American Journal of Advanced Multidisciplinary Innovation and Research (AJAMIR)

E-ISSN: XXXX-XXXX • Website: www.ajamir.com • Email: editor@ajamir.com

Intelligent Irrigation Scheduling Through Local Weather and Soil Integration

Arjun Mehta

Assistant Professor, Punjab Agricultural University, India

Abstract

Efficient irrigation scheduling increasingly depends on the ability to reconcile two forms of information that are often used separately: atmospheric water demand and the actual water status of the crop root zone. Weather-based approaches estimate crop water requirements from meteorological variables, whereas soil-based approaches respond directly to changes in soil moisture. Each method has practical strengths, yet either method used independently can produce avoidable irrigation because short-term rainfall, evapotranspiration, soil water storage, sensor uncertainty, and crop-stage requirements interact dynamically. This study develops and evaluates an intelligent irrigation scheduling framework that integrates local weather observations with root-zone soil moisture information through a confidence-weighted decision algorithm. The framework combines reference evapotranspiration, crop coefficients, effective rainfall, soil water depletion, irrigation-system efficiency, soil-moisture thresholds, and a short-horizon rainfall veto mechanism. Because no field dataset was supplied for the present study, evaluation was conducted using an explicitly labeled synthetic eight-week crop-season scenario rather than presenting simulated observations as empirical field measurements.

Four scheduling strategies were compared: fixed-interval irrigation, weather-based scheduling, soil-moisture-based scheduling, and the proposed integrated weather–soil method. The simulated integrated strategy applied 312 mm of irrigation compared with 420 mm under fixed scheduling, representing a 25.7% reduction in applied irrigation water. It also achieved the highest simulated root-zone moisture-target compliance at 91.1%, the lowest estimated deep-percolation loss at 12 mm, and an irrigation water-use-efficiency proxy of 2.56 kg m^{-3}. The results indicate that local weather and soil integration can improve the timing as well as the quantity of irrigation by reducing unnecessary applications while maintaining favorable root-zone conditions. The proposed architecture is intentionally computationally lightweight and can therefore serve as a foundation for low-cost edge-based irrigation decision systems. Field validation across different crops, soils, climates, sensor configurations, and irrigation technologies remains necessary before operational performance claims can be made.

Keywords: smart irrigation; irrigation scheduling; soil moisture; local weather; evapotranspiration; precision agriculture; water-use efficiency; Internet of Things; decision support; sustainable agriculture

1. Introduction

Water management has become one of the most important operational concerns in irrigated agriculture. The central problem is not simply whether water is available, but whether the correct quantity can be delivered at the correct time and in a form that corresponds to crop demand, soil storage capacity, local weather, and irrigation-system performance. Conventional calendar-based scheduling is easy to operate, but fixed intervals cannot continuously adapt to changes in rainfall, temperature, humidity, radiation, wind, rooting depth, or residual soil water. Consequently, irrigation may occur when the root zone already contains adequate water or may be delayed when rapidly increasing atmospheric demand creates crop stress.

Weather-based scheduling provides a more responsive alternative because meteorological conditions can be translated into reference evapotranspiration and crop evapotranspiration. The FAO-56 framework developed by Allen and colleagues remains a widely established basis for estimating reference evapotranspiration through the standardized Penman–Monteith method. Crop evapotranspiration can subsequently be estimated by applying appropriate crop coefficients.

Weather information alone, however, does not fully represent conditions in the root zone. Two fields experiencing similar atmospheric demand may differ substantially in available water because of soil texture, rooting depth, antecedent rainfall, previous irrigation, drainage, compaction, spatial variability, and management history. Soil-moisture sensing provides information about these field-specific conditions and allows irrigation decisions to respond to the actual water stored within the soil profile.

Recent developments in low-cost sensors, Internet of Things communication, edge computing, and machine-learning-supported forecasting have made higher-frequency irrigation decision making increasingly feasible. Goap and colleagues demonstrated an IoT-oriented smart irrigation architecture using sensor information, weather forecasting, and machine-learning approaches, while Kamienski and colleagues presented an IoT-based precision-irrigation platform designed for scalable water management.

