. By addressing lighting variability through shrouded environments and mechanical instability via active suspension, engineers can maintain the high accuracy required for Individual Plant Treatment (IPT) even in suboptimal field conditions.

7. Conclusion and Future Directions

The integration of Variable Rate Application (VRA) and Pulse Width Modulation (PWM) technologies marks a pivotal shift in agricultural engineering. By moving away from uniform broadcast spraying and toward Individual Plant Treatment (IPT), modern ground equipment has demonstrated the potential to reduce herbicide inputs by over 90%, significantly lowering both operational costs and environmental footprints (Lencsés et al., 2020).

7.1. Key Engineering Takeaways

The success of these systems relies on the seamless synchronization of sensing and actuation. As discussed, the transition to Deep Learning (CNN) models has enabled "green-on-green" identification with high accuracy, while PWM actuators have solved the physical limitations of fluid dynamics by maintaining constant droplet sizes across variable flow rates (Giles & Money, 2015). However, the technical barriers—particularly system latency and mechanical stability in harsh field conditions—remain the primary focus for ongoing engineering refinements.

7.2. Future Trends: Toward Robotic Swarms

The next frontier in precision weed control involves the decentralization of equipment. Rather than single, massive sprayers, the industry is moving toward autonomous robotic swarms. These smaller, lighter platforms offer several advantages:

- **Soil Health:** Minimal soil compaction compared to heavy tractors (Busari et al., 2015).
- **Multi-Modal Weeding:** Combining chemical spot-spraying (Özlüoymak, 2022) with mechanical tools or high-energy lasers to manage herbicide-resistant weeds.
- **Continuous Operation:** 24-hour autonomous cycles enabled by the environmental hardening and active lighting solutions.

In conclusion, the evolution of smart ground equipment is transforming the sprayer from a simple delivery tool into a sophisticated, data-driven diagnostic platform. This trajectory, supported by the integration of Edge Computing and Real-Time Kinematics (RTK), ensures that the future of crop protection is not only more productive but fundamentally more sustainable.

References

Berrer, S., Ohlendorf, J. H., & Klausmann, D. (2023). Artificial intelligence in weed control: A review of deep learning techniques for individual plant treatment. *Journal of Agronomy and Crop Science, 209*(1), 12-34.

Busari, M. A., Kukal, S. S., Kaur, A., Bhatt, R., & Dulazi, A. A. (2015**).** Conservation tillage impacts on soil, crop and the environment. *International Soil and Water Conservation Research, 3*(2), 119-129. https://doi.org/10.1016/j.iswcr.2015.05.002

Dou, H., Zhai, C., Chen, L., Wang, S., & Wang, X. (2021). Field variation characteristics of sprayer boom height using a newly designed boom height detection system. *IEEE Access*, *9*, 1–11. https://doi.org/10.1109/ACCESS.2021.3053035

Carreira, V. dos S., & da Silva, R. P. (2022). Rate errors in sprayer turning and circular movements: PWM valve as compensation system and why spray boom size matters. *Crop Protection, 151*, 105835. https://doi.org/10.1016/j.cropro.2021.105835

Giles, D. K., & Money, N. (2015). Pulse width modulation control of spray pressure and flow rate for precision application. *Transactions of the ASABE, 58*(2), 315-322.

Lencsés, E., Takács, I., & Takács-György, K. (2020**).** Economic efficiency of precision weed control in site-specific crop production. *Sustainability, 12*(19), 7958. https://doi.org/10.3390/su12197958

Lowenberg-DeBoer, J., & Erickson, B. (2019). Setting the record straight on precision agriculture adoption. *Agronomy Journal, 111*(4), 1552-1569. https://doi.org/10.2134/agronj2018.12.0779

Luck, J. D., & Fulton, J. P. (2014). Evaluation of selective control technology on ground propulsion sprayers. *Transactions of the ASABE, 57*(3), 693-703. https://doi.org/10.13031/trans.57.10424

İtmeç, M., & Bayat, A.(2026). A real-time variable rate air and liquid sprayer for orchard applications. Precision Agric 27, 29 (2026). https://doi.org/10.1007/s11119-026-10331-y

Özlüoymak, Ö. B. (2022). Development and assessment of a novel camera-integrated spraying needle nozzle design for targeted micro-dose spraying in precision weed control. Computers and Electronics in Agriculture 199 (2022) 107134

Partel, V., Charan Kanthi, S., Ampatzidis, Y., & Abd-Elrahman, A. (2019). Smart sprayer for site-specific weed management using deep learning in specialty crops. *Transactions of the ASABE, 62*(6), 1755-1777.

Pathak, H. S., Soni, P., Manuel, C., & Al-Redasany, A. (2020). Strategic transition to autonomous weeding: Engineering and social perspectives. *Biosystems Engineering, 198*, 215-230.

Peteinatos, G. G., Reichel, R., Karouta, D., Andújar, D., & Gerhards, R. (2014). Weed identification in maize, sunflower, and winter wheat with the use of optical sensors. *Sensors, 14*(8), 15307-15332. https://doi.org/10.3390/s140815307

Reiser, D., Maughan, T., & Zhang, J. (2022). Integration of deep learning and PWM nozzle control for plant-specific application in row crops. *Computers and Electronics in Agriculture, 194*, 106721. https://doi.org/10.1016/j.compag.2022.106721

Slaughter, D. C., Giles, D. K., & Downey, D. (2008). Autonomous robotic weed control systems: A review. *Computers and Electronics in Agriculture, 61*(1), 63-78. https://doi.org/10.1016/j.compag.2007.05.008

Subeesh, A., & Mehta, C. R. (2021). Automation and AI in agriculture: From monitoring to decision-making. *Artificial Intelligence in Agriculture, 5*, 31-59.

Chapter
2

ADVANCEMENTS IN ACTIVE PREVENTION METHODS FOR SUSTAINABLE AGRICULTURE IN ORCHARDS: A REVIEW

Medet İTMEÇ[1]

---

[1] Department of Agricultural Machinery and Technologies Engineering, Faculty of Agriculture, Çukurova University, Adana 01330, TürkiyeE-mail: mitmec@cu.edu.tr ORCID: https://orcid.org/0000-0003-0714-6232

1. INTRODUCTION

Global climate change, resulting from increasing greenhouse gas emissions and human activities, is causing a continuous rise in average atmospheric temperatures. This phenomenon leads to the rapid melting of polar and mountain glaciers, rising sea levels, and a disruption of the global climate balance (Giorgi and Lionello, 2008). The effects of climate change are causing significant alterations in regional climate characteristics, with dramatic changes in seasonal temperature and precipitation patterns in some areas (Tubiello et al., 2007). Regions with a Mediterranean climate are beginning to exhibit tropical characteristics due to rising temperatures and intense rainfall events, while continental climate regions are increasingly showing transitional climate features (Yuan et al., 2024). Similarly, in countries with high geographical diversity, different climate types are gradually transforming into a more homogeneous climate structure (Hatfield and Prueger, 2015). This transformation increases the frequency and intensity of extreme weather events (such as severe storms, heatwaves, droughts, and heavy rainfall), placing significant pressure on ecosystems (IPCC, 2021). The situation predominantly impacts water resources, regional plant species, biodiversity, as well as agricultural productivity and sustainability.

Global climate change creates direct and indirect impacts on the agricultural sector, threatening the sustainability of agricultural production. In addition, finding enough food for the growing global population will become increasingly challenging due to global warming. Intense and sudden rainfall increases surface runoff in agricultural areas, leading to soil erosion. Moreover, heavy rainfall exposes plants to water stress. Particularly, hailstorms cause physical damage to crops, resulting in yield losses. On the other hand, frost events cause developmental disorders in young shoots, fruits, and leaves. This situation actually harms not only crops (Fuller et al., 2007; Stutsel et al., 2023) but also the cultivated vegetables (Park et al., 2025). Additionally, high temperatures accelerate the rate of evaporation, increasing water loss in plants and causing leaf wilting, slowing down fruit development, or even halting it entirely due to heat stress (Lobell et al., 2011). Drought conditions prevent plants from absorbing sufficient water from the soil, leading to hydric stress and nutrient deficiency, making yield losses inevitable in most cases (Challinor et al., 2014). All these climatic risks complicate efforts to ensure sustainability in agricultural production and pose a global threat to food security (FAO, 2020).

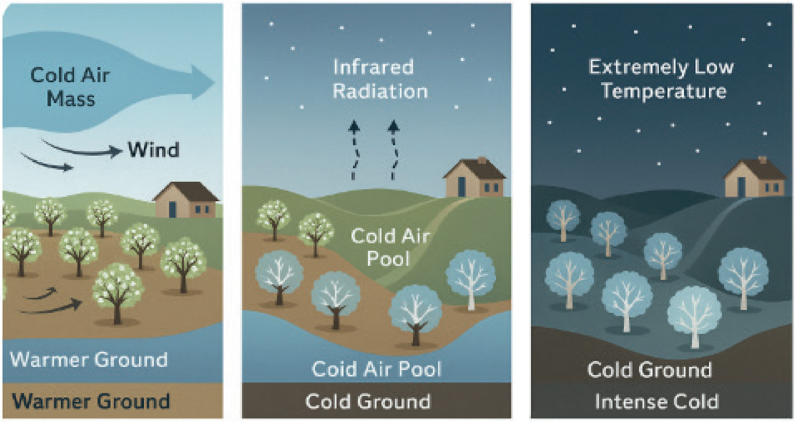
In the face of escalating climatic risks driven by global warming, extreme weather events are becoming more frequent, intense, and unpredictable, posing profound challenges to global agricultural systems. Among these, frost events particularly radiative and advective frosts constitute a major and recurrent threat to crop yield and quality in many regions, especially in temperate and Mediterranean agricultural zones (Zampieri et al., 2017). While droughts, heatwaves, and floods have attracted significant attention due to their visible and large-scale impacts, frost events are often underestimated despite their capacity to inflict sudden and irreversible damage at critical phenological stages. Unlike other extreme phenomena, frost damage typically occurs silently and rapidly during the night, leading to necrosis in vulnerable plant tissues such as blossoms, young fruits, and buds (Thomashow, 1999; Duman and Wisniewski, 2014). The implications of frost damage extend beyond immediate yield reduction; they also disrupt long-term production cycles, alter phenological patterns, and increase the dependency on external inputs such as chemical growth regulators and energy-intensive heating systems (Inouye, 2000; Augspurger, 2013). Consequently, the development and deployment of effective frost protection strategies and technologies have become indispensable components of climate-resilient and sustainable agriculture. These technologies not only buffer crops against acute frost-induced stress but also enhance overall system resilience by safeguarding crop physiological integrity, minimizing input waste, and promoting adaptive capacity in farming practices (Hua et al., 2025).

This review aims to explore the state-of-the-art advancements in crop protection systems developed against climate-induced stressors such as frost, hail, and sunburn. It assesses the performance of various passive and active approaches and highlights the emerging role of novel technologies such as UAVs, automated controls, and sensor-based networks in integrated microclimate management.

2. FROST PROTECTION METHODS

2.1. Definition of Frost

Frost events can cause severe physiological damage and yield losses in warm-climate crops. This risk is particularly high during late spring when buds are in sensitive developmental stages with high water content (Leuning and Cremer, 1988). To mitigate frost damage in agricultural production, various protective strategies are employed. The most appropriate and effective method should be selected based on regional climatic conditions, crop type, and the grower's available resources. In some cases, it may be necessary to implement multiple methods simultaneously. According to meteorological classification, frost events are divided into three main types: advection frost, radiation frost, and severe (polar-origin) frost. Advection frost occurs when cold air masses spread over large areas and is typically associated with wind (Figure 1a). Radiation frost develops during clear and calm nights when rapid heat loss from the earth's surface occurs, leading to more localized effects (Figure 1b). Severe frost, usually occurring in winter, results from prolonged exposure to extremely low temperatures and is considered the most destructive type (Figure 1c). Understanding the mechanisms of these different frost types is crucial for developing effective protection strategies (Gu et al., 2008). On the other hand, topography plays a decisive role in the severity and spatial distribution of frost events. In particular, depressions, valleys, and sloped terrains facilitate the accumulation of cold air, leading to a more rapid decline in near-surface temperatures. This phenomenon is especially evident during radiation frost events, as the cooling air, being denser, flows downslope and accumulates in topographically lower areas, forming what is known as a "cold air pool" (Jemmett-Smith et al., 2018). These zones are subjected to prolonged periods of low temperatures compared to their surroundings and thus experience the most severe frost damage. Similarly, studies have shown that trees located in valleys are more vulnerable to frost injury due to the topographically driven pooling of cold air (Matusick et al., 2014). In contrast, upper slopes and gently inclined areas are generally considered less prone to frost because of the reduced potential for cold air accumulation. Therefore, consideration of topographic features is of critical importance when selecting agricultural production sites and developing frost mitigation strategies.



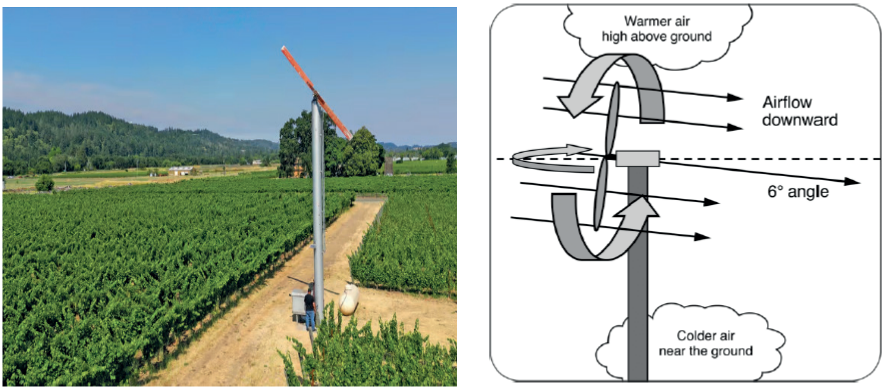
(a) (b) (c)

Figure 1. *Schematic representation of frost types:* (**a**) *cold air movement (advection),* (**b**) *radiative heat loss (radiation), and* (**c**) *extreme cold exposure (severe)*

Frost events during early spring bud development can result in varying degrees of crop loss, from minor yield reductions to total crop failure. Their increasing frequency is linked to warming spring temperatures, which accelerate bud break and heighten frost susceptibility (Vitasse et al., 2014). While the principles of active frost protection are well established, emerging challenges such as labor shortages, rising costs, environmental regulations, the shift to high-density orchards, and new technologies require updated evaluations of these strategies. Frost protection methods are broadly divided into passive and active approaches. Passive methods such as site selection, cultivar choice, orchard floor management, and nutrition aim to reduce susceptibility before frost occurs. Active methods, used during frost events, prevent heat loss through (1) irrigation, (2) heat application, and (3) air mixing (Snyder and de Melo-Abreu, 2005). Their effectiveness depends on both the technique's operational dynamics and site-specific environmental conditions. This study also incorporates insights from growers with proven success in implementing these methods under field conditions (Rieger, 1993).

2.2. Frost Protection with Wind Machines

Wind machines are among the most commonly used active frost protection systems, particularly in fruit orchards threatened by radiation frost events. The fundamental operating principle of these machines relies on the occurrence of a temperature inversion, which typically develops during calm and clear nights. In such conditions, the Earth's surface loses heat rapidly, leading to the formation of a warmer air layer at altitudes ranging from approximately 10 to 30 meters (Bayat, 2022). Wind machines function by drawing this warmer air downward and mixing it with the colder air near the surface, thereby increasing temperatures at plant level by approximately 1 to 3 °C. Typically mounted on towers 10 to 12 meters in height, these large horizontal-axis fans can effectively protect an area of about 3 to 5 hectares (Heusinkveld et al., 2020). Wind machines are effective primarily under radiation frost conditions but perform poorly during advection frost events. Their use is limited by high initial costs, substantial energy requirements, and noise emissions. These constraints can reduce their practicality in certain orchard systems.



(**a**) (**b**)

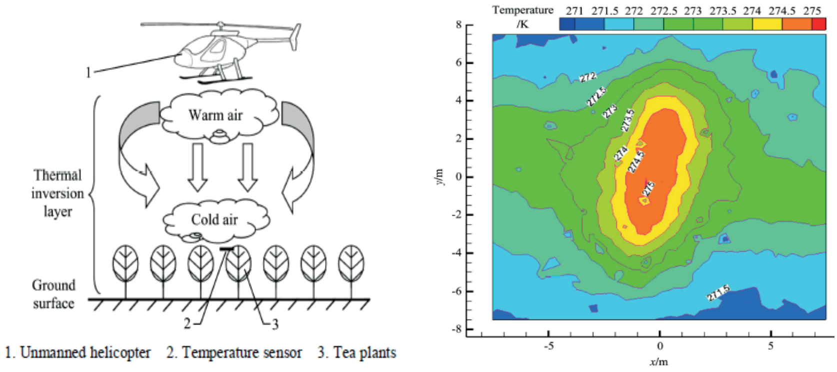
Figure 2. *Illustration of wind machines in a vineyard (***a***), and working principle of wind machines (***b***) (Fraser, 2010)*

Wind machines are typically installed at the center of orchards to ensure uniform protection across the entire area. Numerous studies have evaluated their effectiveness in mitigating frost damage. In a study by (Frith, 1955), a wind machine powered by a 12-horsepower electric motor increased ambient temperature by approximately 2 °C over a 1-hectare orchard. According to Snyder and de Melo-Abreu (2005), wind machines should be shut down when natural wind speeds exceed 2.5 m/s, as their efficiency diminishes under such conditions. Ribeiro et al. (2006) reported that wind machines can reduce frost damage by 37% to 60% under strong inversion conditions. Battany (2012) conducted a comparative study over 12 spring frost nights in 2010 and 2011 to evaluate the performance of upward-suction and discharge fans in vineyard frost protection. Their findings indicated that conventional wind machines provided superior protection during strong inversion events, especially at the typical grapevine canopy height of approximately 1.1 meters. In contrast, upward-suction fans demonstrated limited efficacy under strong inversion conditions and, in cases of weak inversion, even showed potential to slightly lower the ambient temperature. Boekee et al. (2023) investigated the role of wind machines in mitigating frost damage in orchards, highlighting their dual function: mixing warmer upper air into the canopy and enhancing convective heat transfer by increasing airflow. Despite these benefits, leaf temperatures often drop below ambient air due to radiative cooling, and thermal differences among plant organs lead to uneven temperature distributions. The study underscores the importance of accounting for plant–air temperature disparities when assessing frost damage risk. In their study, Dai et al. (2023) quantified the spatial extent and directional pattern of the warming effect by accounting not only for the direct thermal enhancement induced by jet mixing, but also for the convective transport of warm air interacting with the ambient wind field. Nonetheless, Kimura et al. (2017) conducted a spatiotemporal analysis of the thermal effects of an oscillating wind machine on leaves, based on leaf boundary layer conductance (GA). Field studies in tea plantations revealed that the thermal effects of wind machines were spatially and temporally inconsistent, limiting their frost protection efficiency. Performance evaluations incorporating temperature and wind speed measurements indicated suboptimal coverage across the claimed area. Measurements taken at multiple heights and radial distances from the machine center highlighted the need for further optimization. The analysis revealed that the machine was capable of influencing regions where wind speed exceeded 2 m/s, as classified by the Beaufort scale, with the extent of influence varying by both vertical and horizontal position (Civelek et al., 2017; Bayat and İtmeç, 2023). Even in orchards equipped with wind machines, frost damage may still occur during radiation frost events. Particularly under severe conditions (e.g., -16°C), wind machines have been observed to lose their effectiveness due to insufficient temperature inversion (Figure 3).

Figure 3. *Frost damage in lemon orchards in March 2022 in Karataş region Adana / Turkey (Bayat, 2022)*

2.3. Frost Protection Using Helicopters or Drones

Helicopters are employed as an active frost protection strategy in agriculture, particularly during radiation frost events on clear and calm nights. This approach relies on atmospheric temperature inversion, where warmer air resides above cooler surface air. By generating strong downdrafts, helicopters redistribute the upper warm air to crop level, raising near-surface temperatures by several degrees and reducing frost damage (Figure 4a) (Hu et al., 2018). The method's effectiveness depends on the presence and depth of the inversion layer, offering limited benefit during strong advection frosts. Due to high operational costs, helicopter use is generally confined to high-value crop regions. Hu (2013) found that airflow disturbance was greatest at 5–10 m altitude, decreasing with height. A temperature rise of up to 3.83°C was observed near tea canopies. Optimizing flight parameters requires understanding their effect on temperature increase. Hu et al. (2015) emphasized that the use of unmanned helicopters to disrupt airflow during frost events effectively increased the air temperature around the tea canopy, thereby enhancing the effectiveness of frost protection, as demonstrated through a CFD model. (Figure 2b).



(**a**) (**b**)

Figure 4. *Illustration of helicopter-assisted frost protection over an orchard (***a***), and the affected area of an unmanned helicopter (***b***)*

Although helicopters are widely used, some researchers have proposed that drones commonly employed in agriculture for various purposes can also serve as an alternative for frost protection. Qiao et al. (2024) investigated the frost mitigation potential of the downward airflow generated by a multi-rotor unmanned aerial vehicle (UAV) over fruit trees, employing computational fluid dynamics (CFD) simulations alongside field experiments. The CFD results demonstrated that the UAV, operating at an altitude of 6 meters and a rotor speed of 1000 rpm, could rapidly homogenize temperature gradients across vertical layers. Field trials confirmed that the UAV increased near-surface air temperatures by 2.5–3 °C, thereby effectively reducing the risk of frost damage. Similarly, Zhu et al. (2022) modeled the downwash airflow characteristics of a quadrotor plant protection UAV across various flight speeds (1–5 m/s) using CFD and validated the simulations with experimental data. At a flight speed of 5 m/s, spiral vortices generated beneath the rotors extended beyond the UAV's flight altitude, leading to considerable droplet drift. In contrast, flight speeds below 3 m/s enhanced droplet penetration into the canopy, suggesting that lower speeds provide optimal conditions for targeted pesticide application. Although drones are often employed to mitigate frost damage through the generation of airflow, their role is not limited to this mechanism alone. Yuan and Choi (2021) introduced a UAV-based approach to assess heating requirements in apple orchards as part of a comprehensive frost management strategy. Utilizing thermal and RGB imaging, the study successfully mapped frost-prone areas and identified the developmental stages of flower buds, thereby enabling precise determination of localized heating needs. The findings demonstrated that this UAV-assisted method is effective in formulating spatially and phenologically targeted heating strategies to protect orchards from frost damage.

2.4. Heaters

Another widely adopted method for frost prevention in agriculture is the use of heaters, particularly those with high energy output, which are commonly deployed across cultivated fields. However, the effectiveness of these systems depends not only on energy capacity but also on an understanding of psychrometric properties. In this context, the "one-third rule" introduced by Knox et al. (2017) provides a simplified empirical approach for estimating wet-bulb temperature. According to this method, the wet-bulb temperature can be approximated by subtracting one-third of the difference between the dry-bulb temperature and the dew point temperature from the dry-bulb value. This rule offers a practical and sufficiently accurate approximation for operational use, particularly in agricultural frost risk assessments, where it can serve as a guiding parameter in system design.

Active heating techniques such as heaters and wind machines, as employed by Ribeiro et al. (2006) in orchard systems, are often not included in control treatments in comparing conditions because their thermal influence cannot be easily confined to a specific area, making it difficult to ensure a true untreated comparison (Frederiks et al., 2012). In their study, Hua et al. (2022) developed, calibrated, and validated a three-dimensional computational fluid dynamics (CFD) model for frost protection in apple orchards. The results demonstrated that optimizing heater output and placement angle could increase the protected canopy volume from 20% to 91.9%, and that mobile heaters were more effective than stationary ones. Conventional heaters used for agricultural frost protection typically alter only the ambient temperature without affecting humidity. However, Bai et al. (2023) developed a membrane-based heat exchanger capable of simultaneously modifying both temperature and humidity. In the referenced study, the air was conditioned through humidification, and by utilizing psychrometric properties, frost was prevented with reduced energy consumption.

Various heater-based frost protection systems differ significantly in terms of energy output, fuel type, and spatial efficiency. Fuel heaters, particularly when optimized, provide uniform coverage at moderate energy intensities, whereas solid fuel and mobile systems offer localized thermal effects without quantified energy metrics. The selection of heater should consider not only the temperature rise but also operational logistics, fuel availability, and system design efficiency (Table 1).

Table 1. *Technical comparison of various heater-based frost protection methods in agriculture.*

Heater Type	**Energy Output (W/m^2 or Qualitative)**	**Coverage Area Description**	**Fuel Type**
Liquid Fuel Heaters [1]	140–280 W/m^2	1 ha (75–100 units)	Fuel oil / kerosene
Liquid Fuel Heaters (Optimized)[2]	123 W/m^2	1 ha (well-designed system)	Fuel oil / kerosene
Propane/Natural Gas Heaters [3]	Estimated 100–150 W/m^2	1 ha (requires 130–150 heaters)	Propane / natural gas
Solid Fuel Heaters (under trees) [4]	Not quantified (≈ +1.7°C on fruit surface)	Localized effect under individual trees	Solid fuel (oil wax, wood)
Solid Fuel Heaters (coke bricks) [4]	Not quantified (≈ +2.2°C at 1.1 m height)	1 ha (using 375 fuel bricks)	Coke and petroleum wax
Mobile Heater [1]	Not quantified (~100°C outlet air temperature)	Mobile, localized coverage behind tractor	Propane (4 × 45 kg cylinders)

[1](Snyder and de Melo-Abreu, 2005), [2](Atam et al., 2021), [3](Drepper et al., 2022), [4](Miller et al., 1966)

2.5. Sprinkler System

It is a well-established scientific principle that the phase transition of water from liquid to solid releases latent heat, referred to as the heat of fusion. Sprinkler irrigation systems for frost protection leverage this released energy to maintain crop and ambient temperatures above critical levels. Although a brief decline in crop temperature may occur due to evaporative cooling at the onset of irrigation, the overall effect contributes to frost prevention (Pan et al., 2024). However, as the water applied to the crop surface progressively freezes, it releases latent heat that helps maintain the temperature near the freezing point. This phase change emits approximately 80 calories of energy per gram of water. By consistently supplying a fresh layer of water, it becomes feasible to stabilize both crop and ambient temperatures around 0 °C (Von Lengerke, 1978). As water freezes on the plant surface, it releases about 80 calories of latent heat per gram, helping to keep temperatures near 0 °C. Continuous water application ensures this effect is sustained for frost protection (Zamora-Re et al., 2016).

In the design of sprinkler systems, it is essential that the wetted areas of individual sprinklers overlap. This overlap prevents unsprayed zones, thereby ensuring uniform and effective frost protection. The spacing between sprinklers is determined based on this overlap to fully cover the target area. Additionally, depending on the installation height of the sprinkler heads, systems are categorized as either "over-tree" or "under-tree" irrigation. Over-tree irrigation refers to configurations where the sprinkler head is positioned at or above the height of the crop (Figure 5), whereas under-tree irrigation describes setups in which the sprinkler head is placed close to the ground (Parsons et al., 1982; Jarrett and Morrow, 1984). Continuous sprinkler irrigation leads to high water consumption. To address this, Heinemann et al. (1992) tested an automated system using model-based application rates, achieving up to 89% water savings under moderate frost. Similarly, Heisey et al. (1994) showed that such systems could also protect apple blossoms. During three spring frost events, the system kept temperatures above critical levels and reduced water use by 72% compared to continuous irrigation (Koc et al., 2000).

Figure 5. *Application of Over-Tree Sprinkler Systems in Olive and Avocado Orchards (Bursa, Turkey)*

A review of the literature reveals that active frost protection methods such as unmanned aerial vehicles (UAVs), wind machines, heaters, and sprinkler systems each present distinct advantages and limitations. Although UAVs have been scientifically evaluated in some studies, their practical success in commercial agricultural operations remains limited. This is primarily due to their short flight endurance and the fact that their effectiveness appears to be restricted mainly to advective frost conditions. In other types of frost events, such as radiative and evapotranspirative frosts, which require a direct heat source, UAVs are clearly insufficient. A similar limitation applies to wind machines, which although capable of covering larger areas rely solely on air circulation and thus lack efficacy under extremely low temperatures where a heat input is necessary. Although the integration of wind machines with burner systems has emerged as an alternative practice in the field, there has been no systematic or quantitative evaluation of its effectiveness to date. These hybrid systems are intended to provide both air circulation and thermal support; however, such integration significantly increases both the initial investment cost and operational expenses. Heater systems, by contrast, directly increase ambient temperature and can be effective in mitigating frost. However, traditional heaters lack psychrometric control mechanisms to regulate humidity and therefore deliver dry heat to the environment. Furthermore, both fixed and mobile heaters pose a risk of scorching plant tissue when placed too close to trees due to their high thermal output. These systems also involve substantial capital investment and operational costs, which can pose a significant economic burden for growers (Table 2). Compared to these methods, sprinkler systems offer several advantages, including low initial investment, reduced operating costs, and relatively high frost protection potential. The latent heat released during the phase change of water from liquid to solid creates a microclimatic buffer around the plant, thereby reducing the risk of frost injury. Moreover, by applying fine water droplets through low-volume misting, water usage can be minimized while also increasing ambient humidity to protective levels. Even if the system does not completely prevent damage, partial injury is often reversible, and fruit production may resume the following season. In contrast, when severe frost occurs and alternative protection methods are inadequate, recovery may take two to three years, or trees may need to be completely replaced. Additionally, since sprinkler systems can also help mitigate sunburn by cooling and humidifying the plant environment, they offer a dual-purpose, cost-effective, and highly practical solution for mitigating both thermal extremes.

Table 2. *Estimated Costs for Different Frost Protection Methods (Liu et al., 2025)*

Method	Initial Investment (USD)	Annual Operating Cost (USD)	Key Cost Drivers
Wind machines	\$3,000–\$7,000+	\$100–\$600+	High equipment cost; operating expenses include electricity and maintenance
Sprinkler irrigation	\$1,500–\$5,000+	\$150–\$800+	Investment varies with water source; operating costs involve pumping and water use
Heaters	Not specified	\$500–\$2,500+	Requires multiple units; fuel costs dominate; overall operating costs are very high
Unmanned Aerial Vehicles (UAVs)	\$1,500–\$6,000+	\$50–\$400+	High upfront cost; multifunctional use; main cost is electricity for charging

3. HAIL AND HEAVY RAINFALL PROTECTION METHODS

3.1. Definition of Hail and Heavy Rainfall

Hail and heavy rainfall are among the primary meteorological extreme events that cause significant yield and quality losses in the agricultural sector, particularly in fruit production and open-field farming. Hail occurs when ice particles formed in the atmosphere during convective storms fall to the ground, whereas heavy rainfall is defined as an excessive amount of precipitation falling over a specific area within a short period of time. With global climate change, the atmosphere's capacity to hold water vapor has increased, leading to a rise in both the frequency and intensity of hail and extreme precipitation events. Projections indicate that the occurrence of large hailstones particularly those with diameters of 4 cm or more has increased by approximately 15–75% in some regions (Gensini and Brooks, 2024). Similarly, studies conducted in southwestern China have demonstrated a notable increase in extreme rainfall events in recent years, with this trend being directly linked to rising temperatures (Lei et al., 2024).

3.2. Anti-Hailnets

Hail and heavy precipitation are among the major meteorological threats in the agricultural sector, particularly in fruit production areas, where they can cause significant yield and quality losses. One of the most commonly employed active protection strategies against these risks is the use of anti-hail nets. These nets physically cover the crops, preventing direct contact between hailstones and the plant surface, thereby minimizing mechanical damage. Additionally, they can serve as a barrier against certain piercing-sucking insect pests, reducing pest intrusion into orchards. Beyond their mechanical function, anti-hail nets significantly influence microclimatic conditions; by reducing ambient temperature, increasing relative humidity, and lowering fruit surface temperatures, they contribute to the preservation of product quality (Mupambi et al., 2018). During the evaluation of these nets, mechanical strength tests are primarily conducted (Briassoulis et al., 2007). In addition, the color and light transmittance of the net are also taken into consideration (Al-Helal and Abdel-Ghany, 2010; Scarascia-Mugnozza et al., 2012). The effects of these nets may vary depending on their color and duration of use (Castellano et al., 2008). For example, black nets tend to block more light, leading to reduced fruit coloration and delayed ripening, whereas transparent nets exhibit milder effects in this regard (Iglesias and Alegre, 2006). As the efficacy of nets diminishes over time, it is generally recommended that they be replaced after approximately two years of use (Guo et al., 2025). Despite their effectiveness, the high installation and maintenance costs of anti-hail nets limit their applicability in large-scale agricultural operations, restricting their use primarily to high-value fruit orchards (Arakelyan, 2017).

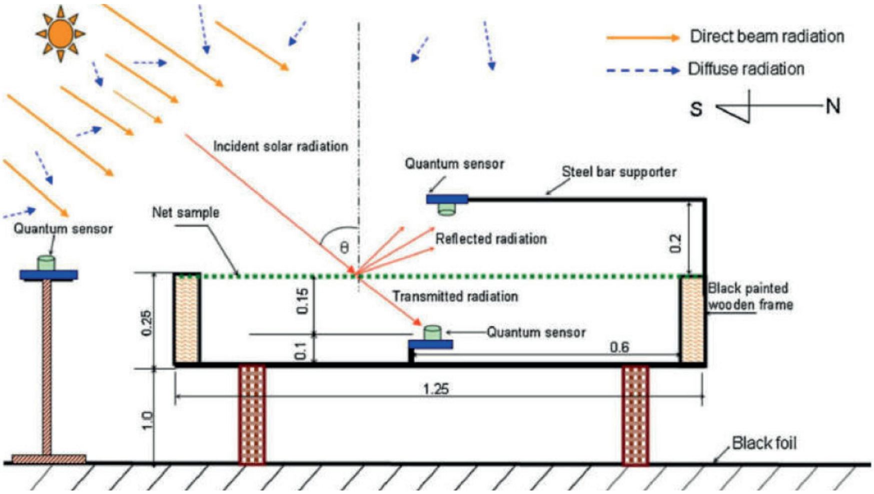


Figure 6. *UV absorption and reflectance in controlled environments fitted with plastic shading nets Test Method (Al-Helal and Abdel-Ghany, 2010)*

Bayat and İtmeç (2023) investigated whether selected anti-hail nets could maintain their structural integrity under local conditions by referencing the diameter of the largest hailstone previously recorded in a specific region for hail protection purposes. To this end, tensile tests were conducted in accordance with the EN ISO 13934-1:2013 standard to determine the breaking strength of the nets, and the rupture energy was calculated based on the force-elongation curve. The obtained energy value was then compared to the kinetic energy of hailstones falling to the ground, taking into account their diameter, mass, and terminal velocity.