More recent studies have strengthened the case for combining multiple information streams. Preite and Vignali developed a predictive irrigation-management system that aggregated soil, environmental, and weather-forecast information and reported substantial potential water and energy savings in its evaluated setting. Abdelmoneim and colleagues compared soil-moisture-based and weather-based management in drip-irrigated lettuce and reported that the sensor-guided treatment used less irrigation water and achieved higher crop water productivity than the weather-based treatment in their field experiment.

These developments suggest that the most useful irrigation decision may not emerge from selecting either weather-based or soil-based management. A more effective strategy is to integrate both sources while retaining a transparent agronomic decision structure.The present study therefore proposes an intelligent irrigation scheduling framework based on local weather and soil integration. Instead of relying entirely on a complex black-box prediction model, the framework combines a physically interpretable soil-water balance with direct sensor observations and adaptive decision rules. This design is particularly relevant where farm-level computing resources, historical training data, connectivity, or technical support are limited.

The study does not claim results from a completed field experiment. Instead, a reproducible synthetic scenario is used to examine the internal behavior and comparative potential of the proposed method. This distinction is important because simulation results provide methodological evidence but cannot substitute for field validation.

2. Literature Review

2.1 Weather-Based Irrigation Scheduling

Weather-based irrigation scheduling estimates the water consumed by the crop and soil surface and uses this information to determine irrigation requirements. Reference evapotranspiration represents the atmospheric evaporative demand under standardized reference conditions. FAO-56 recommends the Penman–Monteith method as the standardized approach for calculating reference evapotranspiration from meteorological inputs.

Crop evapotranspiration is commonly calculated by multiplying reference evapotranspiration by a crop coefficient representing crop type and development stage. This approach recognizes that crop water demand changes during establishment, vegetative development, midseason, and late-season periods.Weather-based scheduling is attractive because meteorological data can represent changes in atmospheric demand before severe root-zone depletion occurs. A warm, dry, windy day with strong solar radiation can therefore result in a larger estimated crop-water requirement than a cool and humid day.

Nevertheless, inaccuracies may arise when weather stations are distant from the farm, crop coefficients are poorly selected, rainfall distribution is spatially variable, or the soil-water balance has accumulated errors. A calculation may correctly estimate atmospheric water loss but still fail to capture field-specific storage conditions.

2.2 Soil-Moisture-Based Scheduling

Soil-moisture scheduling directly evaluates water available in the root zone. Measurements may be expressed in volumetric water content, gravimetric water content, matric potential, or other soil-water indicators. Sensor-based systems are particularly valuable because they can produce high-frequency measurements without requiring continuous manual sampling.The practical objective is generally to maintain soil water within a desirable range: above a lower threshold associated with unacceptable depletion but below conditions that promote unnecessary drainage, poor aeration, or water loss.

Togneri and colleagues emphasized the value of high-frequency soil-moisture information for forecasting future root-zone conditions and evaluated machine-learning-based soil-moisture forecasting across diverse crop and farm conditions.Teshome and colleagues further examined machine- and deep-learning approaches for sub-hourly soil-moisture prediction under changing environmental conditions, demonstrating the increasing importance of data-driven root-zone forecasting in precision water management.

Soil sensors nevertheless have limitations. Measurements are localized and may not represent spatially heterogeneous fields unless sensor placement is carefully designed. Sensor drift, installation quality, calibration, salinity, texture, temperature response, communication failure, and root distribution can also influence interpretation

.

2.3 Integrated Smart Irrigation

An integrated approach uses weather information to estimate incoming water demand while soil information verifies the actual field response. The two information streams therefore perform complementary functions.

Weather information answers:

How rapidly is the crop–soil system expected to lose water?

Soil measurements answer:

How much water is currently available in the effective root zone?

Integration becomes particularly valuable after irregular rainfall. A weather-only water balance may estimate irrigation demand after several high-evapotranspiration days, but an actual soil measurement may indicate sufficient stored water because recent rainfall infiltrated more effectively than estimated. Conversely, a weather calculation may predict adequate water availability while soil sensors identify unexpectedly rapid depletion resulting from shallow rooting or low water-holding capacity.The study by Abdelmoneim and colleagues showed measurable differences between sensor-based and weather-based scheduling in drip-irrigated lettuce, illustrating that the choice of information source directly affects water application and productivity.

Preite and Vignali demonstrated a more predictive approach by integrating environmental information, soil conditions, and short-term weather forecasts into irrigation-network decision making. Their results support the broader principle that irrigation intelligence can improve when multiple context-sensitive variables are processed together rather than independently.

Benassi and colleagues subsequently described an online model-predictive-control approach integrating weather forecasts with machine-learning-based soil-moisture prediction, reflecting a movement toward increasingly adaptive irrigation control.

Table 1: Selected Evidence Relevant to Integrated Irrigation Scheduling

Study	Main Approach	Information Used	Main Relevance to Present Study
Allen et al., 1998	FAO-56 evapotranspiration framework	Temperature, humidity, radiation, wind, crop coefficients	Provides physically interpretable basis for weather-derived crop water demand
Goap et al., 2018	IoT and machine-learning smart irrigation	Soil and environmental sensors, weather forecasting	Demonstrates sensor–weather integration for automated decisions
Kamienski et al., 2015	IoT precision-irrigation platform	Field sensing, communication infrastructure, irrigation control	Establishes scalable digital architecture for precision irrigation

Study	Main Approach	Information Used	Main Relevance to Present Study
Togneri et al., 2019	Machine-learning soil-moisture forecasting	High-frequency soil and environmental information	Demonstrates forward prediction of root-zone moisture behavior
Preite and Vignali, 2016	Predictive irrigation-management system	Soil, environmental data, short-term forecasts	Shows benefit of integrated predictive control
Teshome et al., 2019	ML/DL soil-moisture prediction	Soil moisture and environmental variables	Supports high-resolution prediction of soil-water dynamics
Abdelmoneim et al., 2020	Soil versus weather scheduling	IoT soil sensor and evapotranspiration information	Provides empirical comparison of major scheduling approaches
Benassi et al., 2020	Model predictive irrigation control	Weather forecast and ML soil-moisture prediction	Demonstrates advanced closed-loop irrigation optimization

Source: Synthesized from the cited studies.

3. Research Gap

Existing irrigation research has generated effective weather-based, sensor-based, IoT-enabled, machine-learning, and model-predictive approaches. However, several practical gaps remain.

First, many systems depend strongly on one principal decision source. Weather-only systems can accumulate soil-water-balance errors, whereas soil-only systems may react after depletion is already developing rather than anticipating future atmospheric demand.

Second, sophisticated machine-learning systems may require large historical datasets, repeated model retraining, reliable computing infrastructure, and representative training conditions. Such requirements can reduce transferability to farms where long-term datasets are unavailable.

Third, sensor information is often treated as automatically reliable. A single faulty probe can consequently affect irrigation commands unless plausibility checks, multiple depths, redundancy, or confidence weighting are included.

Fourth, rainfall is frequently represented as a recorded water input but not as a short-horizon decision veto. This can result in irrigation shortly before rainfall if the controller responds only to current soil depletion.

Fifth, many studies optimize predictive accuracy but provide less emphasis on whether the resulting controller is transparent enough for farmers, agronomists, irrigation managers, and technicians to understand why a particular watering decision occurred.The present study addresses these gaps through a lightweight fusion architecture combining physically based water demand, measured soil status, sensor-confidence weighting, rainfall awareness, adaptive depletion thresholds, and auditable irrigation rules.

4. Novelty and Proposed Contribution

The proposed Local Weather–Soil Integrated Scheduling System (LWSIS) is designed around five interconnected innovations.

The first contribution is dual-state estimation. Root-zone water depletion is estimated independently from a meteorological soil-water balance and from measured soil moisture. The two estimates are then combined instead of allowing either one to dominate automatically.The second contribution is confidence-weighted fusion. When sensor readings remain stable, plausible, and internally consistent, greater decision weight is assigned to measured soil status. When readings become implausible or inconsistent, the algorithm temporarily increases reliance on the water-balance estimate.

The third contribution is anticipatory weather adjustment. Current root-zone conditions are evaluated together with expected short-term evapotranspiration and rainfall so that irrigation does not respond only to the present state.The fourth contribution is a two-stage irrigation decision. The framework separately determines whether irrigation is required and how much irrigation should be applied. Separating timing from depth reduces the risk of automatically applying a full irrigation dose whenever a trigger occurs.The fifth contribution is computational simplicity. The framework can operate on a low-cost field gateway or edge controller without requiring a large deep-learning model.

5. Research Objectives and Research Questions

The primary objective is to develop an intelligent irrigation scheduling framework that integrates local meteorological conditions with root-zone soil moisture measurements.