3.3. Hail Cannons

Hail cannon systems are one of the active protection methods used in various countries since the 19th century to prevent hail damage in agriculture. The basic operating principle of these systems is based on preventing the formation of hail embryos in the atmosphere through sequential shock waves generated prior to convective storms. In modern hail cannon systems, a mixture of acetylene and oxygen is ignited to create explosions that propagate upward through a conical structure as shock waves. These waves are assumed to disrupt the internal structure of clouds and suppress hail formation. One of the first scientific attempts to validate this concept is the study by Misan et al. (2023), in which a numerical model developed using isogeometric analysis and variational splitting methods was compared with experimental data, demonstrating that hail cannons could theoretically be effective under certain conditions. On the other hand, there are also contradictory findings in the literature. For example, Rodríguez-Moreno and Estrada-Ávalos (2024) examined the impact of hail cannons on heavy rainfall events in various regions of Mexico. Based on four years of half-hourly resolution data from GPM satellite observations and WRF model outputs, their analysis found no statistically significant relationship between the operation of hail cannons and the suppression of heavy rainfall. Conversely, Arakelyan (2017) emphasized that for hail cannons to be effective, they must be activated at least 15–20 minutes before the onset of storm development; otherwise, their efficiency significantly decreases. In this context, Arakelyan (2017) proposed the use of microwave radiometers as a lower-cost and earlier-stage detection technology for hail-prone clouds compared to conventional Doppler radar systems. This technology plays a critical role in ensuring that active protection systems are activated in a timely manner. In conclusion, although hail cannon technology has been supported by simulation-based studies suggesting potential theoretical effectiveness under specific conditions, field-based empirical findings cast doubt on its reliability and indicate that it may not provide a sufficient standalone solution. Therefore, protecting agricultural production from climate-induced risks requires not only isolated methods, but also scientifically validated, economically feasible, and regionally adapted integrated protection strategies.

The effectiveness of hail cannons in preventing hailstorms remains a subject of scientific debate. Although these systems aim to disrupt hail embryo formation in the atmosphere through acoustic shock waves, field data indicate that their effectiveness is neither statistically significant nor consistently reproducible. Moreover, factors such as application timing, regional topography, and meteorological variability make it difficult to control outcomes, limiting the adoption of hail cannons as a standardized protection method in agricultural production. In contrast, agricultural netting systems not only provide a physical barrier against hailstones but also offer partial protection against pests with piercing-sucking mouthparts, thereby contributing to integrated pest management strategies. Particularly, nets made from high-density polyethylene (HDPE), which are resistant to UV radiation and offer long service life with minimal maintenance, are increasingly preferred in orchards. These nets can also filter solar radiation to some extent, improving fruit quality while offering continuous protection against sudden meteorological events such as hailstorms. Owing to their multifunctionality, durability, and relatively low operational requirements, agricultural nets represent a more effective and sustainable alternative among active hail protection methods.

4. METHODS USED TO PREVENT SUNBURN in CROPS

Sunburn is a non-infectious, abiotic stress-induced physiological disorder characterized by the appearance of necrotic or discolored patches on the surface of fruit, most commonly affecting the sun-exposed side. It is frequently misdiagnosed as a nutrient deficiency due to overlapping symptoms such as chlorosis, bronzing, or tissue collapse; however, sunburn is specifically triggered by environmental factors such as excessive solar radiation and high temperatures. This disorder significantly compromises fruit quality, marketability, and yield across a range of horticultural crops, particularly under increasing global temperatures and solar radiation intensities. It results from a combination of excessive photosynthetically active radiation (PAR), ultraviolet (UV) radiation, and elevated surface temperatures, leading to cellular damage, oxidative stress, and pigment degradation (Munné-Bosch and Vincent, 2019). In grapes, sunburn is classified into subtypes such as sunburn browning (SB) and sunburn necrosis (SN), with symptom severity depending on cultivar, phenological stage, and microclimatic conditions within the canopy (Gambetta et al., 2021). Among these, reflective particle films based on kaolin clay have been extensively studied (İtmeç et al., 2020). Glenn et al. (2002) demonstrated that kaolin application reduced fruit surface temperature and solar injury in apples by increasing light reflectance and decreasing heat load, without negatively affecting photosynthesis. Another promising approach is the use of plastic shading nets, which reduce incident solar radiation and create a more buffered canopy microclimate; however, concerns about their environmental sustainability persist (Maraveas, 2020). The impact of sunburn is further exacerbated under drought stress, which impairs stomatal conductance and water balance, thereby diminishing the plant's thermotolerance and antioxidant response (Yang et al., 2021). Taken together, these findings underscore the complex interplay between environmental conditions and plant physiology in sunburn occurrence, and they highlight the necessity of integrated, crop-specific, and environmentally conscious management strategies to safeguard fruit quality under climate-induced stress.

Studies have shown that kaolin-based reflective coatings significantly reduce the incidence of sunburn by dispersing incoming solar radiation and lowering fruit surface temperature. Although rainfall following application diminishes the protective effect, residual particles on the surface have been reported to provide a limited yet effective level of protection. However, this effect is generally short-lived and requires repeated applications for sustained efficacy. In contrast, agricultural netting systems with low light transmittance not only filter direct sunlight but also stabilize fruit surface temperature through shading, offering a longer-lasting and passive form of protection. Additionally, such nets act as physical barriers against hail, wind, and insect pests, positioning them as a more comprehensive and sustainable alternative to kaolin-based approaches. Considering their fixed structure and minimal maintenance requirements, the use of netting systems is increasingly preferred in regions exposed to high levels of solar radiation.

REFERENCES

Al-Helal, I. M., & Abdel-Ghany, A. M. (2010). Responses of plastic shading nets to global and diffuse PAR transfer: Optical properties and evaluation. NJAS: Wageningen Journal of Life Sciences, 57(2), 125–132. https://doi.org/10.1016/j.njas.2010.02.002

Arakelyan, A. K. (2017). A New Approach in Hail Prevention Technique for a Locally Restricted Area. Agricultural Sciences, 08(07), 559–571. https://doi.org/10.4236/as.2017.87042.

Atam, E., Abdelmaguid, T. F., Keskin, M. E., & Kerrigan, E. C. (2021). A hybrid green energy-based system with a multi-objective optimization approach for optimal frost prevention in horticulture. Journal of Cleaner Production, 329, 129563. https://doi.org/10.1016/j.jclepro.2021.129563

Augspurger, C. K. (2013). Reconstructing patterns of temperature, phenology, and frost damage over 124 years: Spring damage risk is increasing. Ecology, 94(1), 41–50. https://doi.org/10.1890/12-0200.1

Bai, H., Liu, P., & Mathisen, H. M. (2023). Evaluation of frost prevention strategies for membrane energy exchangers. Building and Environment, 244, 110814. https://doi.org/10.1016/j.buildenv.2023.110814

Battany, M. C. (2012). Vineyard frost protection with upward-blowing wind machines. Agricultural and Forest Meteorology, 157, 39–48. https://doi.org/10.1016/j.agrformet.2012.01.009

Bayat, A. (2022). Active frost protection methods used to minimize frost damage in orchards. In: Sustainable Agriculture Technologies-I. Ankara: IKSAD Publishing House, 3–28.

Bayat, A., İtmeç, M. (2023). Technical examination and comparison of frost protection machines. In Proceedings of the BİLTEK-VII International Symposium on Current Developments in Science, Technology and Social Sciences (May 26–27, Ankara, Türkiye).

Boekee, J., Dai, Y., Schilperoort, B., van de Wiel, B. J. H., & ten Veldhuis, M.-C. (2023). Plant–atmosphere heat exchange during wind machine operation for frost protection. Agricultural and Forest Meteorology, 330, 109312. https://doi.org/10.1016/j.agrformet.2023.109312

Briassoulis, D., Mistriotis, A., & Eleftherakis, D. (2007). Mechanical behaviour and properties of agricultural nets. Part II: Analysis of the performance of the main categories of agricultural nets. Polymer Testing, 26(8), 970–984. https://doi.org/10.1016/j.polymertesting.2007.06.010

Castellano, S., Hemming, S., & Russo, G. (2008). The Influence of Colour On Radiometric Performances of Agricultural Nets. Acta Horticulturae, (801), 227–236. https://doi.org/10.17660/actahortic.2008.801.21

Challinor, A. J., Watson, J., Lobell, D. B., Howden, S. M., Smith, D. R., & Chhetri, N. (2014). A meta-analysis of crop yield under climate change and adaptation. Nature Climate Change, 4(4), 287–291. https://doi.org/10.1038/nclimate2153

Civelek, Ç., Bayat, A., Şehri, M. (2017). Comparison of technical specifications and performances of wind machines. J Agric Mach Sci, 13(2): 81–85.

Dai, Y., Boekee, J., Schilperoort, B., ten Veldhuis, M.-C., & van de Wiel, B. J. H. (2023). Wind machines for frost damage mitigation: A quantitative 3D investigation based on observations. Agricultural and Forest Meteorology, 338, 109522. https://doi.org/10.1016/j.agrformet.2023.109522

Drepper, B., Bamps, B., Gobin, A., & Van Orshoven, J. (2022). Strategies for managing spring frost risks in orchards: effectiveness and conditionality—a systematic review. Environmental Evidence, 11(1). https://doi.org/10.1186/s13750-022-00281-z

Duman, J. G., & Wisniewski, M. J. (2014). The use of antifreeze proteins for frost protection in sensitive crop plants. Environmental and Experimental Botany, 106, 60–69. https://doi.org/10.1016/j.envexpbot.2014.01.001

FAO, 2020. Food and Agriculture Organization of the United Nations. The State of Food and Agriculture 2020: Overcoming Water Challenges in Agriculture.

Fraser, H. (2010). Wind machines for minimizing cold injury to horticultural crops. Ontario Ministry of Agriculture, Food and Rural Affairs, Factsheet Order No. 10-045.

Frederiks, T. M., Christopher, J. T., Harvey, G. L., Sutherland, M. W., & Borrell, A. K. (2012). Current and emerging screening methods to identify post-head-emergence frost adaptation in wheat and barley. Journal of Experimental Botany, 63(15), 5405–5416. https://doi.org/10.1093/jxb/ers215

Frith, H. (1955). Trials of a wind machine for frost protection in citrus. Australian Journal of Agricultural Research, 6(6), 903–912. https://doi.org/10.1071/ar9550903

Fuller, M. P., Fuller, A. M., Kaniouras, S., Christophers, J., & Fredericks, T. (2007). The freezing characteristics of wheat at ear emergence. European Journal of Agronomy, 26(4), 435–441. https://doi.org/10.1016/j.eja.2007.01.001

Gambetta, J. M., Holzapfel, B. P., Stoll, M., & Friedel, M. (2021). Sunburn in Grapes: A Review. Frontiers in Plant Science, 11. https://doi.org/10.3389/fpls.2020.604691

Gensini, V. A., Ashley, W. S., Michaelis, A. C., Haberlie, A. M., Goodin, J., & Wallace, B. C. (2024). Hailstone size dichotomy in a warming climate. Npj Climate and Atmospheric Science, 7(1). https://doi.org/10.1038/s41612-024-00728-9

Giorgi, F., & Lionello, P. (2008). Climate change projections for the Mediterranean region. Global and Planetary Change, 63(2–3), 90–104. https://doi.org/10.1016/j.gloplacha.2007.09.005

Glenn, D. M., Prado, E., Erez, A., McFerson, J., & Puterka, G. J. (2002). A Reflective, Processed-Kaolin Particle Film Affects Fruit Temperature, Radiation Reflection, and Solar Injury in Apple. Journal of the American Society for Horticultural Science, 127(2), 188–193. https://doi.org/10.21273/jashs.127.2.188

Gu, L., Hanson, P. J., Post, W. M., Kaiser, D. P., Yang, B., Nemani, R., Pallardy, S. G., & Meyers, T. (2008). The 2007 Eastern US Spring Freeze: Increased Cold Damage in a Warming World? BioScience, 58(3), 253–262. https://doi.org/10.1641/b580311

Guo, J., Guo, Y., Tong, P., Wang, X., & Wang, J. (2025). Effects of Different Coverage Years of Hail-Proof Nets on Environment, Leaf Traits and Fruit Quality in Apple Orchards. Horticulturae, 11(2), 198. https://doi.org/10.3390/horticulturae11020198

Hatfield, J. L., & Prueger, J. H. (2015). Temperature extremes: Effect on plant growth and development. Weather and Climate Extremes, 10, 4–10. https://doi.org/10.1016/j.wace.2015.08.001

Heinemann, P. H., Morrow, C. T., Stombaugh, T. S., Goulart, B. L. Schlegel, J. (1992). Evaluation of an Automated Irrigation System for Frost Protection. Applied Engineering in Agriculture, 8(6), 779–785. https://doi.org/10.13031/2013.26113

Heisey, L. W., Heinemann, P. H., Morrow, C. T., Crassweller, R. M. (1994). Automation of an Intermittent Overhead Irrigation Frost Protection System for an Apple Orchard. Applied Engineering in Agriculture, 10(5), 669–675. https://doi.org/10.13031/2013.25897

Heusinkveld, V. W. J., Antoon van Hooft, J., Schilperoort, B., Baas, P., Veldhuis, M. ten, & van de Wiel, B. J. H. (2020). Towards a physics-based understanding of fruit frost protection using wind machines. Agricultural and Forest Meteorology, 282–283, 107868. https://doi.org/10.1016/j.agrformet.2019.107868

Hu Yongguang. (2015). Optimal flight parameters of unmanned helicopter for tea plantation frost protection. International Journal of Agricultural and Biological Engineering, 8(5), 50. https://doi.org/10.3965/j.ijabe.20150805.1655

Hu, Y. G., Liu, S. Z., Wu, W. Y., Wang, J. Z., Shen, J. W. (2015). Optimal flight parameters of unmanned helicopter for tea plantation frost protection. International Journal of Agricultural and Biological Engineering, 8(5): 50–57. https://doi.org/10.3965/j.ijabe.20150805.1655.

Hu, Y., Amoah Asante, E., Lu, Y., Mahmood, A., Ali Buttar, N., & Yuan, S. (2018). A review of air disturbance technology for plant frost protection. International Journal of Agricultural and Biological Engineering, 11(3), 21–28. https://doi.org/10.25165/j.ijabe.20181103.3172

Hua, W., He, L., & Heinemann, P. (2022). A Heat Transfer Model for an Apple Orchard Equipped with Mobile Heaters During Frost. In 2022 Houston, Texas July 17-20, 2022. American Society of Agricultural and Biological Engineers. 2022 Houston, Texas July 17-20, 2022. https://doi.org/10.13031/aim.202200191

Hua, W., Heinemann, P., & He, L. (2025). Frost management in agriculture with advanced sensing, modeling, and artificial intelligent technologies: A review. Computers and Electronics in Agriculture, 231, 110027. https://doi.org/10.1016/j.compag.2025.110027

Iglesias, I., & Alegre, S. (2006). The effect of anti-hail nets on fruit protection, radiation, temperature, quality and probability of Mondial Gala apples. Journal of Applied Horticulture, 08(02), 91–100. https://doi.org/10.37855/jah.2006.v08i02.22

Inouye, D. W. (2000). The ecological and evolutionary significance of frost in the context of climate change. Ecology Letters, 3(5), 457–463. https://doi.org/10.1046/j.1461-0248.2000.00165.x

IPCC, 2021. Climate change 2021: Impacts, adaptation, and vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press. https://www.ipcc.ch/report/ar6/wg2/chapter/ccp4/.

İtmeç, M., Bayat, A., Özlüoymak, Ö. B. (2020). Determination of rainfall effects on kaolin clay coverage rates used in prevention plant from sunburn. International Journal of Agriculture, Environment and Food Sciences, 4(2): 225–229.

Jarrett, A. R., C. T. Morrow. (1984). Distribution of Frost Protection Water Applied to Apple Trees During Bud and Leaf Development. Transactions of the ASAE, 27(1), 0089–0092. https://doi.org/10.13031/2013.32741

Jemmett-Smith, B., Ross, A. N., & Sheridan, P. (2018). A short climatological study of cold air pools and drainage flows in small valleys. Weather, 73(8), 256–262. https://doi.org/10.1002/wea.3281

Kimura, K., Yasutake, D., Nakazono, K., & Kitano, M. (2017). Dynamic distribution of thermal effects of an oscillating frost protective fan in a tea field. Biosystems Engineering, 164, 98–109. https://doi.org/10.1016/j.biosystemseng.2017.09.010

Knox, J. A., Nevius, D. S., & Knox, P. N. (2017). Two Simple and Accurate Approximations for Wet-Bulb Temperature in Moist Conditions, with Forecasting Applications. Bulletin of the American Meteorological Society, 98(9), 1897–1906. https://doi.org/10.1175/bams-d-16-0246.1

Koc, A. B., Heinemann, P. H., Crassweller, R. M., Morrow, C. T. (2000). Automated cycled sprinkler irrigation system for frost protection of apple blossoms. Applied Engineering in Agriculture, 16(3), 231–240. https://doi.org/10.13031/2013.5146

Lei, S., Yu, S., Sun, J., Wang, Z., & Liao, Y. (2024). A Methodology for the Prediction of Extreme Precipitation in Complex Terrains: A Case Study of Central Southwest

China. Water, 16(3), 427. https://doi.org/10.3390/w16030427

Leuning, R., & Cremer, K. W. (1988). Leaf temperatures during radiation frost Part I. Observations. Agricultural and Forest Meteorology, 42(2–3), 121–133. https://doi.org/10.1016/0168-1923(88)90072-x

Liu, T., Zhang, S., Sun, T., Ma, C., & Xue, X. (2025). Review of Active Plant Frost Protection Equipment and Technologies: Current Status, Challenges, and Future Prospects. Agronomy, 15(5), 1164. https://doi.org/10.3390/agronomy15051164

Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011). Climate Trends and Global Crop Production Since 1980. Science, 333(6042), 616–620. https://doi.org/10.1126/science.1204531

Maraveas, C. (2020). The Sustainability of Plastic Nets in Agriculture. Sustainability, 12(9), 3625. https://doi.org/10.3390/su12093625

Matusick, G., Ruthrof, K. X., Brouwers, N. C., & Hardy, G. St. J. (2014). Topography influences the distribution of autumn frost damage on trees in a Mediterranean-type Eucalyptus forest. Trees, 28(5), 1449–1462. https://doi.org/10.1007/s00468-014-1048-4

Miller, P. R., Turrell, F. M., Austin, S. W. (1966). Solid fuel candle-type orchard heaters. Calif Agric, 20(7): 4–5. https://californiaagriculture.org/article/112845.

Misan, K., Kozieja, M., Łoś, M., Gryboś, D., Leszczyński, J., Maczuga, P., Woźniak, M., Serra, A. O., & Paszyński, M. (2023). The First Scientiffic Evidence for the Hail Cannon. In Lecture Notes in Computer Science (pp. 177–190). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-35995-8_13

Munné-Bosch, S., & Vincent, C. (2019). Physiological Mechanisms Underlying Fruit Sunburn. Critical Reviews in Plant Sciences, 38(2), 140–157. https://doi.org/10.1080/07352689.2019.1613320

Mupambi, G., Anthony, B. M., Layne, D. R., Musacchi, S., Serra, S., Schmidt, T., & Kalcsits, L. A. (2018). The influence of protective netting on tree physiology and fruit quality of apple: A review. Scientia Horticulturae, 236, 60–72. https://doi.org/10.1016/j.scienta.2018.03.014

Pan, Q., Lu, Y., Hu, H., & Hu, Y. (2024). Review and research prospects on sprinkler irrigation frost protection for horticultural crops. Scientia Horticulturae, 326, 112775. https://doi.org/10.1016/j.scienta.2023.112775

Park, J., Lee, S.-H., Lee, J., Wi, S. H., Seo, T. C., Moon, J. H., & Jang, S. (2025). Growing vegetables in a warming world - a review of crop response to drought stress, and strategies to mitigate adverse effects in vegetable production. Frontiers in Plant Science, 16. https://doi.org/10.3389/fpls.2025.1561100

Parsons, L. R., Wheaton, T. A., & Whitney, J. D. (1982). Undertree Irrigation for Cold Protection with Low-volume Microsprinklers1. HortScience, 17(5), 799–801. https://doi.org/10.21273/hortsci.17.5.799

Qiao, B., Wang, L., Han, H., Huang, Z., Lin, Y., Jia, Z., Nie, H., He, X., & Liu, Y. (2024). Effects of airflow disturbance from a multi-rotor unmanned aerial vehicle on fruit tree frost protection.Biosystems Engineering, 241, 95–112. https://doi.org/10.1016/j.biosystemseng.2024.04.001

Ribeiro, A. C., De Melo-Abreu, J. P., & Snyder, R. L. (2006). Apple orchard frost protection with wind machine operation. Agricultural and Forest Meteorology, 141(2–4), 71–81. https://doi.org/10.1016/j.agrformet.2006.08.019

Rieger, M. (1993). Under- and Overtree Microsprinkler Irrigation for Frost Protection of Peaches. HortTechnology, 3(1), 81–85. https://doi.org/10.21273/horttech.3.1.81

Rodríguez-Moreno, V. M., & Estrada-Ávalos, J. (2024). Heavy Rainfall Events in Selected Geographic Regions of Mexico, Associated with Hail Cannons. Forecasting, 6(2), 418–433. https://doi.org/10.3390/forecast6020023

Scarascia-Mugnozza, G., Sica, C., & Russo, G. (2012). Plastic materials in European agriculture: Actual use and perspectives. Journal of Agricultural Engineering, 42(3), 15. https://doi.org/10.4081/jae.2011.28

Snyder, R. L., de Melo-Abreu, J. P. (2005). Frost protection: Fundamentals, practice and economics. Vol. 1. Rome: Food and Agriculture Organization of the United Nations. https://www.fao.org/4/y7223e/y7223e00.pdf.

Stutsel, B. M., Callow, J. N., Flower, K., Biddulph, T. B., Cohen, B., & Leske, B. (2019). An Automated Plot Heater for Field Frost Research in Cereals. Agronomy, 9(2), 96. https://doi.org/10.3390/agronomy9020096

Thomashow, M. F. (1999). PLANT COLD ACCLIMATION: Freezing Tolerance Genes and Regulatory Mechanisms. Annual Review of Plant Physiology and Plant Molecular Biology, 50(1), 571–599. https://doi.org/10.1146/annurev.arplant.50.1.571

Tubiello, F. N., Soussana, J.-F., & Howden, S. M. (2007). Crop and pasture response to climate change. Proceedings of the National Academy of Sciences, 104(50), 19686–19690. https://doi.org/10.1073/pnas.0701728104

Vitasse, Y., Lenz, A., & Körner, C. (2014). The interaction between freezing tolerance and phenology in temperate deciduous trees. Frontiers in Plant Science, 5. https://doi.org/10.3389/fpls.2014.00541

Von Lengerke, H. J. (1978). On the short-term predictability of frost and frost protection — A case study on Dunsandle Tea Estate in the Nilgiris (South India). Agricultural Meteorology, 19(1), 1–10. https://doi.org/10.1016/0002-1571(78)90033-x

Yang, X., Lu, M., Wang, Y., Wang, Y., Liu, Z., & Chen, S. (2021). Response Mechanism of Plants to Drought Stress. Horticulturae, 7(3), 50. https://doi.org/10.3390/horticulturae7030050

Yuan, W., & Choi, D. (2021). UAV-Based Heating Requirement Determination for Frost Management in Apple Orchard. Remote Sensing, 13(2), 273. https://doi.org/10.3390/rs13020273

Yuan, X., Li, S., Chen, J., Yu, H., Yang, T., Wang, C., Huang, S., Chen, H., & Ao, X. (2024). Impacts of Global Climate Change on Agricultural Production: A Comprehensive Review. Agronomy, 14(7), 1360. https://doi.org/10.3390/agronomy14071360

Zamora-Re, M. I., Dukes, M. D., Stanley, C. D., & Werner, H. (2016). Sprinkler Irrigation Pressure and Spacing Effect for Cold Protection of Strawberries. Journal of Irrigation and Drainage Engineering, 142(1). https://doi.org/10.1061/(asce)ir.1943-4774.0000928

Zampieri, M., Ceglar, A., Dentener, F., & Toreti, A. (2017). Wheat yield loss attributable to heat waves, drought and water excess at the global, national and subnational scales. Environmental Research Letters, 12(6), 064008. https://doi.org/10.1088/1748-9326/aa723b

Zhu, Y., Guo, Q., Tang, Y., Zhu, X., He, Y., Huang, H., & Luo, S. (2022). CFD simulation and measurement of the downwash airflow of a quadrotor plant protection UAV during operation. Computers and Electronics in Agriculture, 201, 107286. https://doi.org/10.1016/j.compag.2022.107286

Chapter

3

UNMANNED AERIAL VEHICLES IN BIOSYSTEMS ENGINEERING: FROM DIGITAL TRANSFORMATION TO AUTONOMOUS PRECISION

Alper SOYSAL[1]

---

[1] Asst. Prof. Dr. Çukurova University, Vocational School of Ceyhan, Department of Machinery and Metal Technologies, Agricultural Machinery Program, Ceyhan, Adana, Türkiye-E-mail: salper@cu.edu.trORCID: 0000-0002-7987-8945

1. INTRODUCTION

The global agricultural landscape is currently navigating a "triple threat" of unprecedented scale: a surging global population projected to reach 9.7 billion by 2050, the intensifying volatility of climate change characterized by erratic precipitation and temperature extremes and the alarming degradation of arable land and freshwater resources. Biosystems engineering, as a multidisciplinary field that bridges the gap between biological sciences and engineering principles, addresses these systemic vulnerabilities by pivoting toward the "Agriculture 4.0" framework.

This shift represents a fundamental departure from the Third Agricultural Revolution's focus on mechanization and chemistry. Instead, it is characterized by the transition from traditional, uniform field-based management to a high-granularity, per-plant management strategy (Trendov et al., 2020). By integrating Cyber-Physical Systems (CPS), the Internet of Things (IoT), and Big Data analytics, biosystems engineers can now optimize resource efficiency at a resolution previously thought impossible.

1.1. The Strategic Role of UAVs in the Sensing Hierarchy

Unmanned Aerial Vehicles (UAVs) have emerged as the cornerstone of this digital transformation. In the traditional remote sensing hierarchy, a significant "information gap" existed between satellite platforms and ground-based observations. Satellites, while capable of covering vast areas, frequently suffer from atmospheric attenuation, cloud interference, and revisit times that are often too infrequent for rapid phenological changes. Conversely, ground-based sensing is labor-intensive, geographically limited, and risks causing soil compaction and crop damage (Zhang and Kovacs, 2012).

UAVs resolve these constraints by offering an "on-demand" sensing capability. Operating at low altitudes (typically 30–120 m), they provide ultra-high spatial resolution often at the centimeter level allowing for the identification of individual leaves or specific pest infestations. This temporal and spatial flexibility is not merely a technical upgrade; it is a fundamental requirement for Precision Agriculture (PA) to move from theory to operational reality.

1.2. Engineering Complexity and Technological Synergy

The integration of UAVs into biosystems engineering is not a standalone solution but a synergy of three distinct engineering domains:

Aerospace Engineering: Development of VTOL (Vertical Take-Off and Landing) and fixed-wing airframes with optimized power-to-weight ratios for extended flight endurance.

Optical Engineering: The miniaturization of multispectral, hyperspectral, and LiDAR (Light Detection and Ranging) sensors that can operate on low-payload platforms.

Computational Engineering: The use of Structure from Motion (SfM) algorithms and machine learning to process terabytes of raw image data into actionable prescription maps (Zhai et al., 2020).

1.3. Identification of Research Gaps and Current Limitations

Despite the rapid adoption of UAVs, several "gaps" remain that prevent their universal application in biosystems engineering:

The "Data-Rich, Information-Poor" Paradox: While UAVs collect massive amounts of data, the automated translation of this data into real-time agronomic decisions remains a bottleneck. Most workflows still require significant post-processing time, which limits their use for immediate field actions (Wolfert et al., 2017).

Battery and Energy Constraints: The limited flight duration of multi-rotor systems (typically 20-35 minutes) remains a barrier for large-scale industrial farming, necessitating research into hydrogen fuel cells or hybrid propulsion systems.

Standardization Gap: There is a lack of standardized protocols for sensor calibration across different environmental conditions. Spectral signatures captured at 10:00 AM may differ from those at 2:00 PM, leading to inconsistencies in vegetation index (e.g., NDVI) calculations.

Regulatory and Legal Barriers: The integration of UAVs into "beyond visual line of sight" (BVLOS) operations is still heavily restricted by aviation authorities globally, hindering the full automation of rural monitoring (Pathak et al., 2020).

2. UAV HARDWARE ARCHITECTURE AND SPECIALIZED SENSOR TECHNOLOGIES

To optimize the application of UAVs in biosystems engineering, the selection of hardware must be treated as a strategic engineering decision. The performance of the system is governed by the interplay between aerodynamic constraints, power density, and sensor integration capabilities.

2.1. Platform Selection: Engineering Trade-offs and Flight Dynamics

The choice of airframe dictates the operational envelope of the mission. Modern biosystems research primarily categorizes platforms into three aerodynamic configurations:

· **Fixed-Wing Platforms:** Functioning on the principle of aerodynamic lift generated by forward motion, these platforms are the industry standard for high-throughput mapping.

· **Engineering Advantage:** Their high lift-to-drag ratio allows for significantly lower energy consumption per kilometer compared to multi-rotors. This enables the coverage of vast areas (e.g., 500–2,000 hectares) in a single sortie with endurance reaching up to 4 hours in high-end models (Zhang and Kovacs, 2012).

· **Constraints:** They are limited by the need for specialized launch/recovery systems (runways or catapults) and a lack of maneuverability in confined spaces.

· **Multi-Rotor Platforms (Quadcopters, Hexacopters, Octocopters):** These rely on thrust-driven lift, offering unparalleled agility.

· **Engineering Advantage:** Vertical Take-Off and Landing (VTOL) and precise hovering capabilities make them indispensable for high-resolution "spot" inspections and active intervention tasks such as precision spraying or "See-and-Spray" operations.

· **Constraints:** The energy cost of maintaining lift is high, typically restricting flight endurance to 20–40 minutes. Furthermore, the motor-induced vibrations can introduce "noise" into high-precision sensor data if not properly dampened (Hassler and Baysal-Gurel, 2019).

· **VTOL-Hybrid Platforms:** A burgeoning area in biosystems engineering is the hybrid VTOL, which combines the takeoff convenience of a multi-rotor with the long-range efficiency of a fixed-wing. These are increasingly used for monitoring linear infrastructure like irrigation canals or large-scale forest boundaries.

2.2. The Sensor Suite: Advanced Payloads and Data Fusion

The sensor is the primary interface between the engineering platform and the biological system. In Agriculture 4.0, sensors must be calibrated to detect physiological changes that occur beyond the visible spectrum.

· **Multispectral Sensors:** These are the workhorses of crop vigor assessment. They capture discrete spectral bands, most notably Near-Infrared (NIR) and the Red Edge (the region of rapid change in reflectance between red and NIR).

· **Biological Context:** Healthy, turgid leaves exhibit high NIR reflectance due to the internal structure of the mesophyll cells, while the chlorophyll absorbs visible red light. By calculating the ratio between these bands (e.g., NDVI), engineers can detect "invisible" stressors such as nitrogen deficiency or early-stage disease before wilting occurs (Yang et al., 2017).

· **Thermal Infrared (TIR) Sensors:** These uncooled microbolometers measure long-wave infrared radiation (typically 8–14 μm).

· **Biological Context:** Canopy temperature is a proxy for the transpiration rate. When a plant experiences water stress, stomata close to conserve moisture, leading to a reduction in evaporative cooling and a subsequent rise in leaf temperature. TIR data is critical for calculating the Crop Water Stress Index (CWSI), allowing for the automation of high-precision irrigation systems (Maes and Steppe, 2019).

· **LiDAR (Light Detection and Ranging):** LiDAR systems emit laser pulses and measure the Time-of-Flight (ToF) of the reflected light to create high-density 3D point clouds.

· **Engineering Context:** LiDAR is unique in its ability to penetrate the upper canopy, providing data on the vertical structure of the crop. By processing these points, engineers generate the Digital Surface Model (DSM) and the Digital Terrain Model (DTM). The difference between these layers provides the Canopy Height Model (CHM), which is used for accurate biomass estimation and carbon sequestration modeling with centimeter-level precision.

· **Hyperspectral Sensors:** Unlike multispectral sensors with 4–10 broad bands, hyperspectral sensors capture hundreds of narrow, contiguous bands. While historically limited by weight and cost, miniaturized hyperspectral sensors now allow for "spectral fingerprinting," which can distinguish between specific weed species or identify nutrient deficiencies (e.g., Potassium vs. Phosphorus) with high specificity.