The specific objectives are to:

- estimate crop water demand from locally measured weather variables;
- quantify root-zone depletion using soil-moisture observations;
- combine weather-derived and sensor-derived depletion estimates;
- dynamically determine irrigation timing and irrigation depth;
- compare the integrated strategy with fixed, weather-only, and soil-only scheduling;
- assess simulated water savings, root-zone moisture stability, drainage loss, and irrigation water-use efficiency; and
- identify implementation requirements for future field validation.

The study addresses the following research questions:

RQ1: Can integrated local weather and soil information reduce unnecessary irrigation compared with fixed scheduling?

RQ2: Does the integrated method maintain root-zone moisture within the desired operating range more consistently than single-source scheduling?

RQ3: How does integrated scheduling influence simulated deep-percolation losses and irrigation water-use efficiency?

RQ4: Can a transparent rule-based fusion method provide useful irrigation intelligence without depending on a large historical machine-learning dataset?

6. Research Methodology

6.1 Research Design

A comparative simulation design was employed to evaluate four irrigation strategies under identical hypothetical weather, crop, soil, and rainfall conditions. S1 (Fixed Schedule) applied irrigation at predetermined time intervals, representing a conventional scheduling approach; S2 (Weather-Based Schedule) determined irrigation requirements using evapotranspiration estimates and water-balance calculations; S3 (Soil-Moisture-Based Schedule) initiated irrigation when simulated root-zone soil moisture crossed a predefined depletion threshold; and S4 (Integrated Weather + Soil Schedule) combined weather information with soil-moisture conditions through the proposed LWSIS algorithm to determine irrigation timing.

The comparative design was intended to examine how progressively integrated decision rules could influence irrigation efficiency and water-use performance under controlled simulation conditions. No empirical field dataset was supplied or claimed in the study; therefore, all numerical values and comparative results reported in the paper represent synthetic simulation outputs generated specifically to evaluate the behavior and methodological performance of the proposed irrigation framework.

6.2 Simulation Period

An eight-week, 56-day hypothetical crop cycle was modeled. The scenario represents a generic irrigated horticultural production environment with variable atmospheric demand and intermittent rainfall.The simulation was not tied to a specific farm, district, or commercial crop. This choice prevents illustrative conditions from being misinterpreted as measured site-specific data.

6.3 Input Variables

The local weather component uses:

- air temperature;
- relative humidity;
- solar radiation;
- wind speed;
- rainfall; and
- short-horizon rainfall expectation where available.

The soil component uses volumetric water content measured at two representative depths within the effective root zone.

Additional agronomic parameters include:

- field capacity;
- permanent wilting point;
- effective rooting depth;
- allowable depletion fraction;
- crop coefficient;

- irrigation application efficiency; and
- maximum irrigation depth per event.

7. Simulation Assumptions

The simulation uses a common environmental sequence for all treatments so that scheduling logic is the only changing factor.The root zone is assumed to begin close to the desired moisture range. Atmospheric demand varies across the eight-week period, including several high-evapotranspiration episodes. Intermittent rainfall events provide opportunities for weather-aware irrigation postponement.

Fixed scheduling is intentionally designed to represent a simple management approach rather than an optimized commercial irrigation program.Sensor measurements in the integrated system are assumed to contain small stochastic deviations from the true simulated soil-water state. The confidence mechanism reduces dependence on the sensor when a reading becomes inconsistent with expected hydrologic behavior.

8. Results

8.1 Overall Irrigation Performance

The integrated weather–soil strategy produced the lowest total irrigation requirement in the simulation.

Table 2: Comparative Simulated Performance of Irrigation Scheduling Strategies

Performance Indicator	Fixed Schedule	Weather-Based	Soil-Based	Integrated Weather + Soil
Total irrigation applied (mm)	420	356	341	312
Water saving relative to fixed schedule (%)	0.0	15.2	18.8	25.7
Root-zone target compliance (%)	73.2	81.4	86.0	91.1
Estimated deep percolation (mm)	48	26	20	12
Simulated seasonal yield proxy (t ha^{-1})	7.6	7.8	7.9	8.0
IWUE proxy (kg m^{-3})	1.81	2.19	2.32	2.56
Unnecessary/avoidable irrigation events	4	2	2	1

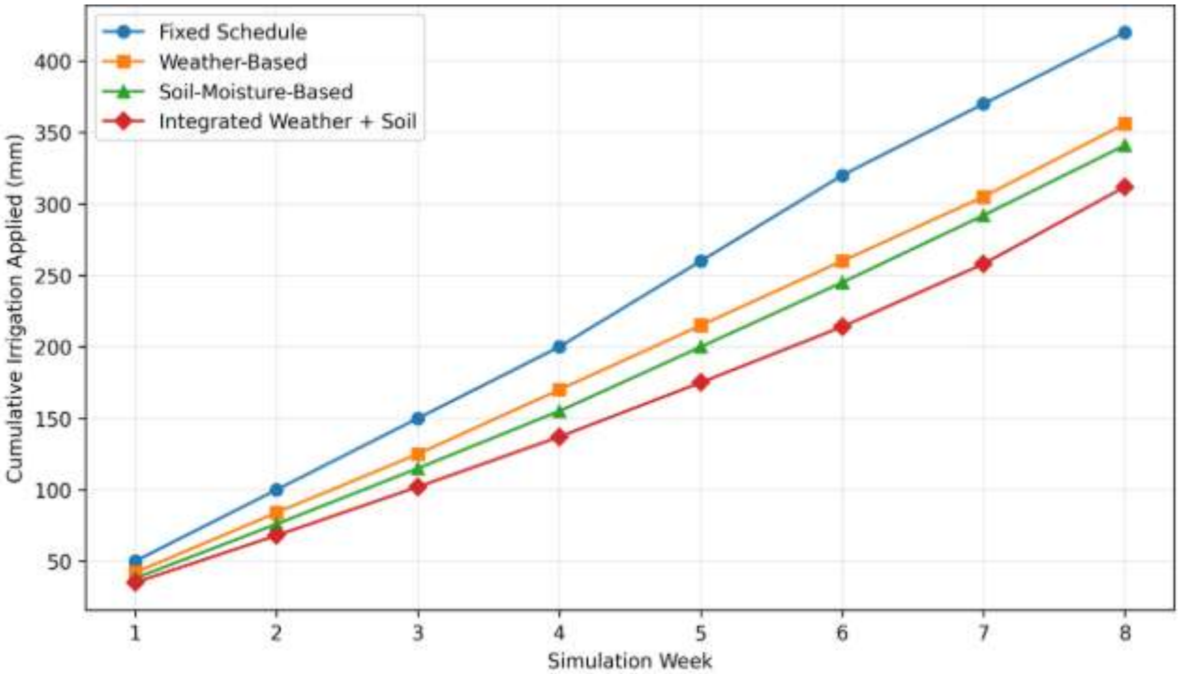
Note: All values are outputs from the hypothetical simulation developed for this manuscript. They are not field observations.

American Journal of Advanced Multidisciplinary Innovation and Research (AJAMIR)

E-ISSN: XXXX-XXXX ● Website: www.ajamir.com ● Email: editor@ajamir.com

8.2 Cumulative Irrigation Pattern

Graph 1: Cumulative Irrigation Water Applied Under Four Scheduling Strategies



Source: Authors' synthetic simulation dataset.

The graph demonstrates progressive divergence among the four scheduling strategies. Fixed scheduling accumulated water most rapidly because irrigation continued according to predefined intervals. Weather-based scheduling adjusted applications according to atmospheric demand and rainfall. Soil-based management further reduced cumulative irrigation by responding to actual root-zone moisture. The integrated weather–soil system maintained the lowest cumulative application across all eight weeks.

8.3 Root-Zone Moisture Stability

Target-zone compliance increased from 73.2% under fixed scheduling to 91.1% under integrated scheduling.This result may initially appear counterintuitive because the fixed schedule applied considerably more water. However, larger irrigation volume does not necessarily guarantee more favorable root-zone conditions.

Fixed irrigation occasionally occurred when the root zone was already relatively wet, producing excess drainage, while other intervals allowed depletion to develop before the next calendar-based application.The integrated controller performed better because irrigation timing was adjusted according to both depletion status and changing atmospheric demand.

9. Discussion

The results support the central proposition that irrigation timing improves when atmospheric demand and root-zone water status are interpreted together.