Optical sensors placed on both ends of the spraying robot were used to move the mobile system back and forth automatically. Inductive proximity sensor that provides a counter output proportional to the motor shaft speed was also used to measure the speed of the mobile robot (Özlüoymak et al., 2019).

3. DATA ACQUISITION, PHOTOGRAMMETRY, AND VEGETATION INDICES

The transformation of raw aerial imagery into high-fidelity, actionable geospatial data is a multi-stage engineering process. It requires the integration of ballistic flight dynamics, computational geometry, and plant physiology.

3.1. Flight Planning and the Mechanics of Overlap

Autonomous flight planning is the foundation of data quality. Unlike manual flight, autonomous missions use specialized software (e.g., Pix4Dcapture, DJI Terra, Mission Planner) to execute a "lawnmower" grid pattern at a constant altitude and speed.

· **Overlap Dynamics:** For successful orthomosaicking (the process of stitching images into a single, geometrically corrected map), high overlap is non-negotiable.

· **Front Overlap (80%):** The overlap between consecutive images along the flight line.

· **Side Overlap (70%):** The overlap between adjacent flight strips.

· **Structure from Motion (SfM):** These high overlap rates allow Structure from Motion algorithms to identify "tie points" (matching pixels) across multiple images. By calculating the parallax shift of these points from different camera positions, the software reconstructs the 3D geometry of the scene. This results in the creation of a Dense Point Cloud, from which the Digital Surface Model (DSM) and orthomosaics are derived (Mulla, 2013).

· **Ground Control Points (GCPs):** To achieve absolute spatial accuracy (sub-centimeter level), physical markers with known GPS coordinates (GCPs) are often placed on the field. Alternatively, UAVs equipped with Real-Time Kinematic (RTK) or Post-Processing Kinematic (PPK) GPS systems can achieve similar precision by correcting satellite signals in real-time.

3.2. Vegetation Indices (VI): Quantitative Bio-Analysis

Vegetation indices are mathematical transformations of two or more spectral bands designed to accentuate specific plant properties while minimizing atmospheric or soil interference.

· **NDVI (Normalized Difference Vegetation Index):**

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

NDVI is the most widely used index for monitoring biomass and vigor. However, it tends to "saturate" in high-density canopies (e.g., late-stage corn or wheat), where additional leaf layers do not significantly increase NIR reflectance (Bendig et al., 2015).

· **GNDVI (Green NDVI):**

$$GNDVI = \frac{NIR - Green}{NIR + Green}$$

GNDVI replaces the Red band with Green. Since the Green band is more sensitive to internal leaf chlorophyll concentration than the Red band, GNDVI is superior for detecting nitrogen deficiencies and monitoring crops in advanced phenological stages (Yang et al., 2017).

· **SAVI (Soil Adjusted Vegetation Index):**

$$SAVI = \frac{(NIR - Red)}{(NIR + Red + L)} \times (1 + L)$$

In early growth stages, the soil surface reflects significant light, which can artificially lower NDVI values. SAVI introduces a soil brightness correction factor (L). An L value of 0.5 is typically used to neutralize the soil background "noise."

· **NDRE (Normalized Difference Red Edge):**

$$NDRE = \frac{NIR - RedEdge}{NIR + RedEdge}$$

This index utilizes the transition zone between Red and NIR. Because Red Edge light can penetrate deeper into the canopy than Red light, NDRE is more effective for managing permanent crops (orchards) and high-biomass row crops where NDVI saturates (Maes and Steppe, 2019).

3.3. Research Gaps in Data Processing

The current photogrammetric workflow faces several "Gaps" that prevent real-time deployment:

· **The Atmospheric Correction Gap:** Most UAV data is processed using "Digital Numbers" (DN) rather than surface reflectance. Without rigorous radiometric calibration using sunshine sensors or calibration targets, VIs cannot be accurately compared across different dates or lighting conditions.

· **Processing Latency:** Current SfM processing for a 100-hectare field can take several hours on a high-end workstation. For "real-time" biosystems engineering (e.g., immediate swarm response), Edge-Cloud collaborative processing models are required to reduce latency (Puri et al., 2017).

4. PRECISION AGRICULTURE APPLICATIONS: ACTUATING THE DATA

In the framework of Biosystems Engineering, UAVs have evolved from passive observation platforms into active robotic actuators. The transition from "seeing" to "doing" is defined by the integration of geospatial intelligence with automated mechanical response systems.

4.1. Variable Rate Application (VRA): The Prescription-to-Action Pipeline

The pinnacle of UAV data utilization is the generation of a **Prescription Map** (VRA map). This process transforms spectral indices into quantitative application commands for agricultural inputs.

· **The Decision Matrix:** By correlating Vegetation Indices (e.g., NDVI, NDRE) with soil sampling data, engineers create a zone-based management map. Areas exhibiting low vigor due to nutrient deficiency are assigned higher dosage rates, while high-vigor areas receive maintenance dosages (Mulla, 2013).

· **Operational Efficiency:** In a traditional "blanket" application, a farmer might apply a uniform 200kg of fertilizer per hectare. VRA allows for a dynamic range (e.g., 100kg to 300kg), ensuring that nutrients are not wasted in "saturated" zones—thereby preventing nitrogen leaching into groundwater—and are concentrated in "deficit" zones to maximize yield (Wolfert et al., 2017).

· **Integration with Ground Robotics:** While UAVs can act as the primary applicator, they also serve as the intelligence layer for smart tractors and autonomous ground vehicles (UGVs). The prescription map is exported in standard formats (e.g., Shapefile or ISO-XML) and uploaded to the tractor's task controller via the ISOBUS protocol.

An orchard spraying system was designed and developed to apply VRA spraying method according to the varying tree canopy geometries. Laser sensors were used to instantly determine the tree geometry. The designed orchard sprayer instantly adjusted the air flow according to tree density and geometry (İtmeç and Bayat, 2026).

4.2. Spraying Drones and the Physics of Centrifugal Atomization

The deployment of heavy machinery for plant protection often leads to soil compaction and the "tramline effect," where wheels physically crush crops, leading to a permanent 3–5% yield loss in those tracks. UAVs mitigate these engineering constraints by providing a "non-contact" application method.

· **Centrifugal Nozzles and ULV Spraying:** Unlike traditional hydraulic nozzles that rely on pressure, modern spraying UAVs utilize Centrifugal Atomizers (Rotating Disk Atomizers). By adjusting the rotation speed of the disk, engineers can control the droplet size (Droplet Volume Median Diameter - VMD) with extreme precision. This enables Ultra-Low Volume (ULV) spraying, where a highly concentrated chemical is applied in a fine mist, reducing total water carrier volume by up to 90% (Zhai et al., 2020).

· **The "Downwash" Effect:** One of the most significant engineering advantages of multi-rotor UAVs is the aerodynamic turbulence created by the rotors. This downwash forces the atomized droplets deep into the crop canopy. Studies have shown that UAV-based spraying provides superior coverage on the underside of leaves (abaxial surface) compared to traditional booms, which is critical for controlling pests that reside beneath the foliage (Zhang and Kovacs, 2012).

· **All-Terrain Operability:** UAVs can operate in saturated soil conditions where heavy tractors would get stuck, allowing for timely intervention immediately after rain—a period when fungal disease pressure is at its highest.

4.3. Research Gaps in Actuation and Application

Despite these advancements, several "Gaps" hinder the complete autonomy of UAV-based actuation:

· **Drift Management:** Fine droplets used in ULV spraying are highly susceptible to wind drift. Developing Real-time Drift Compensation algorithms that adjust flight height and speed based on an onboard anemometer is a critical research frontier (Hassler and Baysal-Gurel, 2019).

· **Swarm Coordination:** A single spraying drone has a limited tank capacity (typically 10–50 liters). Scaling this to industrial levels requires Multi-UAV Swarm Coordination, where multiple drones rotate between a refilling station and the field autonomously to maintain continuous operation.

· **Legal Chemical Approval:** Most agricultural chemicals were originally labeled for high-volume hydraulic application. There is a lack of localized research and regulatory approval for concentrated ULV formulations specifically designed for UAV delivery.

5. ADVANCED WATER MANAGEMENT AND THE CROP WATER STRESS INDEX (CWSI)

In the context of global aridification, effective irrigation has become the cornerstone of sustainable biosystems engineering. Traditional irrigation scheduling often based on soil moisture sensors at discrete points or weather-based evapotranspiration (ET) models fails to account for the high spatial variability of plant physiological responses within a single field. UAV-based thermal remote sensing addresses this by providing a spatially continuous map of plant hydration status.

5.1. The Engineering of Thermal Mapping

UAVs equipped with uncooled microbolometer sensors capture the long-wave infrared (LWIR) radiation emitted by the crop canopy. The fundamental principle is that transpiration acts as a cooling mechanism; when a plant has sufficient water, its stomata remain open, and evaporative cooling keeps the leaf temperature (T_{canopy}) below the ambient air temperature. Conversely, water deficiency triggers stomatal closure, leading to a rapid increase in T_{canopy}.

5.2. Quantifying Stress: The CWSI Equation

To normalize the temperature data against varying environmental conditions (solar radiation, wind, and humidity), engineers utilize the Crop Water Stress Index (CWSI):

$$CWSI = \frac{(T_{canopy} - T_{wet})}{(T_{dry} - T_{wet})}$$

In where,

T_{wet} (Lower Baseline): The temperature of a leaf under maximum transpiration (fully hydrated).

T_{dry} (Upper Baseline): The temperature of a leaf where transpiration has completely ceased (severe stress).

And, Interpretation: The index ranges from 0 (no stress) to 1 (maximum stress).

5.3. Variable Rate Irrigation (VRI)

The CWSI map serves as a decision-support layer for Variable Rate Irrigation (VRI) systems. In semi-arid regions such as the Mediterranean, where water is the most expensive and scarce input, VRI allows for the differential application of water. Instead of uniform flooding or sprinkling, precision nozzles direct water only to zones where the CWSI exceeds a specific threshold. Research indicates that UAV-integrated VRI can reduce water consumption by up to 25–50% while maintaining or even improving harvest quality (Maes and Steppe, 2019).

6. MONITORING BIOTIC STRESS AND YIELD FORECASTING

Biosystems engineering relies on the early identification of biological anomalies to minimize chemical intervention and maximize economic output.

6.1. Early Pest and Disease Detection: The Pre-Visual Phase

Pests and pathogens alter the internal leaf structure (mesophyll) and chlorophyll content. These changes manifest in the Near-Infrared (NIR) and Red Edge bands long before the human eye can detect chlorosis or necrosis (yellowing).

- **Spectral Fingerprinting:** Multi-temporal UAV flights allow engineers to observe "spectral shifts." For example, a sudden drop in the Photochemical Reflection Index (PRI) can indicate early-stage fungal infection.

- **Spot-Spraying Strategy:** By identifying "hotspots" of infection at the individual plant level, UAVs enable "spot-spraying." This localized treatment prevents the escalation of a pest outbreak into a field-wide epidemic, reducing pesticide usage by up to 80% (Berrer et al., 2023).

6.2. High-Throughput Phenotyping and Yield Estimation

In both commercial production and plant breeding, UAVs facilitate High-Throughput Phenotyping (HTP) the rapid analysis of plant traits across thousands of plots.

- **Volumetric Analysis:** By utilizing LiDAR or SfM-derived 3D point clouds, engineers calculate canopy volume and height throughout the growing season.

- **Regression Modeling:** By fusing volumetric data with spectral vigor (NDVI/GNDVI), high-accuracy regression models are built to predict final yield.

- **Economic Impact:** Precise yield forecasting is vital for supply chain optimization, allowing for better logistics planning and ensuring food security at both micro and macro-economic levels (Lioutas and Charatsari, 2020).

7. SUSTAINABILITY, ECONOMICS, AND FUTURE PROJECTIONS

7.1. Environmental Impact and Decarbonization

UAVs contribute to the "Green Deal" by reducing the chemical load in the environment. By applying fertilizers and pesticides only where needed, the risk of groundwater contamination is significantly reduced. Furthermore, replacing heavy machinery with electric UAVs reduces the carbon footprint and prevents soil compaction, which is a major cause of land degradation.

7.2. Artificial Intelligence and Edge Computing

The next frontier is Edge AI. Current workflows require uploading data to the cloud for processing. Future UAVs will carry onboard AI processors (like NVIDIA Jetson) to identify weeds or diseases in real-time. This "On-the-Fly" processing will allow for instantaneous spraying, eliminating the need for post-processing and second flights.

7.3. The Swarm Revolution

The concept of "Swarm Intelligence" involves dozens of small, low-cost drones working together. Like a flock of birds, they can communicate and divide tasks—some drones map the area while others follow behind to spray or seed. This approach ensures that even massive agricultural enterprises can be managed with high-resolution precision in a matter of hours (Pathak et al., 2020).

References

Bendig, J., Yu, K., Aasen, H., Bolten, A., Bennertz, S., Broscheit, J., ... Bareth, G. (2015). Combining UAV-based plant height from crop surface models (CSMs) and vegetation indices for the identification of nitrogen status in winter barley. *ISPRS Journal of Photogrammetry and Remote Sensing*, *101*, 111-124. https://doi.org/10.1016/j.isprsjprs.2014.12.002.

Berrer, M., Reiser, D., Griepentrog, H. W. (2023). Deep learning for plant-specific treatment in precision agriculture. *Precision Agriculture*, *24*(1), 112–130. https://doi.org/10.1007/s11119-022-09935-y.

Hassler, S. C., Baysal-Gurel, F. (2019). Unmanned aircraft system (UAS) use in agriculture: A review. *Agronomy*, *9*(8), 441. https://doi.org/10.3390/agronomy9080441.

İtmeç, M., Bayat, A. (2026). A real-time variable rate air and liquid sprayer for orchard applications. Precision Agriculture, 27(29), 1-32. https://doi.org/10.1007/s11119-026-10331-y.

Lioutas, E. D., Charatsari, C. (2020). Smart farming and short food supply chains: Are they compatible? *Land Use Policy*, *94*, 104541. https://doi.org/10.1016/j.landusepol.2020.104541.

Maes, W. H., Steppe, K. (2019). Perspectives for remote sensing with unmanned aerial vehicles in agriculture for precision horticulture. *Frontiers in Plant Science*, *10*, 567. https://doi.org/10.3389/fpls.2019.00567.

Mulla, D. J. (2013). Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosystems Engineering*, *114*(4), 358–371. https://doi.org/10.1016/j.biosystemseng.2012.08.009.

Özlüoymak, Ö. B., Bolat, A., Bayat, A., Güzel, E. (2019). Design, development, and evaluation of a target oriented weed control system using machine vision. Turkish Journal of Agriculture and Forestry, 43(2): 164-173. https://doi.org/10.3906/tar-1803-8.

Pathak, H., Kumar, S., Mehta, C. R. (2020). Automation and ICT in Indian agriculture. *Indian Journal of Agricultural Sciences*, *90*(1), 3–11.

Puri, V., Nayyar, A., Schuetz, L. (2017). Agriculture drones: A modern breakthrough in agriculture. *Design Automation for Embedded Systems*, *21*, 125–144. https://doi.org/10.1007/s10617-017-9188-4.

Trendov, N. M., Varas, S., Zeng, M. (2020). *Digital technologies in agriculture and rural areas: Status and pathways*. Food and Agriculture Organization of the United Nations. https://doi.org/10.4060/ca7961en.

Wolfert, S., Ge, L., Verdouw, C., Bogaardt, M. J. (2017). Big data in smart farming

– A review. *Agricultural Systems*, *153*, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023.

Yang, G., Liu, J., Zhao, C., Li, Z., Huang, Y., Yu, H., ... Xu, B. (2017). Unmanned aerial vehicle remote sensing for field-based crop phenotyping: Current status and perspectives. *Frontiers in Plant Science*, *8*, 1111. https://doi.org/10.3389/fpls.2017.01111.

Zhai, Z., Martínez, J. F., Beltran, V., Martínez, N. L. (2020). Decision support systems for agriculture 4.0: Survey and challenges. *Computers and Electronics in Agriculture*, *170*, 105256. https://doi.org/10.1016/j.compag.2020.105256.

Zhang, X., Kovacs, J. M. (2012). The application of small unmanned aerial systems for precision agriculture: A review. *Precision Agriculture*, *13*(6), 693–712. https://doi.org/10.1007/s11119-012-9274-5.

Chapter
4

ARTIFICIAL INTELLIGENCE IN BIOSYSTEMS ENGINEERING

Ömer Barış ÖZLÜOYMAK[1]

---

[1] Assoc. Prof. Dr. Çukurova University, Faculty of Agriculture, Department of Agricultural Machinery and Technologies Engineering, 01330 Adana, Türkiye E-mail: ozluoymak@cu.edu.tr ORCID: 0000-0002-6721-0964

1. INTRODUCTION

Agriculture is one of the world's oldest industries and it is still very important today. The world's population is growing day by day quickly, which means more people will need food and employment. Biosystems engineering is an interdisciplinary field that integrates engineering principles with biological systems to enhance agricultural productivity, environmental sustainability, and resource efficiency. Traditionally, biosystems engineering has focused on agricultural production, soil and water management, agricultural machinery and post-harvest systems.

Artificial Intelligence (AI) has been extensively applied in agriculture recently. The agriculture sector is turning to AI technology to cultivate healthier crops, manage pests, monitor soil and growing conditions, analyse data for farmers, and enhance other management activities (Javaid et al., 2023). The fast progress of digital technologies has changed biosystems engineering a lot and turning it into a field that is all about using data. Artificial intelligence, including machine learning (ML) and deep learning (DL), has emerged as a transformative technology in the field of biosystems engineering.

ML methodologies involves a learning process with the objective to learn from "experience" (training data) to perform a task. DL extends classical ML by adding more "depth" (complexity) into the model as well as transforming the data using various functions. Data in ML and DL consist of a set of examples. In order to train the models, AI allows the processing of large datasets of images obtained from field sensors, imaging systems, enhanced machinery, UAV, airborne or satellite based remote sensing, and environmental monitoring platforms, enabling more accurate and efficient decision-making processes (Kamilaris and Prenafeta-Boldú, 2018; Liakos et al., 2018). Recent developments in ML and DL have enabled the analysis of large-scale agricultural datasets, facilitating improved accuracy in crop monitoring, yield prediction, and environmental assessment. Traditionally, biosystems engineering has focused on the design and optimization of systems involving biological materials, including agricultural production, soil management, and environmental control. However, the rapid advancement of sensing technologies, data acquisition systems, and computational power has significantly expanded the role of AI in this field.

In recent years, the integration of AI with biosystems engineering has accelerated due to the adoption of smart farming technologies such as the recent developments in Internet of Things (IoT), advanced (remote) sensing, robotics, unmanned aerial vehicles, and big data analytics (Wolfert et al., 2017; Ayaz et al., 2019). Based on real-time data, these advancements and technologies have contributed to the evolution of precision agriculture, where site-specific management practices and remote sensing applications are applied to optimize resource use and improve sustainability (Gebbers and Adamchuk, 2010; Mulla, 2013). The main concept of AI in agriculture is its flexibility, high performance, accuracy, and cost-effectiveness. AI-driven approaches have demonstrated significant potential in addressing global challenges such as food security, oil/crop/disease/weed management, climate change, and environmental degradation by improving agricultural efficiency and reducing input waste (Eli-Chukwu, 2019; Talaviya et al., 2020; Javaid et al., 2023). Consequently, AI-driven approaches are being increasingly adopted to improve the efficiency, sustainability and productivity of biosystems engineering applications.

2. ARTIFICIAL INTELLIGENCE TECHNIQUES IN BIOSYSTEMS ENGINEERING

The use and integration of AI and machine learning technologies into biosystems engineering create unprecedented opportunities for modelling, optimisation, and decision support across agriculture, livestock, food systems, environmental management, and related domains (Vallejo et al., 2026). AI applications in biosystems engineering primarily rely on machine learning and deep learning techniques.

2.1. Machine Learning

Machine learning is an aspect of artificial intelligence that competently performs automation in the process of building analytical models that allow machines to adapt independently to new scenarios, enabling software to successfully predict and react to the deployment of scenarios based on past results (França et al., 2021). Actually, ML is a type of artificial intelligence that allows machines to learn from data without being explicitly programmed.

Machine learning techniques are widely used in the multi-disciplinary agri-technologies for improving the predictive performance of a given statistical learning or model fitting technique. Various statistical and mathematical models are used to calculate the performance of ML models and algorithms. After the end of the learning process, the trained model can be used to classify, predict, or cluster new examples (testing data) using the experience obtained during the training process (Liakos et al., 2018). A typical ML approach is given in Figure 1.

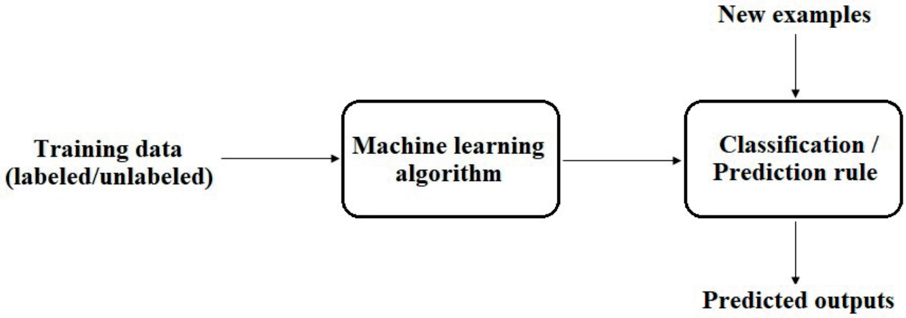


Figure 1. *A typical machine learning approach (Liakos et al., 2018)*

ML models such as Artificial Neural Networks (ANNs), Ensemble Learning (EL), Decision Trees (DT), Regression, Instance Based Models (IBM), Dimensionality Reduction (DR), Bayesian Models (BM) and Clustering are widely used in agricultural systems. A subset of artificial intelligence, namely machine learning, has a considerable potential to handle numerous challenges in the establishment of knowledge-based farming systems (Benos et al., 2021).

2.2. Deep Learning

DL belongs to the machine learning computational field and is similar to ANN. However, DL is about "deeper" neural networks that provide a hierarchical representation of the data by means of various convolutions. This allows larger learning capabilities and thus higher performance and precision (Kamilaris and Prenafeta-Boldú, 2018).

Deep learning has this nomenclature because it deals with neural networks having multiple (deep) layers that allow learning; therefore, it is a subset of machine learning, which considers algorithms inspired by the human brain, the artificial neural networks, which learn from large amounts of data. Deep learning techniques are especially useful for analyzing complex, rich, and multidimensional data such as voice, images, and videos. In short, all deep learning is machine learning, but not all machine learning is deep learning (França et al., 2021).

Deep learning, a subset of machine learning, has revolutionized image-based analysis in biosystems engineering. Convolutional neural networks (CNNs) are extensively used for tasks such as plant disease detection, crop classification and object detection.

CNN is one of artificial neural networks which has distinctive architectures as shown in Figure 2.

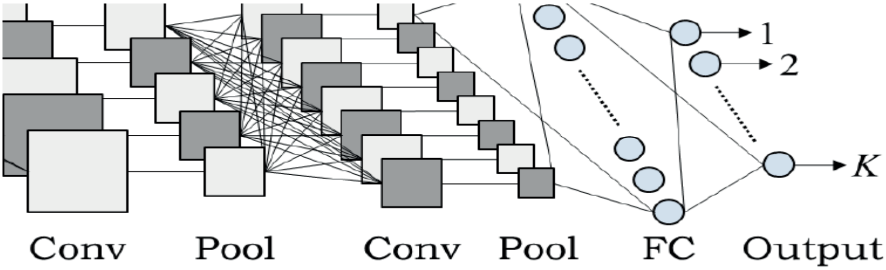


Figure 2. *An example of CNN architecture (Hidaka and Kurita, 2017)*

As shown in Figure 2, input data of CNN are usually RGB images (3 channels) or grayscale images (1 channel). Several convolutional or pooling layers follows the input layer. For classification problems, one or more full connection (FC) layers are often employed. The final layer outputs prediction values for *K* kinds of objects where the input image should be classified (Hidaka and Kurita, 2017).

2.3. Machine Vision

Machine vision is a technology that uses cameras, specialised lighting and software to capture, analyse and process visual information in the same way that humans do automatically. In other words, machine vision is the advanced technology that allows machines to see and understand visual data, similar to our human vision. Machine vision plays a critical role in biosystems engineering by enabling automated analysis of visual data. It allows for real-time and non-destructive analysis of plant characteristics, significantly improving efficiency compared to traditional methods. Agricultural applications such as crop monitoring, plant phenotyping, stress detection, weed detection, fruit counting etc. are carried out by using some special camera systems.

Some cameras used in agricultural applications are (Araus and Cairns, 2014);

- Red, green and blue (RGB) or color infrared (CIR) cameras
- Multispectral cameras
- Hyperspectral visible and near-infrared cameras
- Long-wave infrared cameras or thermal imaging cameras
- Conventional digital cameras

Examples of images taken with different categories of cameras are given in Figure 3.

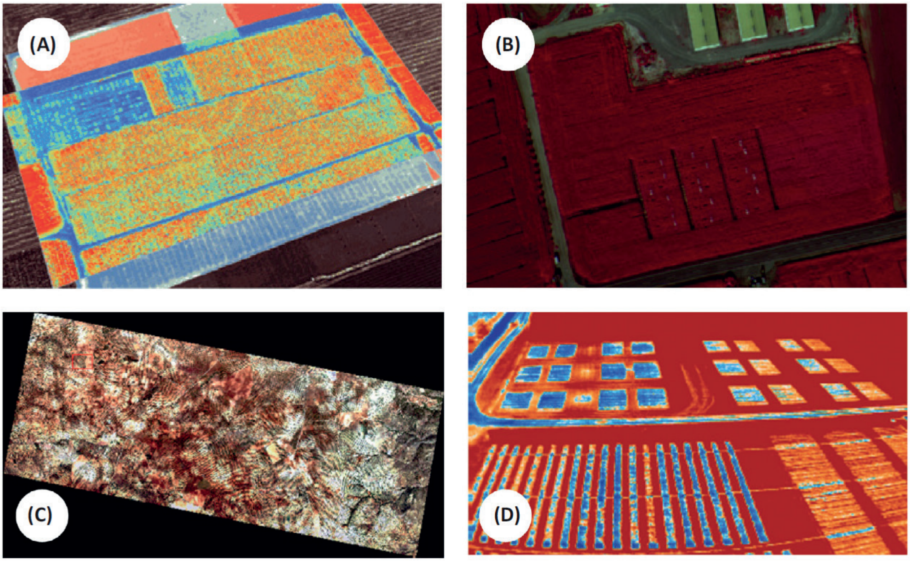


Figure 3. *Examples of images taken with different categories of cameras: (***A***) RGB/CIR, (***B***) multispectral, (***C***) hyperspectral, and (***D***) thermal imaging (Araus and Cairns, 2014)*

Machine vision plays a critical role in AI applications by enabling machines to interpret visual data. The integration of machine vision with AI has significantly improved the accuracy and scalability of agricultural monitoring systems.

3. APPLICATIONS OF AI IN BIOSYSTEMS ENGINEERING

3.1. Crop Monitoring and Phenotyping

Crop monitoring is one of the most important applications of artificial intelligence in biosystems engineering, with significant potential for improving agricultural efficiency and productivity. Unlike traditional monitoring methods, which are labor-intensive and time-consuming, AI-based systems enable the real-time, non-destructive analysis of plant health.

Agricultural-related problems such as seeds identification, soil and leaf nitrogen content, irrigation, plants' water stress detection, water erosion assessment, pest detection, herbicide use, identification of contaminants, diseases or defects on food, crop hail damage and greenhouse monitoring can be detected by using AI models. Larger scale observation is facilitated by using image data collected from drones, satellites, or ground-based cameras (Kamilaris and Prenafeta-Boldú, 2018). High-throughput phenotyping systems leverage deep learning to analyze plant traits such as leaf area, plant growth and performance, and green biomass (Kamilaris and Prenafeta-Boldú, 2018; Araus and Cairns, 2014). These technologies allow for early detection of issues, enabling timely interventions and improving overall crop productivity.

3.2. Crop Yield Prediction

Crop yield prediction is one of the challenging problems in precision agriculture. Accurate yield prediction is essential for agricultural planning and food security. AI models can accurately estimate crop yield through image analysis, data modelling and insights from precision agriculture.

AI models focus on climatic variables, weather conditions, soil parameters and agricultural practices to predict crop yields for food security and agricultural sustainability. The integration of AI in predicting crop yields has significant implications for agricultural adaptation (Hernández et al., 2025; Mohan et al., 2025). Machine learning and deep learning, which are branches of AI focusing on learning, are important decision support tools for crop yield prediction. These models require the use of several datasets since crop yield depends on many different factors such as climate, weather, soil, use of fertilizer, and seed variety. These AI models are used to find solutions for effectively predicting crop yields and making informed choices about crop cultivation and management (Van Klompenburg et al., 2020; Vivekrabinson et al., 2025).

3.3. Soil Analysis and Environmental Monitoring

Soil health is a critical factor in agricultural productivity. It is defined as the ability of soil to sustainably support plant growth and maintain or enhance water and air quality while promoting biodiversity.

The agricultural sector faces numerous challenges in ensuring optimal soil health and environmental conditions for sustainable crop production. Traditional soil analysis methods are often time-consuming and labor-intensive, and provide limited real-time data, making it challenging for farmers to make informed decisions. In recent years, Internet of Things (IoT) technology has emerged as a promising solution to address these challenges by enabling efficient and automated soil analysis and environmental monitoring (Pechlivani et al., 2023). AI-based models are increasingly used to analyze multiple soil properties such as moisture content, nutrient levels and organic matter. The increasing availability of soil data that can be efficiently acquired remotely and proximally, and freely available open-source algorithms, have led to an accelerated adoption of ML techniques to analyze soil data (Padarian et al., 2020). DL based architecture is also used for the prediction of soil organic matter in plains and the proposed model can be used for the prediction of other environmental variables (Zeng et al., 2022).

Additionally, the application of AI in environmental monitoring offers accurate disaster forecasts, pollution source detection, and comprehensive air and water quality monitoring. AI technologies enhance environmental monitoring by enabling better understanding, prediction, and mitigation of environmental risks (Olawade et al., 2024). As known, environmental monitoring is a vital practice that involves systematically collecting and analyzing data to track changes in the environment. The integration of ML and AI into environmental monitoring processes significantly advances the field, offering improved data processing, predictive capabilities, enhanced accuracy, and real-time responsiveness to environmental challenges (Sri et al., 2025). These applications contribute to sustainable resource management by enabling precise and efficient use of inputs such as water and fertilizers.

3.4. Precision Agriculture

Precision agriculture is a modern farming management concept. It uses technology, which measures and responds to variability within a field. It allows farmers to apply multiple resources such as water, pesticides and fertiliser with great accuracy to specific areas, thereby improving crop yields, reducing costs and enhancing sustainability. Precision agriculture is a key application of AI in biosystems engineering.

Precision agriculture technologies transform crop production by enabling more sustainable and efficient agricultural practices. These technologies utilize data-driven approaches to optimize the management of crops, soil, and resources, thus enhancing both productivity and environmental sustainability. Technologies such as remote sensing, GPS-guided equipment, variable rate technology (VRT), and IoT devices are key components of precision agriculture technologies. Precision agriculture minimizes waste, reduces environmental impact, and promotes sustainable farming practices by optimizing inputs such as water, fertilizers, and pesticides (Getahun et al., 2024).

AI-driven systems can optimize irrigation schedules, fertilizer application and pest control measurements. Also, VRT allows for the application of inputs in precise amounts, reducing waste and environmental impact. The integration of AI with GPS, GIS and sensor technologies has significantly advanced precision agriculture practices in biosystems engineering.

3.5. Robotics and Automation

Robotics and automation have become essential parts of modern biosystems engineering. AI-powered robots are used to carry out tasks such as planting, harvesting, spraying and monitoring.

Automation in agriculture contributes to many industrial advancements, helps farmers save time and money, and calls for high investment in this area of technology. Recently, various machines, like harvesters, irrigation systems, ploughing machines, and self-driving tractors, have been automated. Moreover, some recent developments in automation machinery and equipment, particularly some equipment that uses AI, can undo some of the damaging environmental effects of earlier automation gear (Emmanuel et al., 2023). Autonomous robot systems integrate computer vision and sensor technologies to perform agricultural operations with minimal or without human intervention, simplifying the task, improving efficiency and reducing labour costs (Bac et al., 2014; Bechar and Vigneault, 2016). Recent studies have demonstrated the integration of AI-based real-time weed detection with robotic spraying systems, significantly enhancing operational accuracy and reducing herbicide usage (Vijayakumar et al., 2025). Recent developments include robotic weed control systems and automated harvesting robots, which demonstrate the potential of AI-driven automation in agriculture.

3.6. Decision Support Systems

A decision support system (DSS) is defined as a computer information system that combines decision analytic models and database access in order to assist the decision maker in choosing the best course of action (Yam, 2012). Modern decision support systems have many applications, including assistance in scheduling tasks. Biosystems engineering combines engineering sciences and physical sciences in order to understand and improve biological systems in agriculture, food production, environment, etc. (Knapczyk et al., 2019).

Biosystems engineering is an important area of knowledge due to its multidisciplinarity. According to the current analysis of research trends in agricultural engineering, which is part of biosystems engineering, DSS are used in such areas as: pest management, crop production, biomass production, operational planning machine activities, etc. (Knapczyk et al., 2019).

Decision support systems, which integrate data, models and AI algorithms to assist farmers and engineers in making informed decisions, are essential tools in biosystems engineering, providing data-driven recommendations for agricultural management. AI-based decision support systems can improve productivity and sustainability by providing recommendations for crop management, irrigation scheduling, fertilization and pest control. The use of cloud computing and IoT technologies enhances the capabilities of decision support systems by enabling real-time data processing and remote access.

4. CHALLENGES IN AI APPLICATIONS

Increase in the world's population as well as decrease in the availability of agricultural labor are demanding a smarter way to fulfill the global supply chain. Defining human intelligence in such a way that a machine can easily mimic it and can execute tasks which are simplest and those that are even more complex is known as AI (Mohan et al., 2023). Despite significant advancements, several challenges remain in the application of AI in biosystems engineering. In many agricultural systems, the availability of high-quality data required for training AI models is either limited or inconsistent, thereby affecting the model's performance. Furthermore, the significant computational requirements and the challenge of integrating AI technologies with existing agricultural systems are major barriers to their widespread adoption.

The lack of availability of quality data is one of the major challenges in the utilization of AI in agriculture. AI systems require large, high-quality datasets to program algorithms effectively. Collecting agricultural data over large geographic areas and seasons is difficult and expensive. The variability in agricultural practices also reduces data quality (Atapattu et al., 2024). Small land holdings and irregular field elevations limit the usage of precision agriculture implements (Mohan et al., 2023).

5. FUTURE TRENDS

In recent years, the field of biosystems engineering has experienced a fast integration of AI tools into research projects, methodologies, and approaches. These advanced computational techniques offer opportunities for analysing complex biological and environmental systems, optimising processes, and solving critical challenges not only in agriculture, livestock farming or food production, but also in healthcare, renewable energy, and environmental sustainability, among many other fields of application (Vallejo et al., 2026).

Emerging technologies such as edge computing, autonomous farming systems, IoT, robotics and digital agriculture platforms are shaping the future of AI in biosystems engineering. These systems will leverage advanced AI hardware to enable real-time data processing and intelligent decision-making. In future, the integration of AI, robotics and digital technologies into the biosystems engineering will pave the way for fully autonomous and sustainable agricultural systems. These advancements are expected to make precision agricultural systems even more efficient and sustainable.

6. CONCLUSION

Artificial intelligence is an important parameter in biosystems engineering, enabling the development of intelligent, data-driven systems for agricultural and environmental applications. AI technologies are transforming agricultural practices by making them more efficient, sustainable and productive through the use of robotics and decision support systems. The integration of AI with biosystems engineering offers significant opportunities for addressing global challenges related to food security, sustainability, environmental protection and climate change.

REFERENCES

Araus, J. L., Cairns, J. E. (2014). Field high-throughput phenotyping: The new crop breeding frontier. Trends in Plant Science, 19(1), 52–61. DOI: http://dx.doi.org/10.1016/j.tplants.2013.09.008.

Atapattu, A. J., Perera, L. K., Nuwarapaksha, T. D., Udumann, S. S., Dissanayaka, N. S. (2024). Challenges in Achieving Artificial Intelligence in Agriculture. Artificial Intelligence Techniques in Smart Agriculture, Chapter 2, 7-34, ISBN 978-981-97-5877-7, ISBN 978-981-97-5878-4 (eBook). DOI : https://doi.org/10.1007/978-981-97-5878-4.

Ayaz, M., Ammad-Uddin, M., Sharif, Z., Mansour, A., Aggoune, E. H. M. (2019). Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk. IEEE Access, 7, 129551–129583. DOI: https://doi.org/10.1109/ACCESS.2019.2932609.

Bac, C. W., van Henten, E. J., Hemming, J., Edan, Y. (2014). Harvesting Robots for High-value Crops: State-of-the-art Review and Challenges Ahead. Journal of Field Robotics, 31(6), 888–911. DOI: 10.1002/rob.21525.

Bechar, A., Vigneault, C. (2016). Agricultural robots for field operations: Concepts and components. Biosystems Engineering, 149, 94-111.

DOI: http://dx.doi.org/10.1016/j.biosystemseng.2016.06.014.

Benos, L., Tagarakis, A. C., Dolias, G., Berruto, R., Kateris, D., Bochtis, D. (2021). Machine learning in agriculture: A comprehensive updated review. Sensors, 21(11), 3758, 1-55.

DOI: https://doi.org/10.3390/s21113758.

Eli-Chukwu, N. C. (2019). Applications of artificial intelligence in agriculture: A review. Engineering, Technology & Applied Science Research, 9(4), 4377–4383.

Emmanuel, K., Ridwanullah, A., Ayomide, A., Funsho, K., Mercy, A., Stephen, A. (2023). Automation in Agricultural and Biosystems Engineering. Journal of Engineering Research and Reports, 25(7), 57-65. DOI: 10.9734/JERR/2023/v25i7938.

França, R. P., Monteiro, A. C. B., Arthur, R., Iano, Y. (2021). An overview of deep learning in big data, image, and signal processing in the modern digital age. Trends in Deep Learning Methodologies, Algorithms, Applications, and Systems, Hybrid Computational Intelligence for Pattern Analysis, Chapter 3, 63-87. DOI: https://doi.org/10.1016/B978-0-12-822226-3.00003-9.

Gebbers, R., Adamchuk, V. I. (2010). Precision agriculture and food security. Science, 327, 5967, 828–831. DOI: 10.1126/science.1183899.

Getahun, S., Kefale, H., Gelaye, Y. (2024). Application of Precision Agriculture Technologies for Sustainable Crop Production and Environmental Sustainability: A Systematic Review. The Scientific World Journal, 2024, 2126734, 1-12. DOI: https://doi.org/10.1155/2024/2126734.

Hernández, G. C. H., Gómez, J. G., Jiménez-Cabas, J. (2025). Predictive Models Based on Artificial Intelligence to Estimate Crop Yield: A Literature Review. Agriculture, 15, 2438. DOI: https://doi.org/10.3390/agriculture15232438.

Hidaka, A., Kurita, T. (2017). Consecutive Dimensionality Reduction by Canonical Correlation Analysis for Visualization of Convolutional Neural Networks. Proceedings of the ISCIE International Symposium on Stochastic Systems Theory and its Applications, 160-167.

DOI: 10.5687/sss.2017.160.

Javaid, M., Haleem, A., Khan, I. H., Suman, R. (2023). Understanding the potential applications of Artificial Intelligence in Agriculture Sector. Advanced Agrochem, 2, 15–30.

DOI: https://doi.org/10.1016/j.aac.2022.10.001.

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

Knapczyk, A., Francik, S., Wróbel, M., Jewiarz, M., Mudryk, K. (2019). Decision support systems for scheduling tasks in Biosystems Engineering. POLSITA 2019, E3S Web of Conferences, 132(01008), 1-13. DOI: https://doi.org/10.1051/e3sconf /201913201008.

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674, 1-29. DOI: https://doi.org/10.3390/s18082674.

Mohan, S. S., Venkat, R., Rahaman, S., Vinayak, M., Babu, B. H. (2023). Role of AI in Agriculture: Applications, Limitations and Challenges: A Review. Agricultural Reviews, 44(2), 231-237.

DOI: 10.18805/ag.R-2215.

Mohan, R. N. V. J., Rayanoothala, P. S., Sree, R. P. (2025). Next-gen agriculture: integrating AI and XAI for precision crop yield predictions. Frontiers in Plant Science, 15,1451607. DOI: 10.3389/fpls.2024.1451607.

Mulla, D. J. (2013). Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. Biosystems Engineering, 114(4), 358–371.

DOI: https://doi.org/10.1016/j.biosystemseng.2012.08.009.

Olawade, D. B., Wada, O. Z., Ige, A. O., Egbewole, B. I., Olojo, A., Oladapo, B. I. (2024). Artificial intelligence in environmental monitoring: Advancements, challenges, and future directions. Hygiene and Environmental Health Advances, 12, 100114, 1-16.

DOI: https://doi.org/10.1016/j.heha.2024.100114.

Padarian, J., Minasny, B., McBratney, A. B. (2020). Machine learning and soil sciences: a review aided by machine learning tools. SOIL, 6, 35–52. DOI: https://doi.org/10.5194/soil-6-35-2020.

Pechlivani, E. M., Papadimitriou, A., Pemas, S., Ntinas, G., Tzovaras, D. (2023). IoT-Based Agro-Toolbox for Soil Analysis and Environmental Monitoring. Micromachines, 14, 1698, 1-17.

DOI: https://doi.org/10.3390/mi14091698.

Sri, L. R., Vetriveeran, D., Sambandam, R. K., Jenefa, J., Thangavel, K. (2025). Transformative Trends in AI for Environmental Monitoring: Challenges, Applications. Environmental Monitoring

Using Artificial Intelligence, Editor(s): A. Suresh, T. Devi, N. Deepa, Ali Kashif Bashir, Wiley Online Library, 1-28. Print ISBN: 978-1-394-27036-1, DOI:10.1002/9781394270392.

Talaviya, T., Shah, D., Patel, N., Yagnik, H., Shah, M. (2020). Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. Artificial Intelligence in Agriculture, 4, 58–73.

DOI: https://doi.org/10.1016/j.aiia.2020.04.002.

Vallejo, M., Chen, C., Rovira-Más, F., Cheein, F. A. (2026). Good practices of artificial intelligence in biosystems engineering research. Biosystems Engineering, 263, 104373, 1-3. DOI: https://doi.org/10.1016/j.biosystemseng.2025.104373.

Van Klompenburg, T., Kassahun, A., Catal, C. (2020). Crop yield prediction using machine learning: A systematic literature review. Computers and Electronics in Agriculture, 177, 105709, 1-18. DOI: https://doi.org/10.1016/j.compag.2020.105709.

Vijayakumar, V., Ampatzidis, Y., Lacerda, C., Burks, T., Lee, W. S., Schueller, J. (2025). AI-driven real-time weed detection and robotic smart spraying for optimised performance and operational speed in vegetable production. Biosystems Engineering, 259, 104288, 1-13.

DOI: https://doi.org/10.1016/j.biosystemseng.2025.104288.

Vivekrabinson, K., Vijaya, K. D., Erana, V. D. S., Bharath, S. J., Shanmuga, R. B. (2025). AI-Driven Crop Yield Prediction: Optimizing Agricultural Practices using Machine Learning Models. 5th International Conference on Expert Clouds and Applications (ICOECA), Bengaluru, India, 2025, 523-528. DOI: 10.1109/ICOECA66273.2025.00095.

Wolfert, S., Ge, L., Verdouw, C., Bogaardt, M. J. (2017). Big data in smart farming-A Review. Agricultural Systems, 153, 69–80. DOI: https://doi.org/10.1016/j.agsy.2017.01.023.

Yam, K. L. (2012). Intelligent packaging to enhance food safety and quality. Emerging Food Packaging Technologies, Principles and Practice, Woodhead Publishing Series in Food Science, Technology and Nutrition, Chapter 8, 137-152.

DOI: https://doi.org/10.1533/9780857095664.2.137.

Zeng, P., Song, X., Yang, H., Wei, N., Du, L. (2022). Digital Soil Mapping of Soil Organic Matter with Deep Learning Algorithms. ISPRS Int. J. Geo-Inf., 11, 299, 1-19.

DOI: https://doi.org/10.3390/ijgi11050299.

Chapter

5

MICRO-IRRIGATION IN SUSTAINABLE AGRICULTURE: PRINCIPLES, PERFORMANCE, CONSTRAINTS, AND EMERGING SMART TECHNOLOGIES

***Burçak KAPUR*[1]**
***Uğur KEKEÇ*[2]**

---

[1] Prof. Dr., University of Cukurova, Faculty of Agriculture, Department of Agricultural Structures and Irrigation, Adana/Türkiye, https://orcid.org/0000-0001-6131-4458

[2] Dr. Öğr. Gör., University of Cukurova, Yumurtalık Vocational School, Department of Organic Farming, Adana/Turkey, https://orcid.org/0000-0003-1321-9135 ***Corresponding Author:*** Burçak KAPUR, bkapur@cu.edu.tr

1. Introduction

Agriculture remains the largest consumer of freshwater resources worldwide, accounting for nearly 70% of global withdrawals, a proportion that is projected to rise with increasing food demand and population growth (Phocaides, 2007). In water-limited regions, particularly in arid and semi-arid environments such as the Mediterranean basin, water scarcity has become a major constraint to agricultural productivity and sustainability. Climate change further intensifies these pressures by altering precipitation regimes, increasing evapotranspiration demand, and exacerbating the frequency and severity of drought events (IPCC, 2021; Santini et al., 2025). Consequently, improving irrigation efficiency and water productivity has emerged as a critical priority in modern agricultural systems.

Traditional irrigation methods, including surface and flood irrigation, are generally characterized by low application efficiency, significant conveyance losses, and non-uniform water distribution across the field (Howell, 2001; Keller & Bliesner, 1990). These inefficiencies often lead to excessive water use, deep percolation losses, nutrient leaching, and soil degradation, ultimately reducing both agronomic and environmental performance. In response, irrigation modernization strategies have increasingly focused on pressurized systems, particularly micro-irrigation technologies, which enable precise and localized water application directly to the crop root zone (Phocaides, 2007).

Micro-irrigation systems, including drip irrigation, subsurface drip irrigation (SSDI), and micro-sprinklers, represent a fundamental shift from field-scale uniform irrigation to plant-scale water management. These systems apply water at low flow rates and high frequency, thereby minimizing evaporation and runoff losses while improving water use efficiency (WUE). Numerous experimental studies and global syntheses have demonstrated that micro-irrigation can significantly enhance crop yield and irrigation water productivity compared to conventional methods (Howell, 2001; Wang et al., 2022). In particular, subsurface drip irrigation has gained attention for its ability to further reduce soil surface evaporation and improve moisture availability within the root zone.

Beyond water savings, micro-irrigation systems strongly influence soil water plant interactions. Localized wetting patterns alter soil moisture distribution and root development, while frequent irrigation events maintain more stable soil water conditions. In addition, the integration of fertigation allows for precise nutrient delivery, improving nutrient use efficiency and reducing environmental losses (Keller & Bliesner, 1990; Phocaides, 2007). These combined effects contribute not only to higher yields but also to improved crop quality, especially in high-value horticultural systems.

Despite these advantages, recent research has highlighted that improvements in irrigation efficiency at the field scale do not necessarily translate into net water savings at larger spatial scales. This phenomenon, often described as the "irrigation efficiency paradox," suggests that increased efficiency may encourage expansion of irrigated areas or intensification of production, thereby offsetting potential water savings (Perry et al., 2009; Santini et al., 2025). Therefore, the evaluation of micro-irrigation systems requires a broader perspective that integrates field-level performance with basin-scale hydrological processes and socio-economic dynamics.

The adoption of micro-irrigation technologies is also influenced by a range of technical and economic constraints. High initial investment costs, maintenance requirements such as emitter clogging, and the need for technical expertise can limit adoption, particularly among smallholder farmers (García-Mollá et al., 2025). Furthermore, discrepancies between theoretical system efficiency and actual field performance are frequently observed due to suboptimal design, poor management practices, and inadequate system maintenance (Howell, 2001). These challenges highlight the importance of integrating engineering design with farmer capacity building and institutional support mechanisms.

In recent years, advances in digital agriculture have significantly enhanced the potential of micro-irrigation systems. The integration of soil moisture sensors, plant-based indicators, and Internet of Things (IoT) technologies enables real-time monitoring and precise irrigation scheduling. Such smart irrigation systems allow for adaptive management based on dynamic soil plant atmosphere conditions, thereby improving both efficiency and productivity (Mansoor et al., 2025). Additionally, emerging innovations such as aerated drip irrigation introduce new opportunities for optimizing root zone conditions by improving oxygen availability and enhancing plant physiological performance (Li et al., 2025).

Given these developments, micro-irrigation should not be viewed solely as a water-saving technology but rather as an integrated management approach that combines hydraulic engineering, crop physiology, economic considerations, and digital innovation. A comprehensive understanding of micro-irrigation systems requires evaluating their benefits, limitations, and broader implications for sustainable agricultural intensification.

This chapter aims to provide a systematic and critical synthesis of micro-irrigation systems by examining their fundamental principles, agronomic and economic performance, operational challenges, and future development pathways. By drawing on both classical and recent literature, the chapter seeks to bridge the gap between theoretical efficiency and practical implementation, offering insights for researchers, practitioners, and policymakers engaged in sustainable water management.

2. Concept and Classification of Micro-Irrigation Systems

2.1. Definition and Core Principles

Micro-irrigation refers to a group of pressurized irrigation methods designed to apply water directly and precisely to the root zone of plants at low flow rates and high frequency. Unlike conventional irrigation systems that distribute water uniformly across the soil surface, micro-irrigation systems deliver water in small, controlled quantities, thereby minimizing non-beneficial losses such as evaporation, runoff, and deep percolation (Phocaides, 2007; Keller & Bliesner, 1990).

The fundamental principle underlying micro-irrigation is the concept of localized water application, where only a portion of the soil surface is wetted, typically corresponding to the active root zone. This approach allows for better control of soil moisture conditions and reduces the total volume of water required to meet crop evapotranspiration demands. From a soil plant atmosphere continuum (SPAC) perspective, micro-irrigation systems aim to maintain optimal soil water potential in the root zone, ensuring continuous water availability while avoiding both water stress and excess saturation (Howell, 2001).

Another defining feature of micro-irrigation is the frequent application of water in small doses, which helps maintain relatively stable soil moisture levels. This reduces fluctuations between field capacity and wilting point, thereby improving plant water uptake efficiency and reducing physiological stress. In addition, the low application rate of micro-irrigation systems is typically matched to the infiltration capacity of the soil, which minimizes surface runoff and enhances water use efficiency (Phocaides, 2007).

Micro-irrigation systems are also closely associated with fertigation practices, where nutrients are applied through the irrigation system. This integration allows for precise timing and placement of nutrients, improving nutrient use efficiency and reducing environmental losses (Keller & Bliesner, 1990). As a result, micro-irrigation is often considered not only a water management technology but also a comprehensive input management system.

2.2. Types of Micro-Irrigation Systems

Micro-irrigation systems can be broadly classified into three main categories based on their method of water application and system configuration: drip irrigation, micro-sprinkler systems, and bubbler irrigation. A comparative overview of these systems is presented in Table 1. Each system differs in its hydraulic characteristics, wetted area, and suitability for specific crops and soil conditions.

Drip irrigation, also referred to as trickle irrigation, is the most widely used form of micro-irrigation. In this system, water is delivered through a network of pipes and emitters that discharge water directly onto or below the soil surface at very low flow rates. The water forms a wetted bulb around the emitter, supplying moisture directly to the plant roots. Drip irrigation is particularly suitable for row crops, orchards, and greenhouse production systems due to its high efficiency and precise water control (Phocaides, 2007; Howell, 2001).

Micro-sprinkler systems, in contrast, distribute water over a larger surface area by spraying water in fine droplets. These systems operate at low pressure and are commonly used in orchards, vineyards, and nurseries where partial wetting of the soil surface is desirable. Micro-sprinklers can also contribute to microclimate modification, such as reducing canopy temperature or increasing humidity, which may be beneficial under certain environmental conditions (Keller & Bliesner, 1990).

Bubbler irrigation systems apply water at relatively higher flow rates compared to drip systems but still maintain localized application. Water is released in small streams or bubbles near the base of plants, allowing for rapid infiltration into the soil. These systems are often used for trees and shrubs, particularly in coarse-textured soils where higher application rates can be accommodated without causing runoff (Phocaides, 2007).

The selection of an appropriate micro-irrigation system depends on several factors, including crop type, soil characteristics, topography, water availability, and management objectives. For example, drip irrigation is generally preferred for crops requiring precise water and nutrient management, while micro-sprinklers may be more suitable for crops that benefit from partial surface wetting or microclimate regulation.

2.3. Subsurface Drip Irrigation (SSDI)

Subsurface drip irrigation (SSDI) is an advanced form of drip irrigation in which the emitters are buried below the soil surface, typically at depths ranging from 10 to 40 cm depending on crop type and soil properties. By delivering water directly into the root zone, SSDI minimizes surface evaporation losses and reduces weed growth, as the soil surface remains relatively dry (Camp, 1998; Phocaides, 2007).

One of the key advantages of SSDI is its ability to maintain a more stable and uniform soil moisture distribution within the root zone. This can enhance root development and improve plant water uptake efficiency. Additionally, SSDI systems are less susceptible to mechanical damage and surface disturbances, making them particularly suitable for perennial crops and mechanized farming systems (Camp, 1998).

However, the performance of SSDI systems is highly dependent on proper design and management. Critical parameters include emitter spacing, burial depth, soil hydraulic properties, and irrigation scheduling. Inappropriate design can lead to uneven water distribution, deep percolation losses, or insufficient wetting of the root zone. Furthermore, emitter clogging and root intrusion represent significant operational challenges that must be addressed through proper filtration, system maintenance, and management practices (Camp, 1998; Wang et al., 2022).

Recent studies have shown that SSDI can significantly improve crop yield and water productivity compared to both surface drip and conventional irrigation systems, particularly under water-limited conditions. Meta-analyses indicate that SSDI can enhance irrigation water productivity while maintaining or increasing yields, although the magnitude of these benefits varies depending on environmental and management factors (Wang et al., 2022).

Overall, SSDI represents a promising advancement in micro-irrigation technology, offering potential benefits in terms of water savings, crop performance, and system longevity. However, its successful implementation requires careful consideration of site-specific conditions and management practices.

Table 1. *Comparison of micro-irriga tion systems based on technical and operational characteristics*

System Type	Water Application Method	Wetted Area	Typical Discharge Rate	Main Advantages	Limitations	Suitable Crops
Drip Irrigation	Point-source application via emitters on soil surface	Localized (root zone)	Low (1–8 L h^{-1} per emitter)	High water use efficiency, precise water and nutrient control, reduced evaporation losses	Emitter clogging, requires filtration, higher initial cost	Vegetables, orchards, greenhouse crops
Subsurface Drip Irrigation (SSDI)	Emitters buried below soil surface	Subsurface root zone	Low (1–4 L h^{-1} per emitter)	Minimal evaporation loss, improved root zone moisture stability, reduced weed growth	Root intrusion, difficult maintenance, higher installation cost	Row crops, orchards, perennial systems
Micro-sprinkler	Sprayed water in fine droplets	Partial surface coverage	Medium (20–150 L h^{-1} per unit)	Uniform wetting, microclimate regulation, suitable for sandy soils	Higher evaporation losses than drip, wind drift	Orchards, vineyards, nurseries
Bubbler Irrigation	Small streams or bubbling flow near plant base	Localized but larger than drip	Medium to high (50–200 L h^{-1})	Simple design, rapid infiltration, suitable for coarse soils	Less precise control, potential runoff in fine soils	Trees, shrubs

3. System Components and Engineering Design

Micro-irrigation systems are composed of interconnected hydraulic and mechanical components designed to deliver water uniformly and efficiently to the crop root zone under controlled pressure conditions. The overall performance of the system depends not only on individual components but also on their integration, design accuracy, and operational management (Keller & Bliesner, 1990; Phocaides, 2007). Proper system design ensures uniform water distribution, minimizes energy losses, and maintains emitter performance under varying field conditions.

3.1 Hydraulic Components

The hydraulic unit forms the core of a micro-irrigation system and typically includes a pump, filtration system, and pressure control devices. The pump provides the necessary energy to move water through the system and must be selected based on total dynamic head and system discharge requirements. Inadequate pump sizing can lead to pressure fluctuations and non-uniform water application (Howell, 2001).

Filtration is a critical component in micro-irrigation systems due to the small orifices of emitters, which are highly susceptible to clogging. Common filtration systems include screen filters, disc filters, and sand media filters, each selected based on water quality characteristics such as suspended solids, organic matter, and dissolved minerals (Phocaides, 2007). Pressure regulators are used to maintain a constant operating pressure within the system, ensuring consistent emitter discharge and improving distribution uniformity.

3.2 Distribution Network

The distribution network consists of mainlines, submains, and lateral lines that transport water from the source to the emitters. Mainlines and submains are typically made of rigid materials such as PVC or HDPE, while lateral lines are flexible polyethylene pipes designed to deliver water directly to the crop rows.

Hydraulic design of the distribution network must account for friction losses, elevation differences, and pressure variations along the pipeline. Pressure loss due to friction is a key factor influencing system performance and must be minimized through appropriate pipe sizing and layout. Uniformity of water application is directly related to maintaining acceptable pressure variation along laterals, typically within ±20% of the nominal operating pressure (Keller & Bliesner, 1990).

3.3 Emitters and Application Devices

Emitters are the most critical components of micro-irrigation systems, as they control the discharge of water from the lateral lines to the soil. Emitter performance is typically characterized by the discharge–pressure relationship, commonly expressed as:

$$q = k \times P^x$$

where q is the emitter discharge, P is the operating pressure, k is a constant, and x is the emitter flow exponent. For pressure-compensating emitters, the exponent (x) approaches zero, indicating stable discharge across a range of pressures, whereas non-compensating emitters have higher sensitivity to pressure variation (Keller & Bliesner, 1990).

Emitter selection significantly affects distribution uniformity, system efficiency, and susceptibility to clogging. Factors such as emitter spacing, discharge rate, and clogging resistance must be carefully considered during system design. In addition, emitter clogging caused by physical particles, chemical precipitation, or biological growth remains one of the most critical operational challenges in micro-irrigation systems (Camp, 1998). Key engineering parameters governing micro-irrigation system performance are summarized in Table 2.

Table 2. *Key engineering parameters in micro-irrigation system design*

Parameter	Description	Typical Range	Importance
Operating Pressure	Pressure required for proper emitter function	0.5–2.5 bar	Ensures uniform discharge
Emitter Discharge	Flow rate per emitter	1–8 L h^{-1}	Determines application rate
Emission Uniformity (EU)	Measure of uniform water distribution	>85% (recommended)	Indicator of system performance
Distribution Uniformity (DU)	Ratio of low quarter to average application	>0.75 (acceptable)	Reflects field variability
Lateral Length	Length of emitter line	20–100 m	Affects pressure variation
Filtration Level	Particle size removed from water	100–200 mesh	Prevents clogging

As shown in Table 2, maintaining appropriate operating pressure and high emission uniformity is essential for achieving efficient irrigation. Poor system design or inadequate maintenance can result in significant variability in water application, leading to yield reduction and inefficient resource use (Howell, 2001).

3.4 Design Criteria and Irrigation Scheduling

The design of micro-irrigation systems must integrate hydraulic, agronomic, and environmental considerations. Key design criteria include crop water requirements, soil hydraulic properties, climatic conditions, and system capacity. Irrigation scheduling, which determines the timing and amount of water application, is critical for optimizing system performance.

Scheduling can be based on soil moisture monitoring, crop evapotranspiration (ETc) estimates, or plant-based indicators. Modern approaches increasingly rely on sensor-based systems and decision support tools to improve scheduling accuracy and responsiveness (Mansoor et al., 2025).

Accurate irrigation scheduling ensures that water is applied in accordance with crop demand, preventing both water stress and excessive irrigation. When properly designed and managed, micro-irrigation systems can achieve high levels of efficiency while maintaining optimal crop growth conditions.

4. Soil Water Plant Interactions under Micro-Irrigation

Micro-irrigation systems significantly modify the interactions between soil, water, and plant processes by altering the spatial and temporal distribution of water within the root zone. Unlike conventional irrigation methods that wet the entire soil surface, micro-irrigation creates localized wetting patterns, resulting in distinct soil moisture gradients and root development dynamics (Keller & Bliesner, 1990; Phocaides, 2007). These changes have important implications for water uptake, nutrient availability, and overall plant performance.

4.1. Wetting Patterns and Soil Moisture Dynamics

Under micro-irrigation, water is applied at discerete through emitters, forming a three-dimensional wetted zone commonly referred to as the wetting bulb. The shape and size of this wetted zone depend primarily on soil texture, emitter discharge rate, and irrigation duration. In coarse-textured soils, water tends to move vertically due to higher infiltration rates, resulting in deeper but narrower wetting patterns. In contrast, fine-textured soils promote lateral water movement, leading to wider but shallower wetting zones (Hillel, 1998).

The distribution of soil moisture within the wetted zone is typically non-uniform, with the highest water content near the emitter and decreasing moisture gradients toward the edges. This spatial variability influences both root distribution and water uptake efficiency. Frequent irrigation in micro-irrigation systems helps maintain relatively stable soil moisture conditions, reducing fluctuations between field capacity and wilting point and minimizing plant water stress (Howell, 2001).

4.2 Root Zone Processes and Water Uptake

The localized wetting patterns created by micro-irrigation systems lead to significant modifications in root system architecture. Roots tend to proliferate within the wetted zone where water and nutrients are readily available, resulting in a more concentrated root distribution compared to conventional irrigation systems. This concentration enhances water uptake efficiency but may also reduce root exploration in drier soil (Keller & Bliesner, 1990).

Water uptake by plants is governed by soil water potential gradients and root hydraulic conductivity. Micro-irrigation systems aim to maintain favorable soil water potentials within the root zone, ensuring continuous water flow from soil to plant. Stable moisture conditions reduce plant stress and improve physiological processes such as stomatal conductance, photosynthesis, and transpiration (Howell, 2001).

In subsurface drip irrigation systems, the placement of emitters below the soil surface further enhances root–water interactions by supplying water directly to deeper root, reducing evaporation losses and encouraging deeper root development. However, improper placement may limit water availability in the upper soil layers, affecting early growth stages or shallow-rooted crops (Camp, 1998).

4.3 Nutrient Transport and Fertigation

Micro-irrigation systems are closely integrated with fertigation practices, enabling the simultaneous application of water and nutrients. Nutrient movement in the soil under micro-irrigation is primarily driven by mass flow and diffusion processes, both of which are influenced by soil moisture distribution.

Localized water application allows nutrients to be concentrated within the wetted zone, increasing their availability to plant roots and improving nutrient use efficiency. Frequent, low-dose fertigation reduces nutrient losses due to leaching and volatilization, particularly in sandy soils where nutrient mobility is high (Phocaides, 2007).

However, nutrient distribution is also subject to spatial variability, as nutrients tend to accumulate near the emitter zone. This may create concentration gradients that influence root uptake patterns. Effective fertigation management requires careful consideration of irrigation frequency, nutrient concentration, and soil properties to ensure uniform nutrient availability within the root zone.

The key interactions between soil, water, and plant processes under micro-irrigation are summarized in Table 3.

Table 3. *Soil water plant interactions under micro-irrigation systems*

Component	Process	Effect under Micro-Irrigation	Implication for Crop Performance
Soil	Moisture distribution	Localized wetting, moisture gradients	Improved water use efficiency
Soil	Water movement	Controlled infiltration, reduced runoff	Reduced water losses
Root system	Root distribution	Concentration in wetted zone	Enhanced water uptake efficiency
Plant	Water uptake	Stable supply due to frequent irrigation	Reduced water stress
Nutrients	Transport and availability	Concentrated near emitters	Improved nutrient use efficiency
Plant physiology	Photosynthesis and transpiration	More stable physiological activity	Increased yield potential

As shown in Table 3, micro-irrigation systems influence multiple components of the soil water plant continuum simultaneously. These interactions contribute to improved resource use efficiency but also require careful management to avoid spatial imbalances in water and nutrient distribution.

4.4 Implications for Irrigation Management

Understanding soil water plant interactions is essential for optimizing micro-irrigation system performance. Irrigation scheduling must be tailored to maintain soil moisture within optimal limits while preventing over-irrigation and nutrient leaching. Soil type, crop characteristics, and climatic conditions should all be considered when determining irrigation frequency and duration.

Advances in sensor-based monitoring technologies, including soil moisture sensors and plant-based indicators, provide new opportunities for managing these interactions more precisely. These tools allow real-time assessment of soil moisture status and plant water needs, enabling dynamic adjustment of irrigation schedules (Mansoor et al., 2025).

Overall, micro-irrigation systems offer significant advantages in managing soil water plant interactions, but their effectiveness depends on proper design, operation, and integration with agronomic practices.

5. Impacts on Crop Productivity and Water Use Efficiency

Micro-irrigation systems have been widely recognized for their ability to improve crop productivity while reducing water consumption. However, the magnitude of these improvements is not uniform and depends on a combination of factors including crop type, soil conditions, irrigation management, and climatic variability. Rather than providing a universal outcome, micro-irrigation tends to create conditions under which crops can use water more effectively, provided that the system is properly designed and managed (Howell, 2001; Wang et al., 2022).

5.1 Yield Response

One of the most frequently reported advantages of micro-irrigation is its positive effect on crop yield. This effect is largely attributed to the ability of these systems to maintain relatively stable soil moisture conditions in the root zone. When plants are exposed to fewer fluctuations in water availability, physiological stress is reduced, leading to improved growth and productivity.

Evidence from experimental studies and global meta-analyses suggests that drip and subsurface drip irrigation systems can either maintain or increase yields compared to conventional irrigation methods, particularly under water-limited conditions. For example, Wang et al. (2022) reported that subsurface drip irrigation systems often lead to measurable gains in both yield and irrigation water productivity across a range of crops. However, these gains are not guaranteed; under well-watered conditions, yield differences between irrigation methods may become less pronounced, highlighting the importance of context-specific evaluation.

5.2 Water Productivity and Water Use Efficiency

Beyond yield, the primary advantage of micro-irrigation lies in improving water productivity, often expressed as irrigation water productivity (IWP) or water use efficiency (WUE). These indicators reflect how effectively water is converted into biomass or yield.

Micro-irrigation systems reduce non-productive water losses by limiting evaporation, runoff, and deep percolation. As a result, a greater proportion of applied water is used for transpiration, which is directly linked to crop production. Howell (2001) emphasizes that improving WUE is not simply about reducing water input, but about optimizing the balance between water supply and crop demand.

That said, increases in WUE should be interpreted carefully. Higher efficiency at the field scale does not necessarily imply reduced total water consumption at larger scales, as changes in management practices may offset these gains (Perry et al., 2009). Therefore, both agronomic and hydrological perspectives should be considered when evaluating system performance.