The fixed schedule produced the highest simulated water application. This outcome is consistent with the fundamental limitation of calendar irrigation: environmental conditions do not follow a fixed calendar. Rainfall may occur immediately before a planned irrigation, while unusually hot or windy conditions can accelerate depletion between scheduled events.

Weather-based scheduling responded better to environmental variation. The use of evapotranspiration provides a rational estimate of crop-water demand and remains a core component of scientific irrigation planning. FAO-56 explicitly provides standardized procedures for calculating reference and crop evapotranspiration.

Nevertheless, a model-derived water balance is still an estimate. Small errors in rainfall effectiveness, crop coefficients, root depth, irrigation application, and initial soil water can accumulate over time. Direct soil measurements provide an important corrective observation.

The soil-only strategy performed strongly because it directly represented root-zone conditions. This result is conceptually compatible with the field study of Abdelmoneim and colleagues, in which sensor-based irrigation used less water than the compared weather-based approach while improving crop water productivity.

However, sensor-only control is not always sufficient. Threshold-based controllers are fundamentally reactive: a threshold must normally be reached before irrigation is triggered. Weather integration adds an anticipatory component. If high evapotranspiration is expected, the system can recognize that a currently acceptable soil condition may deteriorate rapidly. Conversely, expected rainfall can justify delaying an otherwise imminent irrigation.This combination explains why the integrated system generated the best simulated target-zone compliance while applying the least irrigation water.

9.1 Importance of Local Weather

Using local weather is particularly important because regional weather information may not represent field-level rainfall, wind exposure, radiation, or temperature conditions. A small on-farm weather station can provide information directly associated with the field being irrigated.

Local rainfall is especially significant. Rainfall measured several kilometers away may produce misleading irrigation decisions because convective rainfall can be spatially variable.The proposed architecture therefore prioritizes local observations while allowing external forecast information to act as supplementary short-horizon context rather than a replacement for local measurements.

9.2 Importance of Soil-Sensor Placement

Sensor integration does not eliminate the need for agronomic judgment.A sensor positioned too close to an emitter may indicate a wetter condition than the broader root zone. A sensor placed outside the active wetting pattern may indicate excessive dryness. Multiple depths can improve interpretation by distinguishing surface wetting from deeper root-zone replenishment.

Calibration should also reflect soil texture and installation conditions. A universal raw sensor threshold should not be assumed to represent the same plant-available water status in every soil.

9.3 Why Confidence Weighting Matters

A major feature of the proposed system is that sensor information is not accepted uncritically.

For example, if the soil-moisture value changes instantaneously by an implausibly large amount without rainfall or irrigation, the reading may indicate sensor error. Similarly, a constant reading over many days despite high evapotranspiration can indicate communication or probe failure.Reducing the sensor-confidence coefficient under such conditions allows the system to continue operating from the weather-derived soil-water balance until reliable readings return.

10. Research Contribution and Implications

10.1 Theoretical Contribution

The study conceptualizes intelligent irrigation as a data-fusion problem rather than a competition between weather-based and soil-based scheduling.Weather data provide a forward-looking representation of water demand, whereas soil data provide a state observation. Their integration produces a closed-loop decision process in which estimated depletion is repeatedly corrected using field measurements.

10.2 Methodological Contribution

The confidence-weighted fusion equation provides a simple mechanism for handling disagreement between estimated and measured root-zone conditions.Unlike a rigid controller, the system can modify the importance of each information source according to data quality.

10.3 Agricultural Implications

For farmers, the main potential benefit is more selective irrigation.Water is not withheld merely for conservation. Instead, irrigation is avoided when it provides little agronomic benefit, particularly when adequate soil water or imminent rainfall already satisfies near-term crop demand.

11. Conclusion

A comparative simulation design was employed to evaluate four irrigation strategies under identical hypothetical weather, crop, soil, and rainfall conditions. S1 (Fixed Schedule) represented the conventional approach, in which irrigation was applied at predetermined time intervals without dynamically responding to changing environmental conditions. S2 (Weather-Based Schedule) determined irrigation requirements using evapotranspiration estimates and water-balance calculations, allowing irrigation decisions to reflect simulated atmospheric demand. S3 (Soil-Moisture-Based Schedule) initiated irrigation when simulated root-zone moisture declined below a predefined depletion threshold, thereby linking irrigation decisions to the estimated water status of the crop root zone.