5.3 Crop Quality and Physiological Responses

In addition to yield and water efficiency, micro-irrigation can influence crop quality and plant physiological processes. Stable soil moisture conditions support consistent physiological activity, including photosynthesis, stomatal conductance, and transpiration. These processes are closely linked to biomass accumulation and fruit development.

In some cases, moderate water deficit strategies implemented through micro-irrigation can enhance certain quality attributes, such as soluble solids content, phenolic compounds, and other biochemical characteristics, particularly in horticultural crops. This reflects a trade-off between yield and quality, where slight reductions in water availability can trigger beneficial physiological responses without causing severe stress. The main effects of micro-irrigation on yield, water use, and crop quality are summarized in Table 4.

Table 4. *Effects of micro-irrigation on crop performance indicators*

Parameter	Observed Effect	Underlying Mechanism	Implication
Yield	Increase or stabilization	Reduced water stress, improved root zone moisture	Higher productivity under water-limited conditions
Water use efficiency (WUE)	Increase	Reduced evaporation and runoff losses	More efficient water use
Irrigation water productivity (IWP)	Increase	Higher proportion of water used in transpiration	Improved resource efficiency
Fruit quality	Often improved under deficit conditions	Concentration of sugars and metabolites	Enhanced market value
Physiological activity	More stable	Consistent water availability	Improved plant performance

As shown in Table 4, the benefits of micro-irrigation extend beyond simple yield increases. The technology influences multiple aspects of crop performance, often in interconnected ways that reflect both water availability and plant physiological responses.

5.4 Variability and Management Considerations

Although the advantages of micro-irrigation are well documented, outcomes can vary considerably depending on how the system is managed. Factors such as irrigation scheduling, emitter placement, and system maintenance play a critical role in determining actual performance.

For instance, over-irrigation in drip systems can reduce oxygen availability in the root zone and lead to nutrient leaching, while under-irrigation may induce excessive stress and limit yield. Similarly, poorly maintained systems with clogged emitters can result in uneven water distribution, reducing both yield and efficiency.

Recent developments in sensor-based irrigation and decision support systems offer promising tools for addressing these challenges. By enabling more precise control of irrigation timing and quantity, these technologies can help bridge the gap between theoretical efficiency and real-world performance (Mansoor et al., 2025).

Overall, micro-irrigation systems provide a flexible framework for improving both water use efficiency and crop productivity. However, their success ultimately depends on site-specific conditions and informed management practices.

6. Economic Performance and Farm-Level Viability

Micro-irrigation systems are often promoted not only for their agronomic benefits but also for their potential to improve farm profitability. However, economic performance is rarely straightforward. While these systems can reduce water use and increase yields, they also require substantial upfront investment and careful management. As a result, their economic viability depends on how effectively these competing factors are balanced under specific farm conditions (García-Mollá et al., 2025; Howell, 2001).

6.1 Investment and Operational Costs

One of the main barriers to the adoption of micro-irrigation systems is the relatively high initial investment required for installation. Costs typically include pumps, filtration units, pipes, emitters, and, in some cases, automation and control systems. Compared to traditional irrigation methods, these capital costs can be significantly higher, particularly for small-scale farmers.

In addition to installation costs, operational expenses must also be considered. These include energy costs for pumping, labor for system management, and maintenance costs related to filtration and emitter performance. Among these, emitter clogging remains one of the most persistent issues, often requiring regular monitoring and cleaning to maintain system efficiency (Phocaides, 2007).

Despite these costs, micro-irrigation systems can offer long-term savings through reduced water use and improved input efficiency. However, these savings are not always immediately apparent and may depend on factors such as water pricing, energy costs, and crop value.

6.2 Economic Returns and Profitability

The economic benefits of micro-irrigation systems are typically evaluated through indicators such as net return, benefit-cost ratio (BCR), and water productivity. In many cases, higher yields and improved crop quality translate into increased revenue, particularly for high value crops such as fruits and vegetables.

An important aspect often highlighted in the literature is that water savings alone do not guarantee higher profitability. Instead, the key factor is how efficiently water is converted into marketable yield. In this context, irrigation water productivity becomes a central indicator linking agronomic performance with economic outcomes (Wang et al., 2022).

At the same time, profitability can vary significantly across different farming systems. For example, in regions where water is inexpensive or not priced at all, the economic incentive to adopt water saving technologies may be limited. Conversely, in water scarce regions or where water pricing is enforced, micro-irrigation systems tend to become more economically attractive (García-Mollá et al., 2025). The main economic dimensions of micro-irrigation systems are summarized in Table 5.

Table 5. *Economic performance indicators of micro-irrigation systems*

Indicator	Typical Effect	Key Drivers	Implication
Initial investment cost	High	Equipment, installation, system complexity	Barrier to adoption
Operational cost	Moderate	Energy, maintenance, labor	Affects long-term profitability
Yield	Increase or stabilization	Improved water management	Higher revenue potential
Water productivity	Increase	Reduced losses, efficient application	Better resource use
Net return	Variable	Yield, market price, cost structure	Determines economic feasibility
Benefit–cost ratio (BCR)	Often >1 in suitable conditions	Crop value, water savings	Indicator of investment viability

As shown in Table 5, the economic performance of micro-irrigation systems depends on multiple interacting factors rather than a single outcome. While the potential for higher profitability exists, it is closely linked to management practices and local economic conditions.

6.3 Performance Gap and Management Efficiency

A recurring issue in the evaluation of micro-irrigation systems is the gap between expected and actual performance. In theory, these systems can achieve very high levels of efficiency, but in practice, performance is often lower due to design flaws, poor maintenance, or inappropriate irrigation scheduling.

This performance gap has important economic implications. For example, uneven water distribution caused by clogged emitters or pressure variations can lead to yield losses, directly affecting farm income. Similarly, over-irrigation not only wastes water but can also increase energy costs and reduce nutrient use efficiency.

Studies have shown that improving management practices can significantly enhance both technical and economic performance. This includes proper system design, regular maintenance, and the use of monitoring tools to guide irrigation decisions (Howell, 2001).

6.4 Linking Water Use Efficiency to Economic Outcomes

One of the more nuanced aspects of micro-irrigation is the relationship between water use efficiency and economic return. While higher water use efficiency is generally seen as a positive outcome, it does not automatically translate into higher profit.

For instance, deficit irrigation strategies may increase water productivity by reducing water input, but they can also lead to yield reductions if not carefully managed. On the other hand, full irrigation may maximize yield but reduce efficiency. Therefore, the optimal strategy often lies somewhere in between, depending on crop type, market conditions, and resource availability.

This balance highlights the importance of integrating agronomic and economic perspectives when evaluating irrigation systems. Rather than focusing solely on water savings or yield increases, a more comprehensive approach considers how these factors interact to influence overall farm performance.

Recent advances in precision irrigation technologies provide new opportunities to optimize this balance. By enabling more accurate control of irrigation timing and quantity, these systems can help farmers achieve both high efficiency and profitability (Mansoor et al., 2025).

Overall, micro-irrigation systems have the potential to improve farm-level economic performance, but their success depends on a combination of technical design, management practices, and economic context.

7. Irrigation Modernization and System-Level Trade-Offs

Micro-irrigation systems are often presented as a key solution to water scarcity, primarily due to their ability to improve field-level water use efficiency.

While this perspective is supported by a large body of experimental evidence, recent studies suggest that the broader impacts of irrigation modernization are more complex and, in some cases, counterintuitive. In particular, the assumption that improved efficiency automatically leads to water savings has been increasingly questioned in the literature (Perry et al., 2009; Santini et al., 2025).

7.1 From Field Scale to Basin Scale

At the field scale, micro-irrigation systems typically reduce non-beneficial water losses such as evaporation, runoff, and deep percolation. As a result, a higher proportion of applied water is used for crop transpiration, which is directly linked to biomass production. From an agronomic standpoint, this represents a clear improvement in efficiency (Howell, 2001).

However, when these systems are evaluated at larger spatial scales, such as irrigation districts or river basins, the picture becomes less straightforward. Water that is "lost" at the field level is not always lost from the system; it may return to groundwater or downstream users through return flows. When micro-irrigation reduces these return flows, the net effect can be a decrease in water availability at the basin scale (Perry et al., 2009).

This distinction highlights the importance of differentiating between water savings and water depletion. While micro-irrigation reduces water withdrawals at the field level, it may not necessarily reduce overall water consumption when viewed from a hydrological perspective. In some cases, improved efficiency can even lead to increased water use, particularly if farmers expand irrigated areas or shift to more water-intensive crops.

7.2 The Irrigation Efficiency Paradox

The concept often referred to as the "irrigation efficiency paradox" captures this apparent contradiction. As irrigation systems become more efficient, farmers may respond by intensifying production, increasing cropping intensity, or expanding irrigated land. These behavioral responses can offset or even exceed the water savings achieved through technological improvements (Perry et al., 2009; Santini et al., 2025).

In this context, efficiency gains at the micro level do not automatically translate into sustainability at the macro level. Instead, they may contribute to a rebound effect, where improved efficiency leads to increased resource use. This has important implications for water management policies, as it suggests that technological solutions alone may be insufficient to achieve long-term water savings. The key trade-offs associated with irrigation modernization are summarized in Table 6.

Table 6. *Trade-offs associated with micro-irrigation and irrigation modernization*

Dimension	Positive Effects	Potential Trade-offs	System-Level Implication
Water use	Reduced field-level losses	Reduced return flows	Limited basin-scale savings
Productivity	Increased yield and efficiency	Intensification of production	Higher total water demand
Resource use	Improved input efficiency	Expansion of irrigated area	Rebound effect
Environment	Reduced runoff and leaching	Lower groundwater recharge	Altered hydrological balance
Economics	Higher profitability potential	Increased investment and risk	Uneven adoption across farms

As shown in Table 6, irrigation modernization involves a set of interconnected trade-offs that extend beyond simple efficiency gains. These trade-offs need to be carefully considered when evaluating the overall sustainability of micro-irrigation systems.

7.3 Environmental Implications

The environmental impacts of micro-irrigation systems are also multifaceted. On the one hand, reduced surface runoff and improved nutrient management can decrease pollution and soil degradation. On the other hand, changes in water distribution patterns can affect groundwater recharge, surface water availability, and ecosystem functions.

For example, reduced deep percolation may limit the replenishment of aquifers, particularly in regions where irrigation return flows play a significant role in groundwater recharge. Similarly, increased water use efficiency may lead to reduced downstream flows, potentially affecting other users and ecological systems (Perry et al., 2009).

These effects underscore the need for a broader environmental assessment that goes beyond field-level indicators and considers the entire hydrological system.

7.4 Rethinking Efficiency and Sustainability

The growing recognition of these trade-offs has led to a shift in how irrigation efficiency is conceptualized. Rather than focusing solely on maximizing efficiency, there is increasing emphasis on balancing efficiency with equity, resilience, and sustainability.

This broader perspective suggests that micro-irrigation systems should be integrated into a comprehensive water management framework that includes regulatory measures, economic incentives, and institutional support. Policies such as water pricing, allocation limits, and monitoring systems can play a critical role in ensuring that efficiency gains translate into real water savings (Santini et al., 2025).

At the same time, advances in monitoring and digital technologies offer new opportunities to better understand and manage system-level impacts. By combining field-level data with basin-scale analysis, it may be possible to design irrigation strategies that optimize both productivity and sustainability.

Overall, micro-irrigation systems represent a powerful tool for improving agricultural water management, but their broader impacts depend on how they are implemented and governed. Recognizing and addressing the trade-offs associated with irrigation modernization is therefore essential for achieving sustainable outcomes.

8. Operational Challenges, Technological Integration, and Future Perspectives of Micro-Irrigation Systems

While micro-irrigation systems offer clear advantages in terms of water use efficiency and crop productivity, their performance in real-world conditions often depends on how well technical, environmental, and managerial challenges are addressed. In practice, the gap between theoretical potential and actual field performance is frequently shaped by system limitations, maintenance requirements, and the level of user expertise.

One of the most persistent technical challenges in micro-irrigation systems is emitter clogging. Due to the small size of emitter, even minor particles or chemical precipitates can disrupt water flow and lead to non-uniform distribution. Clogging may occur as a result of physical such as suspended sediments, chemical processes such as salt precipitation, or biological growth including algae and microbial biofilms (Phocaides, 2007; Camp, 1998). If not properly managed, these issues can significantly reduce system efficiency and, in some cases, directly affect crop yield.

Water quality therefore becomes a central factor in system performance. Containing high levels of dissolved salts or organic matter require appropriate filtration and periodic maintenance. In many cases, the long-term success of a micro-irrigation system depends less on its initial design and more on the consistency of its operation and maintenance.

Beyond technical issues, management practices play a critical role. Even well-designed systems can underperform if irrigation scheduling is not aligned with crop water requirements. Over-irrigation, for instance, may lead to nutrient leaching and reduced root aeration, while under-irrigation can induce stress and limit yield. These challenges highlight the importance of moving from static irrigation practices toward more adaptive and responsive management approaches.

Recent developments in precision agriculture offer promising tools in this regard. The integration of soil moisture sensors, plant-based indicators, and Internet of Things technologies allows for real-time monitoring of field conditions. Such systems enable farmers to adjust irrigation timing and water application based on actual crop demand rather than fixed schedules (Mansoor et al., 2025). Over time, these technologies can help reduce inefficiencies and narrow the gap between potential and actual performance.

At the same time, emerging innovations are beginning to reshape how micro-irrigation systems are conceptualized. One example is aerated drip irrigation, which introduces oxygen into the root zone along with water. This approach has been shown to improve root activity and microbial processes in the soil, potentially enhancing plant growth under certain conditions (Li et al., 2025). Although still developing, such innovations suggest that future irrigation systems may focus not only on water delivery but also on optimizing the root environment more broadly.

Despite these advances, adoption remains uneven across regions and farming systems. High initial investment costs, limited access to technical knowledge, and institutional barriers continue to restrict the uptake of micro-irrigation technologies, particularly among smallholder farmers. In this context, economic incentives, extension services, and policy support mechanisms play a crucial role in facilitating adoption and ensuring long-term sustainability. The key challenges and opportunities associated with micro-irrigation systems are summarized in Table 7.

Table 7. *Key challenges and future directions in micro-irrigation systems*

Aspect	Current Challenges	Emerging Solutions	Future Implications
Technical performance	Emitter clogging, pressure variation	Advanced filtration, pressure-compensating emitters	More reliable systems
Water management	Inefficient scheduling	Sensor-based irrigation, IoT integration	Higher precision and efficiency
Nutrient management	Uneven distribution, leaching	Optimized fertigation strategies	Improved nutrient use efficiency
Innovation	Limited system functionality	Aerated irrigation, smart systems	Enhanced root zone management
Adoption	High cost, knowledge gaps	Policy support, training programs	Wider implementation

As illustrated in Table 7, the future of micro-irrigation lies not only in improving system efficiency but also in integrating technology, management, and policy dimensions. A shift toward data-driven irrigation and adaptive management is likely to play a central role in this transition.

Looking ahead, it is increasingly clear that micro-irrigation systems should be considered as part of a broader framework of sustainable agricultural intensification. Rather than focusing solely on water savings, future approaches are expected to emphasize resilience, resource optimization, and environmental sustainability. This includes balancing productivity gains with ecosystem considerations and ensuring that efficiency improvements translate into real resource conservation at larger scales.

In this context, the role of policy becomes particularly important. Water pricing, allocation mechanisms, and regulatory frameworks can influence how efficiency gains are used and whether they contribute to sustainable outcomes. Without such measures, there is a risk that technological improvements may lead to unintended consequences, such as increased water use through expansion or intensification.

9. Conclusions

Micro-irrigation systems have become a central component of modern irrigation strategies, offering clear advantages in terms of water use efficiency, crop productivity, and input management. By enabling precise and localized water delivery, these systems create more stable soil moisture conditions and support improved plant performance. In many cases, they also contribute to better crop quality and more efficient use of nutrients, particularly when integrated with fertigation practices. At the same time, the findings discussed throughout this chapter suggest that the benefits of micro-irrigation cannot be fully understood when viewed only at the field scale. While reductions in water losses and improvements in efficiency are well documented, their translation into actual water savings at larger spatial scales remains uncertain. The distinction between water use efficiency and water consumption is therefore critical, and overlooking this difference may lead to overly optimistic conclusions about the role of irrigation technologies in addressing water scarcity.

Another important consideration is the gap between theoretical system performance and real world outcomes. Technical issues such as emitter clogging, pressure variability, and water quality constraints can limit system effectiveness if not properly managed. Similarly, inappropriate irrigation scheduling and insufficient maintenance may reduce both agronomic and economic benefits. These challenges highlight that technology alone is not sufficient; successful implementation requires consistent management and a good understanding of system behavior under field conditions. Recent advances in precision agriculture offer promising opportunities to address some of these limitations. The integration of sensor based monitoring, data-driven decision support tools, and automated control systems can improve irrigation timing and water application accuracy. In parallel, emerging innovations such as aerated drip irrigation indicate that future developments may focus not only on water delivery but also on optimizing the root zone environment. From a broader perspective, the role of micro-irrigation in sustainable agriculture depends on how it is embedded within larger management and policy frameworks. Economic factors, farmer capacity, and institutional support mechanisms all influence adoption and long-term performance. Moreover, policy instruments such as water pricing and allocation strategies are essential to ensure that efficiency gains contribute to real resource conservation rather than increased consumption.

Overall, micro-irrigation systems represent a valuable tool for improving agricultural water management, but their effectiveness is context-dependent. A balanced approach that integrates technological innovation with sound management practices and appropriate policy support is needed to fully realize their potential. Future research should continue to explore not only technical improvements but also the broader interactions between irrigation systems, farming practices, and water resource sustainability.

References

Camp, C. R. (1998). Subsurface drip irrigation: A review. Transactions of the ASAE, 41(5), 1353–1367.

García-Mollá, M., Ortega-Reig, M. V., Sanchis-Ibor, C., and Avellá-Reus, L. (2025). Economic efficiency of drip and flood irrigation: A comparative analysis. *Agricultural Water Management.*

Hillel, D. (1998). Environmental soil physics. Academic Press.

Howell, T. A. (2001). Enhancing water use efficiency in irrigated agriculture. Agronomy Journal, 93(2), 281–289.

IPCC. (2021). *Climate change 2021: The physical science basis*. Cambridge University Press.

Keller, J., and Bliesner, R. D. (1990). *Sprinkler and trickle irrigation.* Van Nostrand Reinhold.

Li, H., Junejo, A. R., Midmore, D. J., & Soomro, S. A. (2025). Significance of aerated drip irrigation: A comprehensive review. Agricultural Water Management, 321, 109886. https://doi.org/10.1016/j.agwat.2025.109886

Mansoor, S., Iqbal, S., Popescu, S. M., Kim, S. L., Chung, Y. S., & Baek, J.-H. (2025). Integration of smart sensors and IoT in precision agriculture: Trends, challenges and future prospectives. Frontiers in Plant Science, 16, 1587869. https://doi.org/10.3389/fpls.2025.1587869

Perry, C., Steduto, P., Allen, R. G., and Burt, C. M. (2009). Increasing productivity in irrigated agriculture: Agronomic constraints and hydrological realities. Agricultural Water Management, 96(11), 1517–1524. https://doi.org/10.1016/j.agwat.2009.05.005

Phocaides, A. (2007). Handbook on pressurized irrigation techniques (2nd ed.). Food and Agriculture Organization of the United Nations (FAO).

Santini, A., Masiero, M., Amato, G., & Pettenella, D. M. (2025). From flood to drip irrigation: A review of irrigation modernization trade-offs. *Water, 17*, 3018. https://doi.org/10.3390/w17203018

Wang, H., Wang, N., Quan, H., Zhang, F., Fan, J., Feng, H., Cheng, M., Liao, Z., Wang, X., & Xiang, Y. (2022). Yield and water productivity of crops, vegetables and fruits under subsurface drip irrigation: A global meta-analysis. *Agricultural Water Management, 269*, 107645. https://doi.org/10.1016/j.agwat.2022.107645

Chapter
6

MICROCLIMATE DYNAMICS AND WATER MANAGEMENT OPTIMIZATION IN AGRIVOLTAIC SYSTEMS

Deniz Levent KOÇ[1]

---

[1] Associate Professor, Çukurova University, Agriculture Faculty, Department of Agricultural Structures and Irrigation, Adana. E-Mail: leventk@cu.edu.tr, ORCID: 0000-0002-4495-3060

1. Introduction

Rising global demand for food and energy, along with climate change and population growth, has increased competition for limited land and water. By 2050, food demand is expected to rise by 70% and energy demand by 50%, highlighting the urgent need for integrated land-use strategies that address the Water-Energy-Food (WEF) nexus (FAO, 2009; EIA, 2021). Agrivoltaic systems (AVS), which place photovoltaic (PV) solar panels and agricultural production on the same land, have become a promising way to turn this competition into cooperation.

Goetzberger and Zastrow (1982) first introduced the concept of agrivoltaics, which involves raising solar panels above crops so that energy can be generated while farming continues below. The main idea is that most crops do not require all the sunlight available for photosynthesis, so the extra sunlight captured by solar panels can be converted into electricity without significantly reducing crop yields (Dupraz et al., 2011). In recent years, this approach has become more popular, with both commercial and research projects now found in many different climates, from the dry American Southwest (Barron-Gafford et al., 2019) to temperate parts of Europe (Weselek et al., 2021) and tropical areas of East Africa (Randle-Boggis et al., 2025).

Agrivoltaic systems have a strong effect on the microclimate under and around PV arrays. When PV panels block some sunlight, they change the energy balance at the ground, which affects air temperature, humidity, wind speed, soil temperature, and soil moisture (Adeh et al., 2018; Sun et al., 2025). These changes in the microclimate then influence how much water crops need and how efficiently they use it. Water-use efficiency is especially important in dry areas where droughts are becoming more common (Elamri et al., 2018).

To design agrivoltaic systems that maximize energy production, crop yields, and water savings, it is important to understand and improve how microclimates work. This chapter brings together what is currently known about how agrivoltaic systems alter local climate conditions and what that means for water management. Using research from different climates and crop types, the chapter looks at how PV panels change microclimates, how these changes affect sunlight, temperature, humidity, wind, and soil moisture, and what this means for crop water needs and evapotranspiration. It also discusses ways to improve water management through system design and smart irrigation, and explains how modeling and decision tools can help guide these efforts. The chapter ends by highlighting current challenges and suggesting areas for future research.

2. Microclimate Modifications in Agrivoltaic Systems

2.1 Solar Radiation Interception and Redistribution

In agrivoltaic systems, the main way the microclimate changes is by reducing the amount of sunlight reaching the crops and the soil. The amount of shade created depends on factors such as panel density, tilt angle, height, orientation, and whether the panels are fixed or can move to track the sun (Abidin et al., 2021; Abubakar et al., 2025).

Fixed-tilt systems with full panel density usually let through about 50% of incoming sunlight, while half-density setups allow around 70% (Elamri et al., 2018; Marrou et al., 2013). Dynamic systems with single-axis tracking can adjust shading as needed, so their transmission rates range from 35% to 65%, depending on the tracking method (Elamri et al., 2018; Chopard et al., 2021). Jung et al. (2024) found a 42% drop in Global Horizontal Irradiation (GHI) under an agrivoltaic system in Chile's semi-arid Metropolitan Region. Zainali et al. (2023) saw similar results in Sweden, where a vertical bifacial system reduced ground-level sunlight by 38%.

The amount of radiation incident on solar panels do not evenly distributed. Studies show there are clear differences between under-panel (UP) and inter-panel (IP) spots (Elamri et al., 2018; Weselek et al., 2021). This unevenness creates small areas with different levels of light, which affects how crops should be chosen and planted. In vertical bifacial systems, the shading pattern differs from that in overhead setups, leading to east-west gradients rather than the usual north-south gradients seen in tilted systems (Zainali et al., 2023).

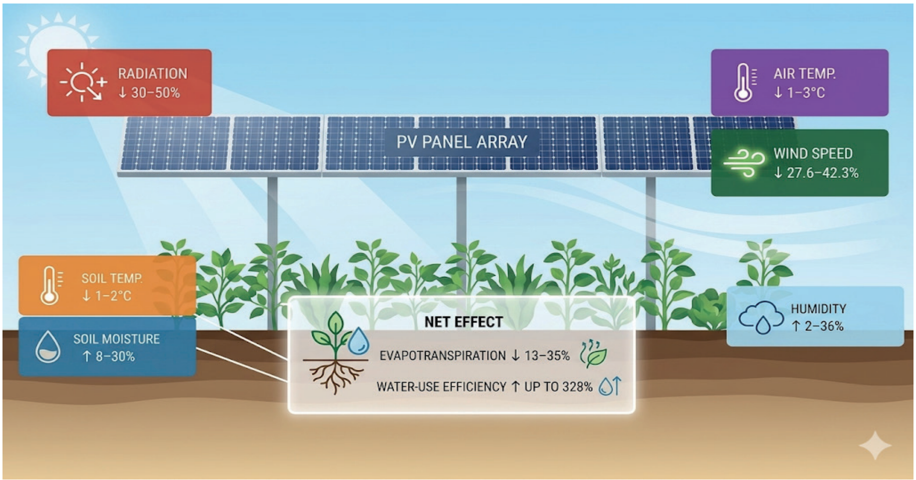


Figure 1. *Conceptual diagram of microclimate modifications in agrivoltaics systems and their combined effect on water dynamics reported in agrivoltaics studies*

2.2 Air Temperature Modifications

PV panels affect air temperature in two main ways. Their shade reduces direct ground heating, but the panels also absorb sunlight and release heat, which can warm the nearby air (Barron-Gafford et al., 2019; Adeh et al., 2018). The overall impact varies with the system setup, time of day, and season.

Most studies find that panels provide some cooling during the day. For example, Barron-Gafford et al. (2019) found that daytime air temperatures were about 1.2°C lower under panels in arid Arizona, but nighttime temperatures rose by about 0.5°C because panels released stored heat. Weselek et al. (2021) reported average air temperature drops of 1.2°C during summer in a temperate German agrivoltaic system. In arid and semi-arid parts of China, Sun et al. (2025) found that PV facilities could raise local air temperature by up to 2.31°C in some setups. This increase is linked to the "heat island" effect, where large installations trap heat near the ground.

Abubakar et al. (2025) found that a 10-kWp system in India reduced soil and air temperatures by 2-3°C. Islam et al. (2024) observed a 2.5°C drop in air temperature and an 8-15% decrease in soil surface temperature under an agrivoltaic system in West Bengal. These results show that temperature changes vary by location, so it is important to assess the microclimate at each site.

2.3 Humidity and Wind Speed

Studies show that relative humidity is usually higher under agrivoltaic panels than in open fields. This happens because the panels lower evaporative demand and trap moisture from plants under the canopy (Adeh et al., 2018). For example, Sun et al. (2025) found humidity increases of up to 35.8% in dry areas of China, and Barron-Gafford et al. (2019) also saw significant rises in humidity in Arizona's drylands.

Many studies have found that wind speed drops in areas with PV panels. These panels block airflow and lower wind speed at crop level. Sun et al. (2025) observed wind speed reductions of 27.6 to 42.3 percent within PV arrays. Adeh et al. (2018) also saw major changes in wind direction and speed at the Rabbit Hills agrivoltaic site in Oregon. Lower wind speed helps reduce evapotranspiration by decreasing the aerodynamic part of the Penman-Monteith equation. However, Paschalis et al. (2025) pointed out that changes in aerodynamic roughness can sometimes have unexpected effects on water dynamics in grasslands.

2.4 Soil Temperature and Moisture

One of the most important microclimate changes for agriculture is the effect on soil moisture. Shading lowers the soil surface temperature and reduces direct evaporation, so soil under panels stays wetter. Adeh et al. (2018) found that soil under PV panels in an unirrigated Oregon pasture kept much more moisture during the study, and water-use efficiency rose by 328%. Jung et al. (2024) also found that soil moisture was on average 29% higher under an agrivoltaic system in Chile than in the reference areas.

Rainfall redistribution from panel surfaces affects how soil moisture is spread out. Elamri et al. (2018) and Marrou et al. (2013) found that panels direct rainwater toward their edges, leading to wetter areas near the edges and drier areas under the panels' centers. This effect is especially strong in fixed-tilt systems and matters for how irrigation and crop rows are planned. (Wu et al. 2022) used long-term models to show that, in arid Northwest China, these PV systems create different hydrological zones that can affect how well vegetation can be restored.

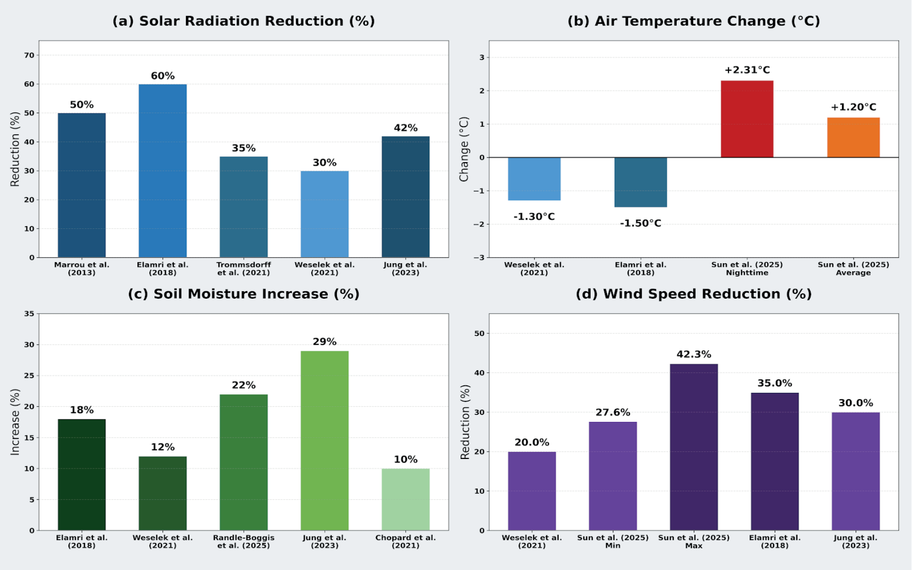


Figure 2. *Synthesis of microclimate modifications according to reported in agrivoltaics studies.*

3. Evapotranspiration and Crop Water Requirements

3.1 Mechanisms of Evapotranspiration Reduction

Evapotranspiration (ET) in agrivoltaic systems drops for several reasons. First, less net radiation at the crop surface means there is less energy for evaporation. Second, lower wind speeds slow down the movement of water vapor. Third, higher humidity lowers the vapor pressure deficit that drives transpiration. Finally, cooler soil temperatures reduce soil evaporation (Marrou et al., 2013; Elamri et al., 2018).

Marrou et al. (2013) studied these effects in a Mediterranean climate and found that actual evapotranspiration dropped by about 29% under full-density panels for lettuce and cucumber. The main reason was less radiation. Later, Elamri et al. (2018) created the AVirrig model to predict these outcomes. Their work showed that dynamic panel systems can help balance shading, which saves water, with the need for enough light for photosynthesis.

Jung et al. (2024) found that potential evapotranspiration (PET) dropped by 31% under an agrivoltaic system in Chile, mainly because global horizontal irradiance (GHI) was reduced by 42%. Disciglio et al. (2025) observed similar reductions in evapotranspiration for medicinal plants in Southern Italy, where the dynamic agrivoltaic system helped ease water stress during the hot Mediterranean summer.

3.2 Quantitative Effects on Irrigation Requirements

Lower ET means less irrigation is needed. Elamri et al. (2018) found that lettuce grown in agrivoltaic plots needed significantly less water, with model simulations suggesting that irrigation could be reduced by 20% while maintaining acceptable yields, despite a minor (10%) decrease. Abubakar et al. (2025) reported that irrigation demand for tomato and groundnut dropped by 15–20% under a semi-transparent and bifacial panel system in India.

Water conservation is especially important in dryland areas. Barron-Gafford et al. (2019) showed that agrivoltaics in the Sonoran Desert benefited both food and water systems. Crops such as chiltepin pepper, cherry tomato, and jalapeño used water more efficiently when grown under solar panels. Rouini et al. (2025) found that zucchini grown in high-shade, dryland agrivoltaic systems had higher carbon uptake and water-use efficiency. These plants kept higher stomatal conductance and photosynthetic rates even during the hottest periods.

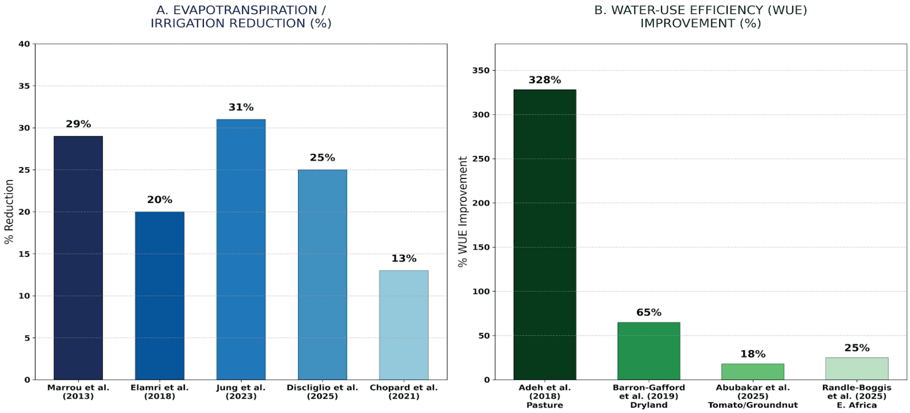


Figure 3. *Water balance improvements in agrivoltaic systems: reductions in evapotranspiration and gains in water use efficiency according to reported in studies.*

3.3 Crop-Specific Responses

Different crop species respond in various ways to changes in water availability. Shade-tolerant and leafy crops often benefit the most from water savings in agrivoltaic systems. Marrou et al. (2013) reported that lettuce varieties kept their yields under 50% shading while using 30% less water. AL-agele et al. (2021) found that tomatoes grown in agrivoltaic systems in Oregon had different water productivity patterns, and their fruit quality changed in response to the new microclimate.

Randle-Boggis et al. (2025) reported from East Africa that leafy greens such as Swiss chard and kale, as well as drought-sensitive crops such as beans, yielded better under panels. In contrast, shade-intolerant crops like eggplant and peppers produced less, but still remained profitable. Scarano et al. (2025) found that *Cichorium intybus* grown under agrivoltaic systems in Southern Italy had improved food quality when both shade and limited irrigation were used.

Magarelli et al. (2024) reviewed recent research on fruit crops such as grapes, blueberries, and stone fruits. They found that partial shade can delay blooming and reduce sunburn, while still keeping or even improving fruit quality. Their review also showed that dynamic agrivoltaic systems are especially useful for fruit production because they let growers adjust shading in real time to fit the needs of the crops as they grow.

4. System Design Strategies for Water Management Optimization

4.1 Fixed and Dynamic Panel Configurations

Choosing between fixed and dynamic (tracking) panel systems can significantly affect water management. Fixed systems provide steady but uneven shading, leading to permanent areas of high and low moisture that need to be considered when planning crops (Weselek et al., 2021). In contrast, dynamic systems can move to spread shading more evenly throughout the day, helping balance radiation and moisture patterns and allowing real-time adjustments based on how much water crops need (Elamri et al., 2018; Chopard et al., 2021).

Elamri et al. (2018) studied three types of shading setups for lettuce over three seasons: fixed full-density (AVfull, about 50% shading), fixed half-density (AVhalf, about 30% shading), and dynamic (DAV, about 35% shading). They found that dynamic systems saved as much water as full-density fixed systems but allowed more sunlight to reach the crops, resulting in better yields under limited water conditions.

The Sun'Agri program in France has led the way in developing commercial dynamic agrivoltaic systems for perennial crops. Their installations now cover 40 hectares and include peach, apricot, apple, cherry, and grape varieties (Magarelli et al., 2024). The systems use algorithms to balance electricity production with crop water needs, demonstrating that managing the microclimate in real time is technically and economically feasible on a commercial scale.

4.2 Panel Height, Spacing, and Orientation

The height of panels influences how much the microclimate changes and how evenly the shade is distributed. When panels are higher, more diffuse sunlight reaches the crops, and shading is less intense in specific spots. However, higher panels also reduce the benefits of blocking wind and keeping humidity (Abidin et al., 2021). In Germany, Weselek et al. (2021) found that panels set at 5 meters allowed regular farm equipment to operate while still improving the microclimate.

The distance between panels affects how much shade is created and how rainfall is spread out. Trommsdorff et al. (2021) found that using wider spacing in an organic crop rotation system in Germany provided enough light for winter wheat and potatoes, while also improving land-use efficiency (LER reached up to 1.86). The direction of the panel rows, whether north-south or east-west, changes the daily shading pattern and should be chosen based on the needs of the crops and the local climate (Abidin et al., 2021).

4.3 Rainwater Harvesting from Panel Surfaces

One water management strategy that is often missed in agrivoltaic systems is collecting and reusing rainwater from the panels. Randle-Boggis et al. (2025) showed that harvesting rainwater from panels provided an extra

12.7% of irrigation needs at their Tanzania site, in addition to a 12.6% drop in irrigation demand thanks to shading. These two water benefits, less demand and extra supply, make agrivoltaic systems especially appealing in areas where water is limited.

When designing rainwater collection systems, it is important to consider how runoff gathers at the edges of panels. Elamri et al. (2018) found that this runoff can create areas with excessive moisture, which may lead to waterlogging if not managed properly. By combining gutter systems with drip irrigation, it is possible to turn this issue into a benefit by collecting and moving the runoff to areas that need more water.

5. Modeling and Decision Support Systems

5.1 Microclimate and Water Balance Models

Researchers have created different models to simulate how microclimate, water, and crops interact in agrivoltaic systems. For example, Elamri et al. (2018) introduced the AVirrig model, which predicts how short-term climate changes affect soil water balance under moving panels. This model combines radiation interception, energy balance, and soil water dynamics to help optimize irrigation schedules using real-time panel positions.

Sun et al. (2025) created the Soil-Plant-PV-Atmosphere Continuum (SPPVAC) model to simulate how ecohydrological processes interact in arid PV installations. After testing it with field data from Zhangjiakou, China, they found that PV facilities can boost the biomass of crops such as soybean (48.3%), alfalfa (42.9%), and parsnip (26.7%) by changing the microclimate. Wu et al. 2022 used a synthetic modeling method to measure the long-term (100-year) effects of PV installations on soil moisture in arid Northwest China.

Paschalis et al. (2025) used an ecohydrological model to show that agrivoltaic systems boost grassland productivity, especially in semi-arid areas where potential evapotranspiration is higher than rainfall. They found that shading mainly drives these gains, while changes in aerodynamic roughness and rainfall redistribution have smaller, often negative, effects.

5.2 Decision Support Systems for Irrigation Management

Chopard et al. (2021) created the crop_sim decision support system (DSS) to evaluate crop performance with dynamic solar panels. The system tracks three main indicators: predawn water potential, canopy temperature, and carbon production. It also uses an expert system to help schedule irrigation. When tested in a mature vineyard, the DSS led to 13% water savings with a conservative panel steering policy.

Ahmad et al. (2022) introduced a solar-powered IoT fertigation system that combines soil, weather, and plant sensors with automated irrigation control. Although it was not made for agrivoltaic systems, its design can be used for them. The system relies on the Hargreaves-Samani model to estimate reference evapotranspiration and uses crop coefficient methods for scheduling. Both methods can be adjusted to reflect the different microclimates found under solar panels.

(Warmann et al., 2024) introduced a framework to help balance energy production, crop yields, and water use in agrivoltaic systems. Their model showed that the best system design depends on local climate, crop choice, and water resources, highlighting the importance of tools tailored to each site.

6. Climate-Specific Considerations

6.1 Arid and Semi-Arid Regions

Agrivoltaic systems are especially helpful for managing water in arid and semi-arid areas, where limited water is the main challenge for farming. Barron-Gafford et al. (2019) found that in the Sonoran Desert, shading from solar panels reduced water stress on crops, while the crops themselves cooled the panels, increasing their efficiency by 1–3%. Rouini et al. (2025) supported these results by showing that high-shade agrivoltaic setups improved both carbon uptake and water-use efficiency in zucchini grown under dryland conditions.

Sun et al. (2025) found that in the arid northern regions of China, PV installations create better microenvironments for ecological restoration, leading to a 26.7-48.3% increase in biomass across different crops. Wu et al. 2022 also showed that over time, soil moisture builds up under the panels in these arid regions, which can significantly change how plant communities develop.

6.2 Mediterranean Climates

Mediterranean climates have hot, dry summers and mild, wet winters, which create both benefits and challenges for managing water in agrivoltaic systems. Research by Marrou et al. (2013) and Elamri et al. (2018) in Montpellier, France, showed that agrivoltaic systems can lower irrigation needs by 20–30% for vegetable crops while still producing good yields. Disciglio et al. (2025) found similar results for medicinal plants in Southern Italy, showing that dynamic agrivoltaic systems can improve both essential oil yield and water-use efficiency.

Scarano et al. (2025) studied chicory growth in agrivoltaic systems in Apulia, Southern Italy. They found that using both shade and less water improved food quality, showing that saving water in these systems does not have to reduce nutritional value.

6.3 Temperate Climates

In temperate regions, where water shortages are less common, agrivoltaics still offer useful water management benefits. Weselek et al. (2021) observed that soil moisture stayed higher under panels in a German organic farm. However, the main advantage was more stable yields during occasional droughts, not regular water savings. Adeh et al. (2018) reported a 328% improvement in water-use efficiency in an Oregon pasture, showing that even in humid areas, agrivoltaics can greatly benefit unirrigated systems.

6.4 Tropical Climates

Randle-Boggis et al. (2025) were the first to show how agrivoltaic systems work in tropical East Africa. In their study, systems in Tanzania and Kenya reached Land Equivalent Ratios of 1.88 and 1.77. They also found that shading reduced irrigation use by 12.6%, and rainwater harvesting added another 12.7% in water savings. These results matter because the region faces serious challenges with water, energy, and food security.

7. Challenges and Future Research Directions

7.1 Current Limitations

Although there is promising evidence, several challenges still need to be addressed to improve water management in agrivoltaic systems. First, the varied microclimate conditions under the panels make management more complex, and current irrigation systems are not equipped to handle this (Elamri et al., 2018). Second, there are few long-term studies that cover multiple growing seasons and different climate scenarios, which makes it hard to be sure that the reported benefits apply more broadly (Weselek et al., 2021). Third, more research is needed to understand the economic side of water management in these systems, especially when weighing the costs of advanced irrigation infrastructure against the potential water savings (Trommsdorff et al., 2021).

When dust builds up on panels, cleaning them becomes necessary and uses water. This can reduce the water savings gained from using less irrigation (Mamun et al., 2022). In dry areas where saving water matters most, this trade-off is even more important.

7.2 Future Research Priorities

This review highlights a few key research priorities. First, we need standardized microclimate monitoring protocols so studies and regions can be compared more easily. Second, developing irrigation systems that adjust to the different moisture patterns caused by panel arrays would make water management more efficient. Third, combining real-time soil moisture sensors with dynamic panel controls could help optimize both energy production and water conservation at the same time.

Using machine learning and artificial intelligence in agrivoltaic management is an exciting new area. By training models to understand how panel placement, microclimate, soil moisture, and crop water needs interact, we could create autonomous systems that optimize water, energy, and food resources in real time (Ahmad et al., 2022; Chopard et al., 2021).

It is important to expand agrivoltaic water management research from small experimental plots to commercial-scale installations. Most studies so far use small systems, but large commercial arrays could affect regional airflow, humidity, and temperature in different ways (Sun et al., 2025).

8. Conclusion

Agrivoltaic systems offer a new way to manage land and water together, helping address challenges in energy, food, and water security. This chapter shows that using PV panels in these systems alters the microclimate, helping manage water. For example, they reduce solar radiation by 30 to 50 percent, lower air temperatures by 1 to 3°C, increase relative humidity by 2 to 35 percent, reduce wind speeds by 27.6 to 42.3 percent, and raise soil moisture by 8 to 30 percent. Together, these changes reduce evapotranspiration by 13 to 35 percent, requiring less irrigation.

Water management benefits depend heavily on the local climate, with the biggest improvements seen in dry areas where water is scarce. Dynamic panel systems can optimize more effectively than fixed ones, enabling real-time adjustments to balance energy production, crop lighting, and water use. Decision support systems that combine microclimate models, crop growth simulations, and irrigation scheduling are key to maximizing these optimizations.

Land Equivalent Ratios above 1.5 in different climates show that agrivoltaic systems create real benefits, not just a balance of trade-offs between energy and farming. Including water savings in the analysis, especially in dry areas, makes the argument for agrivoltaics even stronger.

The world faces connected challenges like climate change, food security, and the shift to sustainable energy. Agrivoltaic systems that use water efficiently can help by turning the competition for land and water into a productive partnership.

References

Abidin, M. A. Z., Mahyuddin, M. N., & Zainuri, M. A. A. M. (2021). Solar photovoltaic architecture Mamand agronomic management in agrivoltaic system: A review. *Sustainability*, *13*(14), 7846. https://doi.org/10.3390/su13147846

Abubakar, S. I., See, C. H., Muhammad-Sukki, F., Sundaram, S., Zainal Abidin, M. I., & Kamarudin, M. K. A. (2025). Model-based optimization of a 10-kWp agrivoltaic system with semi-transparent and bi-facial panels for enhanced crop yield, energy production, and land-use efficiency. *IEEE Access*, *13*, 155287–155305. https://doi.org/10.1109/ACCESS.2025.3622476

Adeh, E. H., Selker, J. S., & Higgins, C. W. (2018). Remarkable agrivoltaic influence on soil moisture, micrometeorology and water-use efficiency. *PLoS ONE*, *13*(11), e0203256. https://doi.org/10.1371/journal.pone.0203256

Ahmad, U., Alvino, A., & Marino, S. (2022). Solar fertigation: A sustainable and smart IoT-based irrigation and fertilization system for efficient water and nutrient management. *Agronomy*, *12*(5), 1012. https://doi.org/10.3390/agronomy12051012

AL-agele, H. A., Proctor, K., Murthy, G., & Higgins, C. (2021). A case study of tomato (*Solanum lycopersicon* var. Legend) production and water productivity in agrivoltaic systems. *Sustainability*, *13*(5), 2850. https://doi.org/10.3390/su13052850

Barron-Gafford, G. A., Pavao-Zuckerman, M. A., Minor, R. L., Sutter, L. F., Barnett-Moreno, I., Blackett, D. T., ... & Macknick, J. E. (2019). Agrivoltaics provide mutual benefits across the food–energy–water nexus in drylands. *Nature Sustainability*, *2*(9), 848–855. https://doi.org/10.1038/s41893-019-0364-5

Chopard, J., Bisson, A., Lopez, G., Persello, S., Richert, C., & Fumey, D. (2021). Development of a decision support system to evaluate crop performance under dynamic solar panels. *AIP Conference Proceedings*, *2361*, 050001. https://doi.org/10.1063/5.0055119

Disciglio, G., Stasi, A., Tarantino, A., & Frabboni, L. (2025). Microclimate modification, evapotranspiration, growth and essential oil yield of six medicinal plants cultivated beneath a dynamic agrivoltaic system in Southern Italy. *Plants*, *14*(15), 2428. https://doi.org/10.3390/plants14152428

Dupraz, C., Marrou, H., Talbot, G., Dufour, L., Nogier, A., & Ferard, Y. (2011). Combining solar photovoltaic panels and food crops for optimising land use: Towards new agrivoltaic schemes. *Renewable Energy*, *36*(10), 2725–2732. https://doi.org/10.1016/j.renene.2011.03.005

EIA. (2021). International Energy Outlook 2021. Washington, DC: U.S. Energy Information Administration. Retrieved from eia.gov

Elamri, Y., Cheviron, B., Lopez, J.M., Dejean, C., & Belaud, G. (2018). Water budget and crop modelling for agrivoltaic systems: Application to irrigated lettuces. *Agricultural Water Management*, *208*, 440–453. https://doi.org/10.1016/j.agwat.2018.07.001

FAO. (2009). How to Feed the World in 2050. Rome, Italy: Food and Agriculture Organization of the United Nations. Retrieved from fao.org

Goetzberger, A., & Zastrow, A. (1982). On the coexistence of solar-energy conversion and plant cultivation. *International Journal of Solar Energy*, *1*(1), 55–69. https://doi.org/10.1080/01425918208909875

Islam, A., Kothari, S. K., Ghosh, B., Satapathy, K. K., Mandal, T. K., & Koley, S. (2024). Agrivoltaics system: Sustainable approach for okra cultivation and energy stability. *Plant Science Today*, *11*(sp3), 329–338. https://doi.org/10.14719/pst.4719

Jung, D., Schönberger, F., & Spera, F. (2024). Effects of agrivoltaics on the microclimate in horticulture: Enhancing resilience of agriculture in semi-arid zones. In *AgriVoltaics World Conference 2023*. https://doi.org/10.52825/agripv.v2i.1033

Magarelli, A., Mazzeo, A., & Ferrara, G. (2024). Fruit crop species with agrivoltaic systems: A critical review. *Agronomy*, *14*(4), 722. https://doi.org/10.3390/agronomy14040722

Mamun, M. A. A., Dargusch, P., Wadley, D., Zulkarnain, N. A., & Aziz, A. A. (2022). A review of research on agrivoltaic systems. *Renewable and Sustainable Energy Reviews*, 161, 112351.

Marrou, H., Dufour, L., & Wery, J. (2013). How does a shelter of solar panels influence water flows in a soil–crop system? *European Journal of Agronomy*, *50*, 38–51. https://doi.org/10.1016/j.eja.2013.05.004

Paschalis, A., Bonetti, S., & Fatichi, S. (2025). Controls of ecohydrological grassland dynamics in agrivoltaic systems. *Earth's Future*, *13*, e2024EF005183. https://doi.org/10.1029/2024EF005183

Randle-Boggis, R. J., Barron-Gafford, G. A., Kimaro, A. A., Lamanna, C., Macharia, C., Maro, J., Mbele, A., & Hartley, S. E. (2025). Harvesting the sun twice: Energy, food and water benefits from agrivoltaics in East Africa. *Renewable and Sustainable Energy Reviews*, *208*, 115066. https://doi.org/10.1016/j.rser.2024.115066

Rouini, N., Salazar, A., Murphy, P., Lepley, K., & Barron-Gafford, G. A. (2025). High-shade dryland agrivoltaic conditions enhanced carbon uptake and water-use efficiency in zucchini (*Cucurbita pepo*). *Frontiers in Sustainable Food Systems*, *9*, 1686773. https://doi.org/10.3389/fsufs.2025.1686773

Scarano, A., Curci, L. M., Semeraro, T., Calisi, A., Lenucci, M. S., Santino, A., Basset, A., & De Caroli, M. (2025). Agrivoltaics as a sustainable strategy to enhance food security under water scarcity. *Horticulturae*, *11*(4), 401. https://doi.org/10.3390/horticulturae11040401

Sun, J., Cui, W., Wang, W., & Yang, X. (2025). The microclimatic and ecohydrological effects of photovoltaic facilities in arid/semi-arid regions of China: An integrated modeling study. *Journal of Environmental Management*, *382*, 125395. https://doi.org/10.1016/j.jenvman.2025.125395

Trommsdorff, M., Kang, J., Reise, C., Schindele, S., Bopp, G., Ehmann, A., Weselek, A., Högy, P., & Obergfell, T. (2021). Combining food and energy production:

Design of an agrivoltaic system applied in arable and vegetable farming in Germany. *Renewable and Sustainable Energy Reviews*, *140*, 110694. https://doi.org/10.1016/j.rser.2020.110694

Warmann, E., Darrel Jenerette, G., & Barron-Gafford, G.A. (2024). Agrivoltaic system design tools for managing trade-offs between energy production, crop productivity and water consumption. *Environmental Research Letters,* 19, 3. https://doi.org/10.1088/1748-9326/ad2ab8

Weselek, A., Bauerle, A., Hartung, J., Zikeli, S., Lewandowski, I., & Högy, P. (2021). Agrivoltaic system impacts on microclimate and yield of different crops within an organic crop rotation in a temperate climate. *Agronomy for Sustainable Development*, *41*(5), 59. https://doi.org/10.1007/s13593-021-00714-y

Wu, C., Liu, H., Yu, Y., Zhao, W., Liu, J., Yu, H., & Yetemen, O. (2022). Ecohydrological effects of photovoltaic solar farms on soil microclimates and moisture regimes in arid Northwest China: A modeling study. *Science of the Total Environment*, *802*, 149946. https://doi.org/10.1016/j.scitotenv.2021.149946

Zainali, S., Qadir, O., Parlak, S. C., Lu, S. M., Avelin, A., Stridh, B., & Campana, P. E. (2023). Computational fluid dynamics modelling of microclimate for a vertical agrivoltaic system. *Energy Nexus*, *9*, 100173. https://doi.org/10.1016/j.nexus.2023.100173

Chapter
7

DIGITAL TRANSFORMATION IN RURAL DEVELOPMENT AND FUTURE PROJECTIONS FOR AGRICULTURAL TECHNOLOGIES

***Ali BAYAT*[1]**

---

[1] Department of Agricultural Machinery and Technologies Engineering, Faculty of Agriculture, Çukurova University, Adana 01330, Türkiye. E-mail: alibayat@cu.edu.tr
ORCID: 000-0002-7104-9544

1. INTRODUCTION

Rural areas are the lifelines of the global ecosystem, providing food, energy, and biodiversity. However, the technological and environmental dynamics of the 21st century are forcing the traditional fabric of rural areas into a profound and irreversible transformation. This transformation process is a multidimensional shift that requires not only the modernization of a physical space but also a fundamental redefinition of agricultural production paradigms.

Underlying this profound transformation lies the globally recognized "triple threat": the imperative to feed a global population expected to reach 9.7 billion by 2050, environmental instabilities such as droughts and irregular rainfall patterns caused by climate change, and the loss of productive agricultural land coupled with declining soil fertility. These limiting factors clearly demonstrate that traditional agricultural methods are no longer sufficient to meet the goals of productivity and sustainability.

Traditional agricultural production processes have evolved from "Agriculture 1.0," historically reliant on human and animal labor, to "Agriculture 2.0," dominated by mechanization, and to "Agriculture 3.0," marked by the chemical revolution. Today, the sector is at the center of a digital revolution known as "Agriculture 4.0" or "Smart Farming." Agriculture 4.0 symbolizes the transition from intuitive and trial-and-error-based traditional management methods to data-driven "evidence-based agriculture" through the integration of the Internet of Things (IoT), big data analytics, autonomous devices, UAVs (Unmanned Aerial Vehicles), and artificial intelligence.

This digitalization process is not only an economic but also a social imperative for rural development. The agricultural labor shortage, exacerbated by the aging rural population and the migration of younger generations to cities, has elevated the adoption of autonomous and smart systems to a critical level. Consequently, digital transformation in rural areas has become not merely a choice but a technological necessity for ensuring resource efficiency, environmental sustainability, and food security. The aim of this study is to conduct an in-depth analysis of the opportunities arising from the integration of these digital tools into rural economies, as well as the structural barriers hindering this transformation.

1.1. The Transition from Traditional to Digital: The Strategic Role of Agriculture 4.0

Agricultural production processes have evolved from "Agriculture 1.0," which historically relied on human labor, to "Agriculture 2.0," dominated by mechanization, and to "Agriculture 3.0," marked by the chemical revolution. Today, the sector is at the center of a digital revolution known as "Agriculture 4.0" or "Smart Farming." Agriculture 4.0 symbolizes the transition from "intuitive farming" to "evidence-based farming" through the integration of big data analytics, cloud computing, and autonomous devices (Zhai et al., 2020).

The strategic importance of this transformation for rural development lies in the efficiency of resource use. Unlike the general practices of traditional methods, smart farming technologies enable "the right intervention, at the right time, in the right place." According to FAO (2020) reports, digitalization can increase agricultural productivity by up to 20% while reducing input costs (water, fertilizer, pesticides) by 15–20%. This situation enhances agricultural profitability on one hand and strengthens the social appeal of rural areas on the other.

1.2. Global Challenges: Food Security and Climate Resilience

The global food system is under three major concurrent pressures: population growth, the climate crisis, and dwindling resources. According to United Nations data, production must increase by 70% by 2050 (UN, 2019). However, this increase must occur amid constraints such as soil degradation and water scarcity. Unpredictable weather events caused by climate change often render farmers' millennia-old experiential knowledge (tacit knowledge) insufficient.

Here, technology emerges as a mechanism for resilience. Digital tools offer the ability to model climate risks and detect biotic stress factors (diseases and pests) before they become visible to the human eye (Lioutas & Charatsari, 2020). Therefore, the widespread adoption of technology is not merely an economic choice but also a defensive line safeguarding global food supply security.

2. CURRENT SITUATION IN RURAL AREAS AND THE DIGITAL DIVIDE

While agricultural digitalization offers significant potential, the adoption of these technologies faces structural barriers known as the "digital divide." This gap is not merely a difference in access to technology, but also a chasm in the capacity to "interpret and transform this technology into added value."

2.1. Infrastructure Issues: Connectivity and Data Highways

Data is the lifeblood of digital agriculture. However, rural areas are often prioritized last in telecommunications investments due to low population density. Globally, broadband internet access in rural areas lags behind urban areas by 20–30% (Mehrida et al., 2022). While next-generation connectivity technologies such as 5G and satellite internet (e.g., Starlink) are critical for the operation of sensor networks (IoT) in remote areas, coverage issues are exacerbating the "connectivity" crisis. On the energy front, the continuous power supply required by smart systems is increasing reliance on solar panels and battery technologies due to the fragility of rural grids, which in turn generates additional costs.

2.2. Demographic Structure: The Youth and Adaptation Paradox

Rural areas face a serious demographic crisis of "aging" and "depopulation." According to World Bank data, the average age of farmers in developing countries has risen to the 55–60 range. The migration of the young population to cities for education and employment (rural flight) is leaving agricultural production in the hands of an older population that is more resistant to technology.

Despite young people's natural affinity for digital tools, older farmers may resist new systems due to their reliance on traditional methods and lack of digital literacy (Long et al., 2017). However, a paradox exists here: While technology reduces the physical workload for the aging population on one hand, it creates a barrier due to its complex interfaces on the other. Therefore, the widespread adoption of technology is not merely a matter of "providing tools" but a process of "developing human capacity."

2.3. Economic Barriers and Uncertainty Regarding ROI (Return on Investment)

The most tangible barrier to technological transformation is the high initial investment cost. Precision agriculture hardware and software licenses can cost many times the annual net profit of small and medium-sized enterprises (SMEs).

Economic analyses show that the payback period (ROI) of the technology is directly related to the size of the farm. Schimmelpfennig (2016) reported that precision spraying and variable-rate application technologies pay for themselves within 2–3 years in large-scale operations, but this period can exceed 10 years on farms smaller than 50 decares. This "scale disadvantage" carries the risk of leaving small-scale producers behind in the technological race and leading to their exclusion from the market (digital exclusion). Consequently, "shared-use models" and "subsidized financing" mechanisms have become a technical necessity in the widespread adoption of technology.

3. KEY AGRICULTURAL TECHNOLOGIES THAT NEED TO BE WIDELY ADOPTED

The success of agricultural transformation in rural areas depends not only on the physical presence of technology but also on a proper understanding of the technical components of the data collection (sensing), data processing (decision-making), and implementation (action) cycle. These tools go beyond labor savings by incorporating "precision"—critical for the conservation of natural resources—into the production process.

3.1. Precision Agriculture and Variable Rate Application (VRA) Systems

Precision agriculture is based on the principle of providing "exactly what is needed at every point" by managing spatial variability in the field.

- Operating Principle and Components: The system determines location with centimeter-level accuracy (RTK) using GNSS (Global Navigation Satellite System) receivers. Digital "prescription maps" are transmitted to the mechanical components via a control unit (Task Controller). Actuators and servo motors instantly adjust the flow rate of fertilizer spreaders or spray nozzles based on this data.

- Data-Driven Outcomes: Studies have shown that the use of VRT results in savings of 10% to 30% in fertilizer costs (Wolfert et al., 2017). Additionally, optical sensors (e.g., GreenSeeker) and soil conductivity probes offer "real-time decision-making" capabilities while reducing laboratory costs.

3.2. Unmanned Aerial Vehicles (UAVs) and Autonomous Systems

In rural areas where labor shortages are critical, autonomous systems are defined as the "next-generation workforce" that fundamentally transforms operational efficiency.

- Operating Principle and Components: UAVs used for imaging collect light reflected from plants using multispectral and thermal cameras. Near-infrared (NIR) rays reflected by healthy plants are analyzed using algorithms such as NDVI and converted into stress maps. Spraying drones, meanwhile, ensure that the pesticide reaches even the undersides of leaves using autonomous route-tracking radars and propeller systems that generate downward airflow (downwash).

- Data-Driven Outcomes: Drone spraying achieves a 90% water savings and a 30–40% reduction in chemical use compared to traditional sprayers. Autonomous tractors, meanwhile, optimize fuel consumption by 10–15% through environmental sensing (SLAM) using LiDAR and cameras (Zhai et al., 2020).

3.3. Internet of Things (IoT) and Decision Support Systems (DSS)

IoT transforms the field into a living data network, making what the farmer “cannot see” measurable.

- Operating Principle and Components: Sensor nodes deployed in the field measure soil moisture, salinity, and air parameters. This data is transmitted to cloud servers via telemetry units (LoRaWAN/GSM). KDS software matches this data with meteorological models to provide the farmer with an action plan via mobile applications.

- Data-Driven Outcomes: Smart irrigation automation systems can increase water use efficiency by 25–50% by managing water based on the plant’s evapotranspiration data. KDS systems minimize crop losses by answering critical questions such as “When should planting be done?” or “When is there a risk of frost?” (FAO, 2020).

3.4. Robotic Systems and Artificial Intelligence

Robotic systems, expected to become widespread in the rural landscape of the future, offer the capability of “selective intervention” beyond driverless operations.

- Operating Principles and Components: Robots equipped with computer vision technology use artificial intelligence processors to distinguish between crop plants and weeds. Robotic arms or laser systems can reduce herbicide use by up to 90% by targeting only the weeds.

4. TECHNOLOGY ADOPTION MODELS AND FARMER BEHAVIOR

The success of agricultural technologies is measured not only by engineering efficiency but also by the speed at which these technologies spread within social systems and the degree to which they are accepted by users. Technology adaptation in rural areas is a cultural and behavioral transformation rather than a purely technical process.

4.1. The Theory of Diffusion of Innovations and Global Success Examples

The Theory of Diffusion of Innovations, developed by Everett Rogers (2003), posits that technology spreads through society in an S-curve, starting with “early adopters” and moving toward “laggards.” This theory explains that a technology spreads not only due to its technical superiority but also because of the “observable benefits” it offers users and its “trials-and-errors” capacity.

The following global examples demonstrate how technology scales along this S-curve across different socio-economic contexts and how it triggers rural development:

- Japan (Autonomy in the Labor Crisis): Japanese agriculture faces an "existential threat" due to the rapid aging of the rural population and labor shortages. This situation has made technology not a choice but a necessity. Autonomous tractors (Agri Robo) developed by giants like Kubota were initially tested by a small "innovative" group, but as labor savings and increased efficiency were proven, they were rapidly adopted by the "early majority." Here, technology has ensured agricultural continuity by replacing traditional labor.

- Brazil (Large-Scale Digitalization): In regions like Mato Grosso, the vast scale of agricultural land (thousands of hectares) has made precision agriculture inevitable. GIS-based soil mapping and satellite monitoring technologies developed under the leadership of Embrapa (Brazilian Agricultural Research Corporation) were initially adopted by large-scale producers (innovators); as their cost-reducing effects became evident, they spread to medium-scale farmers. In this model, technology, combined with "economies of scale," has enhanced global competitiveness.

- Kenya (Mobile Access and the "Leapfrog" Effect): The diffusion of innovations in developing economies often occurs by "leapfrogging" over infrastructure gaps. Platforms like M-Farm in Kenya have enabled farmers to access market prices, weather conditions, and logistics information via their mobile phones. Rogers' theory of "observability" comes into play here; when neighboring farmers saw that a farmer had increased his income by 30% through direct sales, they rapidly adopted the technology. This example demonstrates how technology spreads not merely as a physical machine, but as an "information flow system."

- United States (Corn Belt Auto-Steering): The U.S. "Corn Belt" was the first region to adopt GPS-based auto-steering systems. This technology was initially adopted by "early adopters" due to its advantages of fuel savings and reduced overlap; the operational ease and indirect benefits such as "reduced fatigue" it provided led the "early majority" (the vast majority of farmers) to accept the system. The technology has optimized not only crop yields but also the farmer's quality of life.

- Israel (Limited Water Resources Model): Due to limited water resources, Israel has adopted drip irrigation and IoT-based sensor technologies as a "national necessity." Success stories like Netafim spread across the entire country after the technology was first tested in state-supported cooperatives (Kibbutzim) and the resulting yield increases became "observable." In this model, the technology's success was proven by the economic benefits it provided to farmers.

- Netherlands (Precision Livestock Farming): Robotic milking systems used in dairy cattle farming in the Netherlands, though initially perceived as high-cost, were rapidly adopted by the "Early Majority" due to labor savings and positive effects on animal health.

4.2. The Trust Factor: The Convergence of Traditional Knowledge and Digital Data

For farmers, the most valuable asset is experiential knowledge passed down from generation to generation (tacit knowledge). For technology to be adopted, digital data must not "disregard" this knowledge but rather "validate" it.

- The Turkish Example (Smart Agriculture Village - Kasaplar): The "Smart Village" project implemented in the village of Kasaplar in Aydın is a significant success story in overcoming the trust barrier. Farmers were shown firsthand in the field how sensor data aligns with their traditional knowledge. When the farmer verified the accuracy of the "frost warning" received on their cell phone in the field, the level of "perceived trust" in the technology increased.

These examples demonstrate that digital transformation is not merely a technical process; it is a "social adaptation" process shaped around cultural acceptance, economic incentives, and alignment with local needs.

4.3. Strategic Focus Regions and the Start of Dissemination for Turkey

In the dissemination of agricultural technologies in Turkey, rather than applying a "one-size-fits-all" solution, a dissemination strategy should be followed that begins with regions where technological readiness is high.

•1. Priority Region: Aegean and Marmara (High Technology Readiness):

- Reason: A farmer profile with a high level of education, integration with industry, and export-oriented production (fruits, vegetables, olives).

-Starting Point: These are the most suitable test and pilot areas for drone-based spraying and IoT-based smart irrigation systems.

2. Priority Region: Central Anatolia and Southeastern Anatolia (Economies of Scale):

- Reason: Vast, flat lands with large parcel sizes, such as the Konya Plain and the GAP region.

-Start: Ideal for autonomous tractors, variable-rate fertilization (VRT), and satellite-based crop monitoring systems. The return on investment (ROI) is shorter on large-scale lands.

3. Regional Success Model: To accelerate adoption in Turkey, the "Leasing and Shared Use" model—where agricultural chambers and cooperatives purchase technological equipment and offer it to farmers as a "service"—should be the core strategy to overcome economic resistance.