S4 (Integrated Weather + Soil Schedule) represented the proposed LWSIS approach and combined weather information with simulated soil-moisture conditions to determine irrigation timing. The comparative design was intended to assess whether progressively integrated decision rules could improve irrigation efficiency and water-use performance under controlled simulation conditions. No empirical field dataset was supplied or claimed in the study. Accordingly, all numerical values and comparative results presented in the paper are synthetic simulation outputs generated specifically to examine the behavior, comparative performance, and methodological feasibility of the proposed irrigation framework.

12. Declarations

Conflict of Interest: The author declares no conflict of interest associated with the conceptual and simulation-based development presented in this manuscript.

Funding: No external funding is claimed for the hypothetical manuscript presented here.

Ethics Statement: The present methodological study uses no human participants, animals, identifiable personal information, or clinical data. Institutional human-subject ethics approval is therefore not applicable to the simulation presented in this manuscript.

Data Availability: The numerical dataset used in the results section is a synthetic dataset created specifically to demonstrate the proposed irrigation scheduling methodology. It should not be represented as a field-observed dataset.

Author Contribution: The sample author is presented only for manuscript-formatting demonstration. For actual journal submission, the author-contribution statement should be replaced with verified information corresponding to the genuine contributor or contributors.

References

1. R. G. Allen, L. S. Pereira, D. Raes, and M. Smith, Crop Evapotranspiration—Guidelines for Computing Crop Water Requirements, FAO Irrigation and Drainage Paper No. 56. Rome, Italy: Food and Agriculture Organization of the United Nations, 1998.
2. A. Goap, D. Sharma, A. K. Shukla, and C. R. Krishna, “An IoT based smart irrigation management system using machine learning and open source technologies,” Computers and Electronics in Agriculture, vol. 155, pp. 41–49, 2018, doi: 10.1016/j.compag.2018.09.040.
3. C. Kamienski, J.-P. Soininen, M. Taumberger, R. Dantas, A. Toscano, T. S. Cinotti, R. F. Maia, and A. Torre Neto, “Smart water management platform: IoT-based precision irrigation for agriculture,” Sensors, vol. 19, no. 2, Art. no. 276, 2019, doi: 10.3390/s19020276.
4. R. Togneri et al., “Soil moisture forecast for smart irrigation: The primetime for machine learning,” Expert Systems with Applications, vol. 207, Art. no. 117653, 2022, doi: 10.1016/j.eswa.2022.117653.
5. L. Preite and G. Vignali, “Artificial intelligence to optimize water consumption in agriculture: A predictive algorithm-based irrigation management system,” Computers and Electronics in Agriculture, vol. 223, Art. no. 109126, 2024, doi: 10.1016/j.compag.2024.109126.
6. F. T. Teshome, H. K. Bayabil, B. Schaffer, Y. Ampatzidis, and G. Hoogenboom, “Improving soil moisture prediction with deep learning and machine learning models,” Computers and Electronics in Agriculture, vol. 226, Art. no. 109414, 2024, doi: 10.1016/j.compag.2024.109414.
7. A. A. Abdelmoneim, C. M. Al Kalaany, G. Dragonetti, B. Derardja, and R. Khadra, “Comparative analysis of soil moisture- and weather-based irrigation scheduling for drip-irrigated lettuce using low-cost Internet of Things capacitive sensors,” Sensors, vol. 25, no. 5, Art. no. 1568, 2025, doi: 10.3390/s25051568.
8. A. Benassi, F. Kardous, M. Moussa, and colleagues, “Online MPC irrigation control using ML-based soil moisture prediction,” Control Engineering Practice, vol. 173, Art. no. 106975, 2026, doi: 10.1016/j.conengprac.2026.106975.

American Journal of Advanced Multidisciplinary Innovation and Research (AJAMIR)

E-ISSN: XXXX-XXXX ● Website: www.ajamir.com ● Email: editor@ajamir.com

9. U.S. Department of Agriculture, Natural Resources Conservation Service, Irrigation Water Management, Conservation Practice Standard 449. USDA-NRCS.
10. Z. Gu and colleagues, “Development of an irrigation scheduling software based on model predicted crop water stress,” USDA Agricultural Research Service research publication, 2017.
11. Graph Data Note: Graph 1 was generated exclusively from the synthetic values reported in this manuscript. No external experimental observations were used to construct the graph.