5. ADOPTION STRATEGIES AND POLICY RECOMMENDATIONS

For technological innovations to take root sustainably in rural areas, a comprehensive strategy encompassing education, finance, organization, and the innovation ecosystem is essential—not merely the provision of devices.

5.1. Education and Outreach Activities: Knowledge-Driven Transformation

The "technical fear" barrier to technology adoption can only be overcome through continuous and hands-on training.

- Digital Literacy Training: Farmers should be taught not only how to use devices but also how to interpret the collected data (e.g., making fertilization decisions by analyzing an NDVI map).

- Hands-On Field Days and "Living Labs": Instead of theoretical training, "living labs" should be established where technology is tested under real-world field conditions. The European Union's SmartAgriHubs project is a key example in this regard; here, farmers interact directly with technology developers to experience solutions firsthand.

- Digital Extension Network: Traditional extension staff (agricultural engineers) should be retrained as "digital advisors" and provide farmers with real-time technical support via remote monitoring systems.

5.2. Financial Incentive Models: Overcoming Economic Barriers

High initial investment costs are the biggest barrier to agricultural technologies. To break this barrier, dynamic financial tools are needed instead of static subsidies.

- Performance-Based Subsidies: Tiered grant models should be implemented based not only on equipment purchases but also on the resource savings provided by the technology (e.g., a smart irrigation system that conserves water).

- Low-Interest "Technology Loans": Unlike traditional agricultural loans, long-term loans specifically designed for technological transformation—with repayment schedules optimized for harvest periods—should be encouraged.

- Agricultural Technology Leasing: Leasing models focused on "right of use" rather than ownership—particularly for expensive drones and autonomous systems—minimize the farmer's capital risk.

5.3. Cooperatives and Shared Use: Economies of Scale for Small Businesses

In countries like Turkey with fragmented land structures, individual technology investment is often economically irrational.

- Shared Equipment Pools (CUMA Model): The CUMA (Coopérative d'Utilisation de Matériel Agricole) model in France enables small producers to access cutting-edge technologies through shared ownership. Under this model, a drone or autonomous tractor belongs to the cooperative and is used by members via a reservation system.

- Technology Use Through Service Procurement: Instead of purchasing technology, farmers should be encouraged by the government to utilize services provided by startups (e.g., drone spraying services).

5.4. Public-University-Industry Collaboration: Domestic Technology Ecosystem

Imported technologies may not always adapt to local soil and climate conditions. Therefore, a domestic R&D ecosystem is essential.

- Local Needs Analysis: Agricultural machinery departments at universities should develop projects focused on the "real problems" of local farmers (e.g., autonomous harvesting of hazelnuts or disease monitoring in olive trees).

- Agri-Tech Entrepreneurship Support: Incubators dedicated solely to agricultural technologies should be established in technology parks; startups developing domestic software and hardware should be provided with tax exemptions and R&D support. This is the key to creating a "technology-exporting rural economy."

6. VISION FOR THE FUTURE: SUSTAINABLE AND SMART RURAL LIVING

The ultimate goal of technological transformation is not merely to increase yield per unit area, but to transform the rural areas into economically robust, socially vibrant, and environmentally resilient living spaces. The vision of smart rural living positions technology as a lever for human well-being and the protection of nature.

6.1. Rural Revitalization: Agri-preneurship and the Return of the Young Population

The perception of traditional agriculture as involving "heavy workloads and low prestige" is the primary driver of rural depopulation. However, digitalization is transforming agriculture from a physically labor-intensive industry into a discipline of "software and data management."

- Agri-preneurship: Smart agriculture technologies are encouraging young professionals to return to rural areas and establish "technology-driven agricultural enterprises." Rural areas are no longer merely sources of raw materials but innovation hubs offering new-generation employment opportunities such as drone operation, data analysis, and smart system integration (FAO, 2020).

- Urban-Rural Integration: Remote work opportunities and the development of digital infrastructure are giving rise to the concept of "smart villages," where urban comfort merges with rural tranquility. This trend reverses brain drain, thereby strengthening the intellectual capital of rural areas.

6.2. Data Governance: Security, Ownership, and National Strategy

With Agriculture 4.0, "data" has become a strategic resource at least as important as land and water. However, the question of who will control this data is the most critical area of debate for the future.

- Data Ownership and Ethics: There is a risk that data collected from farmers' fields (soil quality, crop yields, etc.) could be monopolized by major tech giants. Legal frameworks ensuring data ownership remains with farmers and ethical data governance models are essential (Wolfert et al., 2017).

- National Agricultural Data Banks: The anonymized storage of agricultural data collected nationwide in "national data banks" is vital for governments to manage food supply security and develop macro-level strategies against climate change. Data-driven policy-making enables the prevention of agricultural crises before they arise.

6.3. Conclusion: The Social and Environmental Impact of Technology-Driven Rural Development

The process of disseminating agricultural technologies is not merely a drive toward mechanization but a social contract.

- Social Welfare: In a rural area with access to technology, income inequality decreases, and small-scale producers gain easier access to global markets. This is one of the most powerful tools for reducing rural poverty.
- Environmental Sustainability: Precise input management enabled by smart systems minimizes chemical use, thereby protecting groundwater and soil health. Reducing the carbon footprint and supporting biodiversity are the ecological legacy of technology-driven agriculture.

In summary, technology is a tool to overcome the rural underdog's fate. However, the success of this tool depends on bridging the digital divide, ensuring fair data management, and adopting a human-centered digitalization model. The future of rural areas will be an ecosystem where the wisdom of tradition harmonizes with the technology of the future.

REFERENCES

Balafoutis, A., Beck, B., Fountas, S., Vangeyte, J., Walermann, T., Eory, V., ... & Sørensen, C. G. (2017). Precision agriculture technologies positively contributing to greenhouse gas emissions mitigation, farm productivity and economics. *Sustainability, 9*(8), 1339. https://doi.org/10.3390/su9081339

Busse, M., Schwerdtner, W., Siebert, R., Doernberg, A., Kuntosch, A., Casolani, N., & Rose, D. C. (2014). Analysis of intermediaries' role in supporting local innovations in agriculture in Germany. *International Journal of Agricultural Extension, 2*(2), 115-125.

Diederen, P., van Meijl, H., Wolters, A., & Bijak, K. (2003). Innovation adoption in agriculture: Innovators, early adopters and laggards. *Cahiers d'Economie et de Sociologie Rurales, 67*, 29-50.

FAO. (2020). *Digital technologies in agriculture and rural areas: Status and pathways*. Food and Agriculture Organization of the United Nations. https://doi.org/10.4060/ca7961en

Labarthe, P., & Laurent, C. (2013). Privatization of agricultural extension services in the EU: Towards a lack of adequate knowledge for small-scale farms? *Food Policy, 38*, 240-252. https://doi.org/10.1016/j.foodpol.2012.11.005

Lioutas, E. D., & Charatsari, C. (2020). Smart farming and short food supply chains: Are they compatible? *Land Use Policy, 94*, 104541. https://doi.org/10.1016/j.landusepol.2020.104541

Long, T. B., Blok, V., & Poldner, K. (2017). Determinants of acceptance of sustainable innovation in agricultural context: A systematic review. *Journal of Cleaner Production, 154*, 433-447. https://doi.org/10.1016/j.jclepro.2017.03.217

Mehrida, A., Hameed, K., & Adey, P. (2022). The digital divide in agriculture: A review of barriers and opportunities. *Technology in Society, 70*, 102033. https://doi.org/10.1016/j.techsoc.2022.102033

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Rose, D. C., Wheeler, R., Paterson, M., Little, R., & Mumby, P. J. (2021). Learning from agricultural extension to improve the adoption of smart farming technologies. *Frontiers in Sustainable Food Systems, 5*, 639191. https://doi.org/10.3389/fsufs.2021.639191

Rotz, S., Gravely, E., Fraser, E. D. G., Desmarais, A., San Vicente, R., Mitchell, A., ... & Pant, L. (2019). Automated pastures and the digital divide: How agricultural automation is shaping labour and small farms. *Journal of Peasant Studies, 46*(6), 1123-1144. https://doi.org/10.1080/03066150.2019.1591992

Schimmelpfennig, D. (2016). *Farm profits and adoption of precision agriculture*. USDA Economic Research Service Report No. 217.

SmartAgriHubs. (2022). *Connecting the dots: Unleashing the innovation potential for digital transformation of the European agri-food sector*. Final Report.

Trendov, N. M., Varas, S., & Zeng, M. (2020). *Digital technologies in agriculture and rural areas: Status and pathways*. Food and Agriculture Organization of the United Nations. https://doi.org/10.4060/ca7961en

United Nations. (2019). *World Population Prospects 2019: Highlights*. Department of Economic and Social Affairs, Population Division.

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. J. (2017). Big data in smart farming – A review. *Agricultural Systems, 153*, 69-80. https://doi.org/10.1016/j.agsy.2017.01.023

World Bank. (2021). *What's cooking: Digital transformation of the agrifood system*. World Bank Group. https://doi.org/10.1596/978-1-4648-1715-1

Zhai, Z., Martínez, J. F., Beltran, V., & Martínez, N. L. (2020). Decision support systems for agriculture 4.0: Survey and challenges. *Computers and Electronics in Agriculture, 170*, 105256. https://doi.org/10.1016/j.compag.2020.105256

Zhang, X., & Kovacs, J. M. (2012). The application of small unmanned aerial systems for precision agriculture: A review. *Precision Agriculture, 13*(6), 693-712. https://doi.org/10.1007/s11119-012-9274-5

Chapter

8

VAPOR PRESSURE DEFICIT (VPD)-DRIVEN AUTOMATIC IRRIGATION SYSTEMS IN GREENHOUSE PRODUCTION: A COMPREHENSIVE PHYSIOLOGICAL AND ENGINEERING FRAMEWORK

Eser ÇELİKTOPUZ[1]
Çiğdem HOŞGÖREN[2]

---

[1] *Associate Professor, Agricultural Faculty, Department of Agricultural Structures and Irrigation, Çukurova University, Adana, Turkey. eceliktopuz@cu.edu.tr . https://orcid.org/0000-0002-5355-1717

[2] Research Assistant, Agricultural Faculty, Department of Agricultural Structures and Irrigation, Çukurova University, Adana, Turkey. chosgoren@cu.edu.tr . https://orcid.org/0000-0003-0938-5026

1. Introduction: Reconstructing Irrigation Paradigms in Controlled Environment Agriculture

The intensification of greenhouse horticulture over the past decades has necessitated a fundamental re-evaluation of irrigation management strategies, particularly in the context of increasing resource scarcity and environmental constraints. Water, as a limiting factor in agricultural production, has become central to discussions on sustainability, especially under the dual pressures of climate change and growing global food demand. Within this framework, greenhouse systems characterized by their high productivity and controlled conditions offer unique opportunities for optimizing water use. However, these opportunities can only be realized through the adoption of advanced, plant-responsive irrigation strategies that transcend conventional paradigms.

Historically, irrigation scheduling in greenhouse systems has been governed by relatively simplistic approaches, including fixed time intervals, empirical rules, or substrate moisture thresholds. While these methods provide operational simplicity, they fail to capture the inherently dynamic nature of plant water demand, which is continuously modulated by environmental conditions. In particular, such approaches neglect the critical role of atmospheric demand, which can vary substantially within short temporal scales due to fluctuations in temperature, humidity, and radiation.

The emergence of vapor pressure deficit (VPD) as a central variable in greenhouse management represents a pivotal shift toward physiologically informed irrigation control. VPD, defined as the difference between the saturation vapor pressure at leaf temperature and the actual vapor pressure of the surrounding air, encapsulates the evaporative demand imposed on plants. Unlike temperature or relative humidity considered independently, VPD provides a thermodynamically consistent metric that directly governs the driving force for transpiration.

From a systems perspective, VPD serves as a critical interface between atmospheric physics and plant physiology. It integrates environmental inputs into a single variable that determines the rate of water vapor diffusion from leaf tissues to the atmosphere. Consequently, VPD has been widely recognized as a key determinant of transpiration, stomatal behavior, and overall plant water relations (Amitrano et al., 2019; López et al., 2021). Importantly, recent studies have highlighted that global increases in VPD driven by rising temperatures and changing humidity patterns are already exerting measurable impacts on plant productivity and water use (Yuan et al., 2019; Grossiord et al., 2020).

The integration of VPD into irrigation management reflects a broader transition from supply-driven to demand driven water application. In traditional systems, irrigation is applied based on predefined schedules or soil conditions, effectively treating water as an external input. In contrast, VPD-based systems conceptualize irrigation as a response to plant transpiration demand, thereby aligning water supply with physiological need. This shift is not merely conceptual but has practical implications for system design, control algorithms, and overall resource efficiency.

The algorithmic framework in the systems which should provided may exemplifies this transition, incorporating VPD thresholds, radiation triggers, and adaptive irrigation intervals. Such systems represent a convergence of plant science, environmental monitoring, and control engineering, enabling real time decision-making based on dynamic environmental inputs.

Furthermore, the integration of VPD into irrigation control is closely aligned with emerging trends in digital agriculture, including the use of sensor networks, IoT platforms, and data-driven decision systems. These technologies enable high-resolution monitoring of environmental variables, providing the data necessary for implementing VPD based control strategies at scale (Villagran et al., 2024). As a result, irrigation management is increasingly viewed not as a static operation but as a dynamic control process embedded within a broader cyber physical system.

Despite these advances, significant challenges remain. The effective implementation of VPD based irrigation requires accurate measurement of environmental variables, robust control algorithms, and an understanding of crop-specific responses. Moreover, VPD alone does not fully capture the complexity of plant water relations, necessitating its integration with additional variables such as radiation, substrate conditions, and plant physiological status.

In this context, the present chapter aims to provide a comprehensive synthesis of VPD driven irrigation systems, integrating physiological principles, engineering approaches, and empirical evidence. By bridging these domains, it seeks to establish a coherent framework for the development of next-generation irrigation strategies in greenhouse production.

2. Physiological Foundations: VPD as a Determinant of Transpiration Dynamics

The physiological significance of vapor pressure deficit (VPD) lies in its direct control over transpiration, a process that constitutes the primary pathway of water loss in plants and a critical driver of nutrient transport, thermal regulation, and photosynthetic performance. Transpiration is fundamentally governed by the gradient in water vapor pressure between the leaf intercellular spaces assumed to be near saturation and the surrounding atmosphere. This gradient, quantified as VPD, represents the thermodynamic force that drives water vapor diffusion through stomata.

At the leaf level, transpiration can be conceptualized as a function of both atmospheric demand (VPD) and stomatal conductance, which together determine the rate of water vapor flux. However, this relationship is inherently nonlinear due to the active regulation of stomatal aperture in response to environmental and physiological cues. As a result, VPD exerts both a direct physical influence on transpiration and an indirect physiological influence through stomatal behavior.

Under low VPD conditions, typically below 0.4–0.5 kPa, the vapor pressure gradient between the leaf and the atmosphere is minimal, resulting in limited transpiration rates despite relatively open stomata. While such conditions reduce water loss, they can also impede the mass flow of nutrients from the root zone to the aerial parts of the plant. This limitation can manifest in deficiencies of immobile nutrients, such as calcium, and increase the risk of physiological disorders (Shamshiri et al., 2018).

As VPD increases to moderate levels, transpiration rises sharply due to the increased vapor pressure gradient. This phase is generally associated with optimal physiological performance, as enhanced transpiration facilitates nutrient uptake and supports photosynthetic activity. Within this range, stomatal conductance remains relatively high, allowing for efficient gas exchange and carbon assimilation.

However, as VPD continues to increase beyond optimal levels typically above 1.5–2.0 kPa plants initiate protective responses to mitigate excessive water loss. These responses include partial or complete stomatal closure, which reduces transpiration but also limits CO_2 uptake, thereby constraining photosynthesis. This regulatory behavior introduces a nonlinear response in which transpiration no longer increases proportionally with VPD, leading to a decline in water use efficiency (López et al., 2021).

This phenomenon has been extensively documented in experimental studies. Medrano et al. (2005) observed that cucumber transpiration exhibits a near linear response to VPD under moderate conditions but deviates from linearity at higher levels due to stomatal regulation. Similarly, Jo and Shin (2021) developed a mechanistic model for greenhouse tomato that captures the transition from demand-driven to regulation-limited transpiration.

These findings highlight the dual nature of VPD as both a driving force and a regulatory trigger in plant water relations.

Beyond instantaneous responses, VPD also influences long-term plant adaptation and acclimation. Prolonged exposure to high VPD conditions has been shown to alter stomatal sensitivity, hydraulic conductance, and leaf morphology, potentially leading to reduced productivity over time (Grossiord et al., 2020; Yu et al., 2023). Conversely, sustained low VPD conditions can promote excessive vegetative growth and reduce structural integrity, particularly in high humidity environments.

Importantly, the interaction between VPD and other environmental variables further complicates its effects on plant physiology. Radiation, for instance, determines the energy available for transpiration, while CO_2 concentration influences stomatal behavior. Temperature affects both saturation vapor pressure and metabolic processes, creating complex feedback loops that must be considered in irrigation management.

Katsoulas and Stanghellini (2019) emphasized that accurate modeling of greenhouse transpiration requires integrating VPD with energy balance components, including radiation and aerodynamic resistance. This integrated perspective underscores the need for multi variable control strategies that account for the complex interplay between environmental factors.

From an irrigation standpoint, the key implication of these physiological dynamics is that plant water demand cannot be inferred from soil conditions alone. Instead, it must be understood as a function of atmospheric demand, as quantified by VPD, and its interaction with plant regulatory mechanisms. This insight forms the foundation of VPD based irrigation systems, where water application is dynamically adjusted to match transpiration demand.

In summary, VPD serves as both a physical driver and a physiological regulator of plant water relations. Its dual role necessitates careful consideration in irrigation management, particularly in controlled environments where precise regulation of microclimate conditions is possible. By integrating VPD into irrigation control strategies, it becomes possible to align water supply with plant demand, thereby enhancing efficiency and sustainability.

3. Optimal VPD Ranges: Crop-Specific and Developmental Considerations

The determination of optimal vapor pressure deficit (VPD) ranges represents one of the most critical aspects in translating plant physiological understanding into practical greenhouse irrigation strategies. Although VPD is widely recognized as a universal driver of transpiration, its optimal range is inherently species specific and dynamically modulated by developmental stage, canopy structure, and environmental interactions.

In controlled environments, most horticultural crops exhibit optimal physiological performance within a relatively narrow VPD range, typically between 0.8 and 1.2 kPa. Within this interval, stomatal conductance remains sufficiently high to support carbon assimilation, while transpiration is maintained at levels that facilitate nutrient transport without inducing excessive hydraulic stress. However, this generalized range must be interpreted with caution, as deviations in crop physiology, particularly between vegetative and generative stages, necessitate dynamic adjustment.

During the vegetative phase, plants prioritize leaf expansion and canopy development, processes that are highly sensitive to water stress. Under these conditions, maintaining relatively lower VPD values (approximately 0.6–0.9 kPa) promotes sustained stomatal opening and cell expansion. Conversely, during reproductive stages, a moderate increase in VPD (0.9–1.3 kPa) can enhance assimilate partitioning toward fruits, improving yield quality and sugar accumulation (Lu et al., 2015).

Importantly, extreme deviations from optimal VPD ranges lead to distinct physiological constraints. Low VPD conditions (<0.5 kPa) suppress transpiration to the extent that nutrient transport via mass flow becomes limiting, often resulting in deficiencies such as calcium related disorders. High VPD conditions (>1.5–2.0 kPa), on the other hand, induce stomatal closure and increase the risk of hydraulic failure, thereby reducing photosynthetic efficiency and long-term productivity (López et al., 2021).

Recent research has further demonstrated that VPD sensitivity is not static but evolves over time. Yu et al. (2023) reported that prolonged exposure to elevated VPD alters stomatal responsiveness, leading to acclimation effects that may compromise irrigation strategies if not dynamically adjusted. Similarly, Shamshiri et al. (2018) emphasized that optimal VPD thresholds must be considered within the broader context of greenhouse microclimate, including temperature, radiation, and CO_2 concentration.

Thus, optimal VPD management should be understood not as a fixed target but as a dynamic control variable, continuously adjusted according to plant developmental stage and environmental conditions.

4. Evolution of Irrigation Control: From Reactive to Predictive Systems

The evolution of irrigation control systems in greenhouse production reflects a gradual but profound shift from reactive to predictive management paradigms. Early irrigation systems were predominantly manual or timerbased, applying water at fixed intervals without regard for plant physiological status or environmental variability. While simple to implement, such approaches often resulted in over-irrigation or water stress, particularly under fluctuating climatic conditions.

The introduction of soil moisture sensors marked a significant advancement, enabling irrigation to be triggered based on substrate water content. However, these systems remain inherently reactive, as they respond to water deficits after they have already developed. Moreover, soil moisture alone does not adequately capture atmospheric demand, which plays a dominant role in determining transpiration.

The integration of climatic variables, particularly VPD, represents a transition toward predictive irrigation control. By linking irrigation decisions to atmospheric demand, VPD based systems anticipate plant water requirements before stress occurs. This approach is supported by the development of transpiration models that estimate water use based on environmental inputs (Katsoulas and Stanghellini, 2019).

Sánchez et al. (2012) introduced virtual sensing techniques that combine temperature, humidity, and radiation data to estimate crop transpiration, laying the foundation for modern VPD driven systems. More recent advances have incorporated machine learning and data driven approaches, enabling irrigation systems to adapt to complex environmental interactions.

Furthermore, integrated greenhouse control systems now coordinate irrigation with ventilation, shading, and cooling strategies, using VPD as a common control variable (Soussi et al., 2022). This convergence of climate and irrigation control represents a systems level approach in which water management is no longer an isolated process but part of a holistic environmental control strategy.

5. Algorithmic Design: Translating Physiology into Control Logic

The successful implementation of VPD based irrigation systems requires the translation of plant physiological principles into robust algorithmic structures. This process involves converting continuous environmental signals into discrete control actions, a task that necessitates both biological insight and engineering precision.

The multi layered algorithmic framework presented in your system exemplifies this translation. At its core, the algorithm establishes a causal link between VPD and irrigation frequency, reflecting the direct relationship between evaporative demand and plant water consumption. This approach contrasts sharply with conventional systems, where irrigation timing is predefined and independent of plant demand.

From a control theory perspective, the system can be interpreted as a hybrid control architecture combining feedforward and feedback elements. The feedforward component is driven by VPD and radiation, which predict transpiration demand, while the feedback component incorporates drainage and substrate measurements to correct deviations.

Recent studies have highlighted the potential for further refinement through adaptive and intelligent control systems. He et al. (2025) demonstrated that VPD driven irrigation can influence circadian transpiration patterns, suggesting that irrigation timing can be optimized not only in magnitude but also in temporal distribution. Similarly, Choi and Shin (2020) emphasized the importance of integrating nonlinear transpiration models into control algorithms to improve prediction accuracy.

Thus, algorithmic design in VPD based irrigation represents a convergence of plant physiology, environmental physics, and control engineering, requiring interdisciplinary approaches to achieve optimal performance.

6. Coupling VPD with Radiation and Energy Balance: Toward Integrated Transpiration-Driven Irrigation Control

Although vapor pressure deficit (VPD) is widely recognized as a primary determinant of plant transpiration, its predictive capacity is fundamentally constrained when considered in isolation from the energy balance governing evaporative processes. Transpiration is not solely a function of atmospheric demand but rather the outcome of a tightly coupled interaction between aerodynamic forces (represented by VPD) and available energy (primarily derived from radiation). Consequently, a comprehensive understanding of plant water use and, by extension, the design of advanced irrigation strategies requires an integrated framework that simultaneously accounts for both components.

At the core of this interaction lies the physical principle that the phase transition of water from liquid to vapor requires energy, specifically the latent heat of vaporization. In plant systems, this energy is supplied predominantly by net radiation absorbed at the canopy level. Therefore, even in conditions of high VPD, transpiration cannot proceed at high rates unless sufficient radiative energy is available to sustain evaporation. This fundamental constraint explains why VPD driven irrigation models that neglect radiation often overestimate plant water demand under low light conditions.

The classical Penman Monteith equation provides a theoretical foundation for this coupling, expressing evapotranspiration as a function of both radiative energy and aerodynamic demand. In greenhouse environments, where boundary layer conditions and microclimate control differ from open field systems, adaptations of this framework have been widely applied. Katsoulas and Stanghellini (2019) emphasized that greenhouse transpiration models must explicitly incorporate both energy balance and vapor transport processes, highlighting that VPD alone cannot capture the complexity of transpiration dynamics.

Empirical evidence further supports this integrated perspective. Jo and Shin (2021) demonstrated that transpiration in greenhouse grown tomato is jointly regulated by radiation and VPD, with radiation primarily determining the magnitude of transpiration and VPD modulating its efficiency. Their model revealed that under low radiation conditions, transpiration remains limited regardless of VPD due to insufficient energy input. Conversely, under high radiation, even moderate VPD levels can drive substantial transpiration rates, reflecting the synergistic interaction between energy supply and vapor pressure gradient.

This interaction becomes particularly relevant when considering diurnal patterns of greenhouse climate. During early morning hours, radiation levels are typically low, while relative humidity is high, resulting in low VPD. As solar radiation increases throughout the day, both temperature and VPD rise, leading to peak transpiration during midday. In the late afternoon, declining radiation reduces energy availability even if VPD remains elevated, causing a decoupling between atmospheric demand and actual transpiration. These temporal dynamics underscore the inadequacy of irrigation strategies based solely on VPD thresholds without accounting for energy input.

The incorporation of cumulative radiation, often expressed as daily light integral (DLI), into irrigation control systems represents a significant advancement in addressing this limitation. By linking irrigation events to accumulated photosynthetically active radiation (PAR), systems can ensure that water supply is synchronized with plant metabolic activity. This approach is particularly effective in soilless cultivation systems, where frequent, small irrigation events are required to maintain optimal root zone conditions. In Dutch greenhouse practice, for instance, irrigation is commonly triggered after a predefined amount of accumulated radiation (e.g., 2–3 MJ m ^{2}), reflecting the close coupling between light-driven photosynthesis and water uptake.

From a physiological perspective, the integration of radiation into irrigation control is justified by the strong coupling between photosynthesis and transpiration. Both processes are regulated by stomatal conductance, which responds to light intensity, CO_2 concentration, and VPD. Under high radiation, stomata tend to open to facilitate CO_2 uptake, thereby increasing transpiration. However, this response is modulated by VPD, as excessive atmospheric demand can induce partial stomatal closure. Thus, radiation and VPD interact not only at the physical level but also through complex physiological feedback mechanisms.

Recent studies have further highlighted the importance of energy balance components beyond radiation alone. Net radiation, which accounts for both incoming shortwave and outgoing longwave radiation, determines the actual energy available for evaporation. Additionally, sensible heat flux and aerodynamic resistance influence the partitioning of energy between heating and evaporation processes. Ghiat et al. (2021) emphasized that accurate estimation of evapotranspiration requires consideration of these factors, particularly in controlled environments where microclimatic conditions can be actively manipulated.

The integration of VPD and radiation also enables the development of more sophisticated irrigation control strategies that account for spatial and temporal variability within greenhouse systems. For example, variations in shading, canopy density, and ventilation can create heterogeneous microclimates, leading to localized differences in transpiration demand. By incorporating both VPD and radiation into control algorithms, it becomes possible to address such variability and optimize water distribution at finer scales.

From an engineering perspective, the coupling of VPD with radiation transforms irrigation control from a simple threshold-based system into a multi-variable optimization problem. Advanced control strategies may involve the use of model predictive control (MPC), where future environmental conditions are predicted and irrigation decisions are optimized accordingly. Such approaches require accurate models of transpiration that integrate both energy balance and vapor transport processes.

Moreover, the integration of VPD and radiation is essential for addressing the challenges posed by climate variability and energy efficient greenhouse operation. In high tech greenhouses, climate control strategies such as shading, cooling, and ventilation directly influence both radiation and VPD, creating feedback loops that affect transpiration and irrigation demand. For instance, shading reduces radiation and thus transpiration, but it may also increase relative humidity, thereby reducing VPD. Understanding these interactions is critical for designing coordinated control strategies that optimize both water and energy use.

In this context, the coupling of VPD with radiation can be viewed as a cornerstone of next-generation irrigation systems, where water application is dynamically adjusted based on a comprehensive understanding of plant environment interactions. Such systems move beyond simplistic control rules toward integrated decision-making frameworks that account for multiple environmental drivers and their interactions.

In conclusion, while VPD provides a powerful indicator of atmospheric demand, its effective use in irrigation management depends on its integration with radiation and energy balance considerations. The interplay between these variables governs transpiration at both physical and physiological levels, necessitating mult dimensional control strategies for optimal water management. The incorporation of radiation-based metrics such as DLI into VPD-driven irrigation systems represents a critical step toward achieving this integration, enabling more accurate, efficient, and sustainable greenhouse production systems.

7. Feedback Mechanisms: Toward Closed-Loop Irrigation Systems

The integration of feedback mechanisms represents a critical step in the evolution of irrigation systems from open-loop to closed-loop control architectures. In open-loop systems, irrigation decisions are based solely on environmental inputs, without considering the actual response of the plant–soil system. While effective under stable conditions, such systems are vulnerable to errors arising from sensor inaccuracies or environmental variability.

Closed loop systems address these limitations by incorporating feedback from the root zone, typically in the form of drainage volume, substrate moisture, or electrical conductivity (EC). These measurements provide direct information about the effectiveness of irrigation events, enabling continuous adjustment of control parameters.

Zhang et al. (2021) demonstrated that co-regulation of atmospheric demand (VPD) and soil water supply significantly improves irrigation efficiency and sustainability. This dual-control approach ensures that water application is aligned with both plant demand and substrate conditions, reducing the risk of over-irrigation and nutrient leaching.

Your system's integration of drainage-based feedback reflects this advanced control philosophy, enabling adaptive responses to deviations in system performance. Such systems represent the foundation of next-generation irrigation technologies, where decision making is continuously refined through real time data.

8. Empirical Evidence and System Performance

A substantial body of experimental research supports the effectiveness of VPD-based irrigation systems across a wide range of crops and environmental conditions. Zhang et al. (2017) demonstrated that regulating VPD in greenhouse tomato production leads to significant improvements in water productivity, with optimized conditions reducing water consumption while maintaining or increasing yield.

Similarly, Song et al. (2022) reported that combining VPD regulation with soil moisture control enhances both plant growth and water-use efficiency. Their findings indicate that VPD based strategies are particularly effective when integrated with complementary control variables, reinforcing the importance of multi parameter irrigation systems.

Nikolaou et al. (2021) further showed that optimizing VPD conditions improves both energy and water efficiency in Mediterranean greenhouse systems, highlighting the broader sustainability benefits of VPD based control. Yu et al. (2023) provided additional evidence that VPD regulation influences not only water use but also plant physiological processes, including photosynthesis and stomatal behavior.

These results collectively demonstrate that VPD based irrigation systems offer a robust and scalable solution for improving greenhouse productivity and resource efficiency.

9. Limitations and Future Research Directions

Despite its advantages, VPD based irrigation is not without limitations. One of the primary challenges lies in the accurate measurement of environmental variables. Errors in temperature or relative humidity measurements can lead to significant inaccuracies in VPD calculation, potentially resulting in suboptimal irrigation decisions.

Additionally, VPD does not fully capture plant specific responses or root-zone heterogeneity. Factors such as root distribution, substrate properties, and plant genotype can influence water uptake independently of atmospheric conditions. As a result, VPD based systems must be complemented by additional measurements to achieve optimal performance.

Future research is likely to focus on integrating VPD with advanced modeling techniques, including machine learning and artificial intelligence.

These approaches can capture complex, nonlinear interactions between environmental variables and plant responses, enabling predictive irrigation strategies that anticipate future conditions.

The development of digital twins virtual representations of greenhouse systems represents another promising direction, allowing for real-time simulation and optimization of irrigation strategies. Combined with IoT technologies, such systems have the potential to revolutionize greenhouse management.

10. Conclusion

The integration of VPD into greenhouse irrigation systems represents a paradigm shift toward plant-centered water management. By aligning irrigation with transpiration demand, these systems overcome the limitations of traditional approaches and provide a foundation for more efficient and sustainable agricultural production.

The framework presented here demonstrates how physiological principles can be translated into practical engineering solutions, highlighting the importance of interdisciplinary approaches in modern agriculture. As technology continues to advance, VPD based irrigation systems are expected to play an increasingly central role in the development of smart greenhouse systems.

References

Amitrano, C., Arena, C., Rouphael, Y., De Pascale, S., and De Micco, V. (2019). Vapour pressure deficit: The hidden driver behind plant morphophysiological traits in controlled environments. *Annals of Applied Biology*, 175(3), 313–325. https://doi.org/10.1111/aab.12544

Choi, Y. B., & Shin, J. H. (2020). Development of a transpiration model for precise irrigation control in tomato cultivation. *Scientia Horticulturae,* 267, 109358.

Ghiat, I., Mackey, H. R., and Al-Ansari, T. (2021). A review of evapotranspiration measurement models. *Water*, 13(18), 2523, 1–34. https://doi.org/10.3390/w13182523

Grossiord, C., Buckley, T. N., Cernusak, L. A., Novick, K. A., Poulter, B., Siegwolf, R. T. W., Sperry, J. S., and McDowell, N. G. (2020). Plant responses to rising vapor pressure deficit. *New Phytologist*, 226(6), 1550–1566. https://doi.org/10.1111/nph.16485

He, J., Ma, L., Li, W., Zhu, C., Liu, M., and Li, J. (2025). VPD-driven irrigation alters transpiration dynamics. *Journal of Plant Growth Regulation*. https://doi.org/10.1007/s00344-024-11461-1

Jo, W. J., and Shin, J. H. (2021). Development of a transpiration model for precise irrigation control in greenhouse tomato cultivation. *Plant Physiology and Biochemistry*, 162, 362–371. https://doi.org/10.1016/j.scienta.2020.109358

Katsoulas, N., and Stanghellini, C. (2019). Modelling crop transpiration in greenhouses: Different models for different applications. *Agronomy*, 9(7), 392, 1–20. https://doi.org/10.3390/agronomy9070392

López, J., Way, D. A., and Sadok, W. (2021). Systemic effects of rising atmospheric vapor pressure deficit on plant physiology and productivity. *Global Change Biology*, 27(9), 1704–1720. https://doi.org/10.1111/gcb.15548

Lu, N., Nukaya, T., Kamimura, T., Zhang, D., Kurimoto, I., Takagaki, M., ... and Yamori, W. (2015). Control of vapor pressure deficit (VPD) in greenhouse enhanced tomato growth and productivity during the winter season. *Scientia Horticulturae*, 197, 17-23.Medrano, E., Lorenzo, P., Sánchez-Guerrero, M. C., and Montero, J. I. (2005). Evaluation and modelling of greenhouse cucumber transpiration. *Scientia Horticulturae*, 105(3), 343–356. https://doi.org/10.1016/j.scienta.2005.01.031

Medrano, E., Lorenzo, P., Sánchez-Guerrero, M. C., and Montero, J. I. (2005). Evaluation and modelling of greenhouse cucumber-crop transpiration under high and low radiation conditions. *Scientia Horticulturae*, 105(2), 163-175.

Nikolaou, G., Neocleous, D., Christou, A., Polycarpou, P., and Kittas, C. (2021). Energy and water-related parameters in greenhouse crops. *Horticulturae*, 7(12), 521, 1–23. https://doi.org/10.3390/horticulturae7120521

Sánchez, J. A., Rodriguez, F., Guzmán, J. L., and Arahal, M. R. (2012). Virtual sensors for designing irrigation controllers in greenhouses. *Sensors*, 12(11), 15244-15266.

Shamshiri, R. R., Jones, J. W., Thorp, K. R., Ahmad, D., Man, H. C., and Taheri, S. (2018). Review of optimal temperature, humidity, and vapor pressure deficit for greenhouse tomato production. *International Agrophysics*, 32(2), 287–302. https://doi.org/10.1515/intag-2017-0005

Song, X., Miao, L., Jiao, X., Ibrahim, M., and Li, J. (2022). Regulating VPD and soil moisture improves greenhouse crop productivity. *Horticulturae*, 8(2), 147, 1–16. https://doi.org/10.3390/horticulturae8020147

Soussi, M., Chaibi, M. T., Buchholz, M., and Saghrouni, Z. (2022). Climate control and cooling systems in greenhouses. *Agronomy*, 12(3), 626, 1–25. https://doi.org/10.3390/agronomy12030626

Villagran, E., Toro-Tobón, G., Velázquez, F., and Estrada-Bonilla, G. (2024). IoT-based greenhouse climate control systems. *AgriEngineering*, 6(4), 227–245. https://doi.org/10.3390/agriengineering6040227

Yu, X., Zhang, Y., Zhao, X., and Li, J. (2023). Systemic effects of vapor pressure deficit on greenhouse vegetable physiology. *Vegetable Research*, 3, 20, 1–15. https://doi.org/10.48130/VR-2023-0020

Yuan, W., Zheng, Y., Piao, S., Ciais, P., Lombardozzi, D., Wang, Y., Ryu, Y., Chen, G., Dong, W., Hu, Z., Jain, A., et al. (2019). Increased atmospheric vapor pressure deficit reduces global vegetation growth. Science Advances, 5(8), eaax1396, 1–8. https://doi.org/10.1126/sciadv.aax1396

Zhang, D., Du, Q., Zhang, Z., Jiao, X., Song, X., and Li, J. (2017). Vapour pressure deficit control and water productivity. *Scientific Reports*, 7, 43461, 1–12. https://doi.org/10.1038/srep43461

Zhang, J., Ding, J., Ibrahim, M., Jiao, X., Song, X., Bai, P., and Li, J. (2021). Effects of the interaction between vapor-pressure deficit and potassium on the photosynthesis system of tomato seedlings under low temperature. *Scientia Horticulturae*, 283, 110089.

Chapter 9

SMART IRRIGATION SYSTEMS INTEGRATING IOT, WIRELESS SENSOR NETWORKS, AND MACHINE LEARNING FOR SUSTAINABLE WATER MANAGEMENT IN AGRICULTURE

***Uğur KEKEÇ*[1]**
***Burçak KAPUR*[2]**

---

[1] Dr. Öğr. Gör., University of Cukurova, Yumurtalık Vocational School, Department of Organic Farming, Adana/Turkey, https://orcid.org/0000-0003-1321-9135

[2] Prof. Dr., University of Cukurova, Faculty of Agriculture, Department of Agricultural Structures and Irrigation, Adana/Türkiye, https://orcid.org/0000-0001-6131-4458 ***Corresponding Author:** Uğur KEKEÇ, ukekec@cu.edu.tr

1. Introduction

Agriculture is the largest consumer of freshwater resources worldwide, accounting for nearly 70% of total global water withdrawals. This dependency has become increasingly critical under the combined pressures of rapid population growth, climate change, and the need for sustainable food production systems. It is projected that the global population will reach approximately 10 billion by 2050, requiring a significant increase in agricultural productivity to meet food demand (Ndunagu et al., 2022). Consequently, efficient water management has emerged as a fundamental challenge in modern agriculture.

Traditional irrigation practices, including surface and basin irrigation systems, continue to be widely used due to their simplicity and relatively low initial cost. However, these systems are typically characterized by low application efficiency, resulting in substantial water losses through runoff, deep percolation, and evaporation (Pramanik et al., 2022). Moreover, irrigation decisions are often based on subjective judgment rather than real-time data, leading to either excessive or insufficient water application. Such inefficiencies not only waste valuable water resources but also negatively impact crop yield and soil quality.

In recent years, the concept of smart irrigation systems (SIS) has gained prominence as part of the broader framework of Agriculture 4.0. These systems leverage emerging technologies such as the Internet of Things (IoT), wireless sensor networks (WSNs), and machine learning (ML) to enable data-driven and automated irrigation management. By continuously monitoring environmental parameters such as soil moisture, temperature, humidity, and rainfall, smart irrigation systems can make real-time decisions regarding irrigation scheduling and water application rates (Ndunagu et al., 2022).

The integration of IoT technologies has significantly enhanced the capability to collect, transmit, and analyze agricultural data. IoT-based irrigation systems typically consist of distributed sensor nodes, communication modules, cloud-based data storage platforms, and user interfaces that allow remote monitoring and control. For instance, systems utilizing cloud platforms such as ThingSpeak enable real-time data visualization, analysis, and decision-making through web or mobile applications (Ndunagu et al., 2022). These technologies reduce the need for manual intervention and improve overall system efficiency.

In parallel, machine learning techniques have been increasingly incorporated into smart irrigation systems to improve decision-making accuracy. Algorithms such as K-Nearest Neighbors (KNN), Support Vector Machines

(SVM), and neural networks are used to analyze historical and real-time data to predict crop water requirements and optimize irrigation schedules. Studies have demonstrated that ML-based models can achieve high prediction accuracy, thereby enhancing water use efficiency and reducing resource wastage (Tace et al., 2022).

Another key component of smart irrigation systems is sensor-based automation. Soil moisture sensors, temperature sensors, and weather data inputs are used to determine the exact water requirements of crops. Once predefined threshold values are reached, the system automatically activates or deactivates irrigation through pumps, valves, or gates. This approach ensures precise water application, minimizes losses, and improves crop performance (Kansara et al., 2015).

Despite these advancements, several challenges remain in the implementation of smart irrigation systems. These include high initial costs, sensor calibration requirements, energy constraints, and the need for reliable communication infrastructure. Additionally, system performance can vary depending on environmental conditions and regional characteristics, necessitating site-specific adaptation and optimization.

This chapter aims to provide a comprehensive overview of smart irrigation systems by examining the integration of IoT technologies, wireless sensor networks, and machine learning approaches. It further explores system architectures, operational mechanisms, performance improvements, and existing challenges, offering insights into the future development of intelligent irrigation solutions for sustainable agriculture.

2. Water Scarcity and Irrigation Challenges

Water scarcity has become one of the most critical constraints affecting agricultural sustainability in the 21st century. Increasing population pressure, climate variability, and inefficient water management practices have intensified competition for limited freshwater resources. Agriculture, as the dominant water-consuming sector, is particularly vulnerable to these pressures, necessitating a transition toward more efficient and adaptive irrigation practices (Ndunagu et al., 2022).

Globally, irrigation systems are responsible for a substantial proportion of freshwater withdrawals, yet a significant fraction of this water is lost due to inefficiencies in application and management. Traditional irrigation methods, especially surface irrigation techniques such as basin irrigation, often exhibit low application efficiency due to deep percolation, runoff losses, and non-uniform water distribution (Pramanik et al., 2022). These inefficiencies not only reduce water productivity but also contribute to soil degradation and nutrient leaching.

One of the fundamental challenges in irrigation management is the mismatch between water application and crop water requirements. In many agricultural systems, irrigation scheduling is still based on fixed calendars or farmer experience rather than real-time field conditions. This often leads to over-irrigation or under-irrigation, both of which negatively affect crop productivity and water use efficiency (Kansara et al., 2015).

Additionally, irrigation systems often require significant labor and energy inputs. Conventional systems depend heavily on manual operation, including switching pumps on and off and regulating water flow. This increases operational costs and introduces human error, reducing overall system performance (Kansara et al., 2015).

Climate change further complicates irrigation management by introducing variability in rainfall patterns, increasing temperatures, and more frequent extreme weather events. These factors directly influence soil moisture dynamics and crop water demand, making traditional irrigation approaches increasingly unreliable (Ndunagu et al., 2022).

Another important challenge is the spatial variability of soil properties within agricultural fields. Differences in soil texture, structure, and infiltration capacity can lead to uneven water distribution, even under controlled irrigation conditions. Without precise monitoring and control, some areas may receive excess water while others remain under-irrigated (Pramanik et al., 2022).

To overcome these challenges, there has been a growing interest in automated and intelligent irrigation systems. These systems utilize sensors, communication technologies, and control mechanisms to optimize water application in real time. By delivering water only when and where it is needed, such systems can significantly improve water use efficiency and crop productivity (Ndunagu et al., 2022).

However, despite their advantages, the adoption of smart irrigation technologies is still limited in many regions due to economic, technical, and infrastructural constraints. Addressing these barriers is essential for achieving sustainable water management in agriculture.

3. Evolution from Conventional to Smart Irrigation

Irrigation practices have undergone significant transformation over time, evolving from traditional, labor-intensive methods toward highly automated and data driven systems. This transition has been primarily driven by the increasing need to enhance water use efficiency, reduce labor dependency, and improve crop productivity under conditions of water scarcity and climate variability.

Conventional irrigation systems, including surface, sprinkler, and drip irrigation, have historically formed the backbone of agricultural water management. Surface irrigation methods, such as basin and furrow irrigation, are among the oldest and most widely used systems due to their simplicity and low capital investment requirements. However, these systems often suffer from low application efficiency, primarily due to water losses through runoff, deep percolation, and nonuniform distribution (Pramanik et al., 2022). Similarly, sprinkler systems improve water distribution but are still prone to evaporation losses and require substantial energy inputs (Howell, 2001).

Drip irrigation represents a significant advancement over conventional methods by delivering water directly to the root zone in controlled quantities. This method minimizes evaporation and runoff losses and improves water use efficiency. Studies have shown that drip irrigation can significantly increase water productivity and crop yield compared to traditional methods (Postel et al., 2001). Despite these advantages, drip systems still rely heavily on proper scheduling and management to achieve optimal performance.

The major limitation of conventional irrigation systems lies in their reliance on static scheduling and manual operation. In most cases, irrigation decisions are based on fixed time intervals or farmer experience rather than real-time field conditions. This often results in inefficient water application, either exceeding or failing to meet crop water requirements (Kansara et al., 2015). Additionally, manual control of irrigation infrastructure increases labor requirements and introduces variability in system performance.

The emergence of automated irrigation systems marked the first step toward intelligent water management. These systems utilize basic control mechanisms, such as timers, soil moisture thresholds, and simple feedback loops, to regulate irrigation processes. Sensor based automation enables the system to respond dynamically to changes in soil moisture conditions, thereby improving water use efficiency and reducing human intervention (Kansara et al., 2015). However, early automation systems were limited by their lack of connectivity and inability to process large volumes of data (Table 1).

Table 1. *Comparison of conventional and smart irrigation systems in terms of key performance indicators*

Criteria	Conventional Irrigation Systems	Smart Irrigation Systems
Water use efficiency	Low due to runoff and deep percolation losses	High due to precise and controlled water application
Irrigation scheduling	Fixed schedule or farmer experience	Real-time, sensor-based and data-driven
Labor requirement	High (manual operation required)	Low (automated control systems)
Energy consumption	Moderate to high, often inefficient	Optimized through intelligent control
Water losses	High (evaporation, leakage, runoff)	Significantly reduced
System control	Manual or semi-automatic	Fully automated and remotely controllable
Adaptability to environment	Low	High (responsive to soil and weather conditions)
Data usage	Minimal or none	Continuous monitoring and data analytics
Initial cost	Low	Moderate to high
Long-term efficiency	Low	High (resource optimization and yield improvement)

Source: Adapted from Howell (2001), Postel et al. (2001), Pramanik et al. (2022), and Ndunagu et al. (2022).

The integration of wireless sensor networks (WSNs) introduced a new dimension to irrigation management by enabling real-time monitoring of environmental parameters across spatially distributed locations. WSNs consist of interconnected sensor nodes that collect data on soil moisture, temperature, humidity, and other variables, transmitting this information to a central system for analysis and control (Ndunagu et al., 2022). This development allowed for more precise and site-specific irrigation practices, addressing the issue of spatial variability within agricultural fields.

Building upon WSN technology, the adoption of the Internet of Things (IoT) has further revolutionized irrigation systems. IoT based irrigation systems integrate sensors, communication technologies, cloud computing, and user interfaces to create fully connected and remotely controllable systems. These systems enable continuous data collection, storage, and analysis, facilitating real-time decision-making and automation (Ndunagu et al., 2022). Farmers can monitor field conditions and control irrigation processes through mobile applications or web platforms, significantly improving operational efficiency.

The most recent stage in the evolution of irrigation systems involves the incorporation of machine learning and data analytics. Unlike traditional rule-based systems, machine learning models can analyze historical and real-time data to identify patterns and predict crop water requirements. Algorithms such as K-Nearest Neighbors, Support Vector Machines, and neural networks have been successfully applied to optimize irrigation scheduling and improve system performance (Tace et al., 2022). These models enhance decision-making accuracy and enable adaptive irrigation strategies that respond to changing environmental conditions.

Furthermore, modern smart irrigation systems integrate multiple data sources, including weather forecasts, soil conditions, and crop characteristics, to provide a holistic approach to water management. This integration allows for predictive irrigation scheduling, where irrigation decisions are made not only based on current conditions but also on anticipated future scenarios. Such systems significantly reduce water wastage and improve crop productivity.

Despite these advancements, the transition from conventional to smart irrigation systems is not uniform across regions. Factors such as economic constraints, lack of technical expertise, and limited access to infrastructure continue to hinder adoption, particularly in developing countries. Nevertheless, the long-term benefits of smart irrigation systems, including water savings, increased yield, and reduced labor costs, make them a critical component of sustainable agricultural practices.

In summary, the evolution of irrigation systems reflects a shift from manual, experience-based practices toward automated, data driven, and intelligent systems. This transformation is essential for addressing the challenges of water scarcity, climate change, and increasing food demand, and it lays the foundation for the development of fully autonomous agricultural systems in the future.

4. IoT and Wireless Sensor Networks in Agriculture

The integration of the Internet of Things (IoT) and Wireless Sensor Networks (WSNs) into agricultural systems has fundamentally transformed irrigation management by enabling real-time monitoring, data acquisition, and automated decision-making. These technologies constitute the backbone of modern smart irrigation systems, providing the necessary infrastructure for precision agriculture and efficient resource utilization.

A Wireless Sensor Network (WSN) is composed of spatially distributed sensor nodes capable of sensing environmental parameters, processing data, and communicating wirelessly with other nodes or central systems. In agricultural applications, WSNs are commonly used to monitor soil moisture, temperature, humidity, and other field conditions, allowing for continuous assessment of crop water requirements (Ndunagu et al., 2022). These sensor nodes are typically deployed across different locations within a field to capture spatial variability, which is critical for site-specific irrigation management.

The effectiveness of WSNs lies in their ability to collect high-resolution data from the field and transmit it to a central processing unit. This data can then be analyzed to support irrigation decisions, reducing uncertainty and improving water use efficiency. For example, soil moisture sensors placed at different depths and positions within the field provide valuable insights into root zone conditions, enabling more precise irrigation scheduling (Pramanik et al., 2022).

The emergence of IoT has significantly enhanced the capabilities of WSN-based systems by enabling connectivity between physical devices and digital platforms. IoT can be defined as a network of interconnected devices equipped with sensors, software, and communication technologies that allow them to collect and exchange data over the internet (Ndunagu et al., 2022). In the context of irrigation, IoT facilitates the integration of sensors, actuators, cloud computing, and user interfaces into a unified system.

A typical IoT-based irrigation system consists of several key components: (i) sensing units, (ii) communication modules, (iii) data processing and storage platforms, and (iv) control units. Sensing units include soil moisture sensors, temperature sensors, rainfall sensors, and humidity sensors that collect real-time environmental data. Communication modules, such as GSM, Wi-Fi, LoRa, and ZigBee, are used to transmit this data to cloud-based platforms or local servers (Kansara et al., 2015).

Cloud computing platforms play a central role in IoT-based irrigation systems by providing data storage, processing, and visualization capabilities. Platforms such as ThingSpeak allow users to monitor environmental conditions, analyze trends, and make informed decisions through web or mobile applications (Ndunagu et al., 2022). These platforms also enable remote access and control, allowing farmers to manage irrigation systems from virtually any location.

Another critical component of IoT-based systems is the actuator mechanism, which includes pumps, valves, and control gates. These components receive commands from the control unit and execute irrigation actions based on predefined conditions or real-time data analysis. For instance, when soil moisture levels fall below a specified threshold, the system can automatically activate the irrigation process and stop it once optimal conditions are achieved (Kansara et al., 2015).

The communication architecture of IoT-based irrigation systems can vary depending on the scale and complexity of the application. Short-range communication technologies such as Wi-Fi and Bluetooth are commonly used in small-scale systems, while long-range communication technologies such as LoRa and GSM are more suitable for large agricultural fields (Pramanik et al., 2022). Each communication protocol presents trade-offs in terms of energy consumption, data transmission range, and system cost.

One of the key advantages of IoT and WSN integration is the ability to implement real-time and automated irrigation management. By continuously monitoring environmental conditions and dynamically adjusting irrigation schedules, these systems significantly improve water use efficiency and reduce labor requirements. Additionally, the use of data analytics enables predictive capabilities, allowing systems to anticipate irrigation needs based on historical patterns and weather forecasts (Tace et al., 2022).

However, the implementation of IoT-based irrigation systems is associated with several challenges. These include energy constraints in sensor nodes, data transmission reliability, network scalability, and system maintenance. Sensor nodes often operate on limited power sources, such as batteries or solar panels, which necessitates energy-efficient communication protocols and data processing techniques (Ndunagu et al., 2022). Furthermore, ensuring data accuracy and system reliability is critical for effective decision-making.

Security and data privacy also represent emerging concerns in IoT-based agricultural systems. As these systems rely on internet connectivity and cloud platforms, they are potentially vulnerable to cyber threats and unauthorized access. Therefore, the development of secure communication protocols and data protection mechanisms is essential for the widespread adoption of IoT technologies in agriculture.

In conclusion, the integration of IoT and WSN technologies has revolutionized irrigation management by enabling real-time monitoring, automated control, and data driven decision making. These systems provide a robust framework for precision agriculture, improving water use efficiency and crop productivity while reducing labor and operational costs. Despite existing challenges, ongoing technological advancements are expected to further enhance the performance and accessibility of IoT-based irrigation systems.

5. Soil Moisture Sensing and Automation Mechanisms

Soil moisture sensing constitutes the core component of smart irrigation systems, as it directly reflects the water availability in the root zone and determines the timing and quantity of irrigation. Accurate measurement and interpretation of soil moisture data enable precise water application, thereby improving irrigation efficiency and crop performance.

Soil moisture sensors operate based on different physical principles, including capacitance, resistance, and dielectric properties of the soil. Among these, capacitance based sensors are widely used in smart irrigation systems due to their low cost, durability, and compatibility with microcontroller-based platforms (Pramanik et al., 2022). These sensors estimate soil moisture by measuring the dielectric constant, which varies significantly between water and soil particles. As soil water content increases, the dielectric constant increases, allowing indirect quantification of moisture levels.

In IoT-based irrigation systems, soil moisture sensors are typically integrated with microcontrollers and communication modules to enable continuous monitoring and data transmission. The collected data are processed either locally or through cloud platforms, allowing real-time assessment of soil water status and automated irrigation control (Ndunagu et al., 2022). This integration enables dynamic irrigation scheduling based on actual field conditions rather than predefined time intervals.

One of the most critical aspects of soil moisture sensing is sensor placement, which significantly influences the accuracy and reliability of irrigation decisions. Soil moisture distribution varies both vertically and horizontally within the field due to differences in soil properties, infiltration rates, and root distribution. Therefore, proper placement of sensors is essential to capture representative soil moisture conditions.

Experimental studies have demonstrated that sensor placement at different depths and field locations can improve irrigation efficiency. For example, sensors placed at varying depths within the root zone (e.g., 7.5 cm, 15 cm, and 37.5 cm) and at different distances along the field (e.g., 25%, 50%, and 75% of field length) provide a more comprehensive understanding of water movement and distribution in the soil profile (Pramanik et al., 2022). Such configurations allow the system to detect both surface drying and deeper moisture retention, enabling more accurate irrigation control.

In addition to placement, threshold-based control mechanisms are commonly used in automated irrigation systems. These systems operate by defining upper and lower soil moisture limits. When soil moisture falls below a predefined threshold, the system activates irrigation, and when the desired moisture level is reached, irrigation is stopped. This simple yet effective control logic reduces water wastage and ensures optimal soil moisture conditions for plant growth (Kansara et al., 2015).

Advanced systems further enhance this approach by integrating multiple environmental parameters, such as temperature, humidity, and rainfall, into the decision making process. For instance, irrigation may be delayed if rainfall is detected or predicted, even if soil moisture levels are below the threshold. Such multi-parameter control strategies improve system efficiency and prevent unnecessary irrigation (Ndunagu et al., 2022).

Automation mechanisms in smart irrigation systems rely on actuators such as pumps, solenoid valves, and automated gates. These components are controlled by microcontrollers, which receive input from sensors and execute irrigation commands accordingly. The automation process typically follows a feedback loop: sensors collect data, the system evaluates conditions based on predefined rules or models, and actuators respond by adjusting water flow (Kansara et al., 2015).

Recent advancements have introduced adaptive and intelligent control systems that go beyond fixed threshold values. These systems utilize machine learning algorithms and data analytics to dynamically adjust irrigation thresholds based on historical data, crop type, and environmental conditions. Such adaptive systems can optimize water use efficiency while maintaining optimal soil moisture conditions for plant growth (Tace et al., 2022).

Another important consideration in soil moisture sensing is sensor calibration and accuracy. Soil type, bulk density, salinity, and temperature can influence sensor readings, leading to measurement errors if not properly calibrated. Therefore, calibration against standard methods, such as gravimetric soil moisture measurement, is essential to ensure reliable data (Pramanik et al., 2022). Without proper calibration, automated irrigation systems may make incorrect decisions, resulting in inefficient water use.

Energy consumption is also a critical factor in sensor-based irrigation systems, particularly in remote or large-scale agricultural fields. Sensors and communication modules often rely on battery or solar power, necessitating energy-efficient designs and communication protocols. Techniques such as intermittent data transmission and low-power communication technologies can help extend system lifespan and reduce maintenance requirements (Ndunagu et al., 2022).

In summary, soil moisture sensing and automation mechanisms form the foundation of smart irrigation systems. Accurate sensor measurements, proper placement strategies, and effective control mechanisms enable precise irrigation management, reducing water losses and improving crop productivity. The integration of advanced sensing technologies with automated control systems represents a significant step toward sustainable and efficient agricultural water management.

6. Machine Learning, Integrated Systems, Performance, Challenges and Future Trends in Smart Irrigation

The rapid advancement of smart irrigation systems has been significantly supported by the integration of machine learning (ML), data analytics, and intelligent decision support mechanisms. These technologies enhance the capability of irrigation systems to process large volumes of data and generate optimized irrigation strategies under dynamic environmental conditions.

Machine learning plays a critical role in transforming traditional rule-based irrigation systems into adaptive and predictive systems. Unlike conventional threshold-based control mechanisms, ML algorithms can learn from historical and real time datasets to identify complex relationships between environmental variables and crop water requirements. Algorithms such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Random Forest models have been widely applied in irrigation scheduling and water demand prediction (Tace et al., 2022; Jones et al., 2003). These approaches enable the estimation of soil moisture trends, evapotranspiration rates, and irrigation timing with high accuracy.

One of the key advantages of machine learning based irrigation systems is their ability to incorporate multiple data sources. These include soil moisture data, temperature, humidity, solar radiation, and weather forecasts. The integration of meteorological data allows predictive irrigation scheduling, where irrigation decisions are made based not only on current soil conditions but also on expected climatic variations (Allen et al., 1998). This predictive capability significantly reduces water wastage and improves crop productivity.

The integration of IoT, WSN, and ML technologies has led to the development of fully integrated smart irrigation architectures. These systems typically follow a layered structure consisting of sensing, communication, processing, and actuation layers. The sensing layer collects environmental data using distributed sensors, while the communication layer transmits this data through wireless protocols such as LoRa, GSM, or Wi-Fi. The processing layer, often cloud-based, applies machine learning algorithms and data analytics to generate irrigation decisions. Finally, the actuation layer executes these decisions through pumps, valves, or automated gates (Ndunagu et al., 2022).

Such integrated systems enable real-time monitoring and control, providing farmers with the ability to manage irrigation remotely through mobile or web applications. Cloud based platforms further enhance system functionality by enabling data storage, visualization, and advanced analytics. These features facilitate long-term analysis of irrigation performance and support data-driven decision-making (Tace et al., 2022).

The performance of smart irrigation systems is typically evaluated based on several criteria, including water use efficiency, crop yield, energy consumption, and economic feasibility. Studies have shown that automated irrigation systems can reduce water consumption by 20% to 50% compared to conventional methods, depending on system design and environmental conditions (FAO, 2012). In addition, improved irrigation scheduling contributes to increased crop yields and better quality produce by maintaining optimal soil moisture levels.

From an economic perspective, smart irrigation systems can reduce labor costs and optimize resource utilization. Automated systems eliminate the need for manual operation of irrigation infrastructure, thereby reducing labor requirements and minimizing human error (Kansara et al., 2015). However, the initial investment cost of these systems can be relatively high, which may limit their adoption, particularly among smallholder farmers.

Despite their advantages, smart irrigation systems face several technical and practical challenges. One of the primary challenges is the reliability and accuracy of sensor data. Soil moisture sensors are influenced by factors such as soil type, salinity, and temperature, which may affect measurement accuracy if not properly calibrated (Pramanik et al., 2022). Additionally, sensor malfunction or communication failure can lead to incorrect irrigation decisions.

Energy consumption is another significant concern, especially for systems deployed in remote areas. Sensor nodes and communication modules often rely on battery or solar power, requiring energy-efficient system design. Low-power communication protocols and intermittent data transmission strategies are commonly used to address this issue (Ndunagu et al., 2022).

Data management and system scalability also present challenges in large-scale applications. As the number of sensors increases, the volume of data generated can become difficult to manage and process efficiently. Advanced data processing techniques and cloud computing solutions are required to handle such large datasets effectively (Jones et al., 2003).

Security and data privacy have emerged as important considerations in IoT-based irrigation systems. Since these systems rely on internet connectivity and cloud platforms, they are vulnerable to cyber threats and unauthorized access. Ensuring secure data transmission and implementing robust authentication mechanisms are essential for system reliability.

Looking forward, the future of smart irrigation systems lies in the integration of emerging technologies such as artificial intelligence, big data analytics, and digital twins. Digital twin technology, which involves creating virtual replicas of physical systems, can be used to simulate irrigation scenarios and optimize system performance under different conditions. Similarly, the integration of remote sensing technologies and satellite data can enhance large-scale irrigation management by providing spatially distributed information on crop and soil conditions.

Another promising direction is the development of fully autonomous irrigation systems capable of self-learning and adaptive decision-making. These systems will be able to continuously update their models based on new data, improving their performance over time without human intervention. Such advancements are expected to play a crucial role in achieving sustainable water management and ensuring food security in the face of global challenges.

In summary, the integration of machine learning, IoT, and sensor based technologies has significantly advanced irrigation systems from simple automation to intelligent decision support systems. While challenges related to cost, data reliability, and infrastructure remain, ongoing technological developments are expected to enhance system performance and accessibility, making smart irrigation a key component of future agricultural systems.

7. Conclusion

The increasing pressure on global water resources, driven by population growth, climate change, and the need for sustainable food production, has made efficient irrigation management a critical priority in modern agriculture. Traditional irrigation practices, although widely adopted, are often characterized by low water use efficiency, high labor requirements, and limited adaptability to dynamic environmental conditions. These limitations have necessitated the transition toward more advanced, intelligent irrigation systems.

This chapter has demonstrated that the integration of IoT, wireless sensor networks, and machine learning technologies represents a transformative approach to irrigation management. By enabling real-time monitoring of environmental parameters such as soil moisture, temperature, and weather conditions, smart irrigation systems provide a data driven framework for optimizing water application. The use of sensor-based automation ensures that irrigation is applied precisely when and where it is needed, significantly reducing water losses and improving crop productivity (Pramanik et al., 2022).

The incorporation of machine learning techniques further enhances the capabilities of these systems by enabling predictive and adaptive decision-making. Unlike conventional rule based approaches, machine learning models can analyze complex interactions among environmental variables and generate optimized irrigation strategies based on both historical and real-time data (Tace et al., 2022). This advancement marks a shift from reactive irrigation practices toward proactive and intelligent water management.

Another important contribution of smart irrigation systems is their ability to address spatial variability within agricultural fields. Through the deployment of distributed sensor networks, these systems capture variations in soil and environmental conditions, allowing for site-specific irrigation management. This capability is particularly important in improving overall system efficiency and ensuring uniform crop growth.

Despite these advantages, several challenges remain in the widespread adoption of smart irrigation technologies. Issues related to sensor accuracy, system calibration, energy consumption, and data reliability can affect system performance. Additionally, economic constraints and limited technical expertise may hinder the implementation of such systems, particularly in developing regions (Ndunagu et al., 2022). Addressing these challenges requires continued research, technological innovation, and the development of cost-effective and user-friendly solutions.

Future developments in smart irrigation are expected to focus on the integration of advanced technologies such as artificial intelligence, big data analytics, and digital twin systems. These innovations will enable more sophisticated modeling and simulation of irrigation processes, allowing for further optimization of water use. Additionally, the integration of remote sensing and satellite data is likely to expand the applicability of smart irrigation systems to larger spatial scales.

In conclusion, smart irrigation systems represent a crucial step toward achieving sustainable agricultural water management. By combining sensing technologies, automation, and intelligent decision-making, these systems offer significant potential to enhance water use efficiency, reduce environmental impact, and increase agricultural productivity. As technological advancements continue and adoption barriers are addressed, smart irrigation is expected to play a central role in the future of precision agriculture and global food security.

References

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). *Crop evapotranspiration: Guidelines for computing crop water requirements (FAO Irrigation and Drainage Paper No. 56)*. Food and Agriculture Organization (FAO).

FAO. (2012). *Coping with water scarcity: An action framework for agriculture and food security*. Food and Agriculture Organization of the United Nations.

Howell, T. A. (2001). Enhancing water use efficiency in irrigated agriculture. *Agronomy Journal*, 93(2), 281–289. https://doi.org/10.2134/agronj2001.932281x

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., & Ritchie, J. T. (2003). The DSSAT cropping system model. *European Journal of Agronomy*, 18(3–4), 235–265. https://doi.org/10.1016/S1161-0301(02)00107-7

Kansara, K., Zaveri, V., Shah, S., Delwadkar, S., & Jani, K. (2015). Sensor based automated irrigation system with IoT: A technical review. *International Journal of Computer Science and Information Technologies*, 6(6), 5331–5333.

Ndunagu, J. N., Ukhurebor, K. E., Akaaza, M., & Onyancha, R. B. (2022). Development of a wireless sensor network and IoT-based smart irrigation system. *Applied and Environmental Soil Science*, 2022, Article 7678570. https://doi.org/10.1155/2022/7678570

Postel, S. L., Polak, P., Gonzales, F., & Keller, J. (2001). Drip irrigation for small farmers: A new initiative to alleviate hunger and poverty. *Water International*, 26(1), 3–13. https://doi.org/10.1080/02508060108686882

Pramanik, M., Khanna, M., Singh, M., Singh, D. K., Sudhishri, S., Bhatia, A., & Ranjan, R. (2022). Automation of soil moisture sensor-based basin irrigation system. *Smart Agricultural Technology*, 2, 100032. https://doi.org/10.1016/j.atech.2021.100032

Tace, Y., Tabaa, M., Elfilali, S., Leghris, C., Bensag, H., & Renault, E. (2022). Smart irrigation system based on IoT and machine learning. *Energy Reports*, 8, 1025–1036. https://doi.org/10.1016/j.egyr.2022.07.088