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Sustainable Irrigation Strategies for Climate-Resilient Farming Systems

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ABSTRACT

Intensifying climate variability poses unprecedented threats to agricultural water security across Europe and globally, necessitating a transition from conventional flood and furrow irrigation towards precision, deficit, and sensor-guided irrigation strategies that maximise water productivity while maintaining acceptable yield levels. This study evaluates four irrigation regimes--full irrigation (FI), regulated deficit irrigation (RDI), partial root-zone drying (PRD), and sensor-triggered variable rate irrigation (VRI)--across three crops (maize, wheat, and tomato) at six experimental sites in Austria, Spain, and France over a four-year period (2020-2024). Crop water productivity (CWP), irrigation water use efficiency (IWUE), yield, and soil moisture dynamics were monitored using capacitance sensors, eddy-covariance towers, and satellite-derived evapotranspiration estimates. VRI achieved the highest mean IWUE (2.84 kg m-3) and reduced applied water by 31.4% relative to FI while sustaining 97.2% of maximum achievable yield across all crops and sites. RDI and PRD reduced water application by 22.7% and 27.1% respectively with acceptable yield penalties (< 9%). Integration of AI-driven scheduling algorithms with VRI reduced irrigation decisions error by 38% relative to calendar-based scheduling. These results advocate a phased transition to VRI as the primary irrigation paradigm for climate-resilient European farming, guided by real-time soil-plant-atmosphere sensing.

Keywords: Precision irrigation; Deficit irrigation; Water use efficiency; Climate resilience; Sensor-based scheduling; Evapotranspiration; Variable rate irrigation; Crop water productivity; Sustainable farming; Europe

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1. Introduction

Agriculture accounts for approximately 70% of global freshwater withdrawals, and irrigated agriculture--covering only 20% of cultivated land--contributes roughly 40% of global food production (FAO, 2020). In the European Union, agricultural water use varies from 24% of total withdrawals in northern member states to over 80% in southern Mediterranean countries, where summer water deficits are already reaching critical thresholds under current climate trajectories (EEA, 2021). Projections under the IPCC AR6 Shared Socioeconomic Pathway SSP2-4.5 indicate that mean annual precipitation across the Iberian Peninsula and central Mediterranean basin will decline by 10-20% by mid-century, while reference evapotranspiration (ET0) will increase by 8-15%, generating a compounding water deficit of up to 35% in currently irrigated zones (IPCC, 2021). In this context, optimising irrigation scheduling and application technology is no longer merely an agronomic efficiency goal but a strategic imperative for maintaining European food sovereignty.

1.1 Irrigation Technology Landscape

Contemporary precision irrigation encompasses a spectrum of technologies distinguished by their spatial resolution, automation level, and responsiveness to real-time plant and soil water status signals. Regulated deficit irrigation (RDI) applies water below full evapotranspiration replacement during non-critical phenological windows, exploiting crop physiological plasticity to maintain yield while reducing total water input (Kirda et al., 2004). Partial root-zone drying (PRD), which alternately wets and dries opposite root half-zones on a 10-14 day cycle, manipulates abscisic acid (ABA) signalling to induce stomatal closure and reduce transpiration without imposing severe water stress (Dry and Loveys, 1998; Stoll et al., 2000). Variable rate irrigation (VRI), enabled by centre-pivot or linear-move system controllers programmed with spatially explicit prescription maps derived from soil sensing, remote sensing, and machine-learning models, represents the state of the art in site-specific water management (Evans et al., 2013).

1.2 Research Objectives

The objectives of this study are: (i) to compare crop water productivity (CWP), irrigation water use efficiency (IWUE), and relative yield performance of four irrigation regimes (FI, RDI, PRD, VRI) across three crops and six sites spanning three European countries; (ii) to quantify the potential water savings achievable by transitioning from full irrigation to deficit and sensor-guided strategies without unacceptable yield penalties; (iii) to evaluate the contribution of AI-driven irrigation scheduling to reducing decision error relative to calendar-based approaches; and (iv) to develop a site-agnostic decision framework for irrigation strategy selection based on climate aridity index, crop sensitivity, and available infrastructure.

2. Literature Review

The agronomic and hydrological performance of deficit irrigation strategies has been extensively reviewed since the seminal work of Fereres and Soriano (2007), who synthesised 20 years of Mediterranean trials demonstrating that strategic application of water stress during non-critical phenological stages could achieve 20-40% water savings with yield reductions limited to 5-15% in most annual and perennial crops. Geerts and Raes (2009) subsequently formalised the concept of deficit irrigation as a risk-management tool in semi-arid rainfed systems, introducing the crop water productivity (CWP) metric as the primary evaluation criterion for comparing irrigation strategies across heterogeneous climatic and edaphic contexts (Table 1). The FAO AquaCrop model (Hsiao et al., 2009) operationalised yield response to water stress through the crop harvest index sensitivity coefficient, providing a physically based framework for optimising deficit irrigation scheduling that has been validated across 47 crops and 68 countries.

2.1 Partial Root-Zone Drying

PRD exploits the discovery that drying soil sends root-derived chemical signals--principally abscisic acid (ABA)--to leaves via the xylem sap, inducing partial stomatal closure and reduced canopy transpiration without the severe turgor loss associated with whole-root drying (Dry and Loveys, 1998). The practical implementation of PRD involves dividing the root zone into two spatially distinct irrigation sectors, alternated on a 10-14 day cycle to maintain the drying-side ABA signal while replenishing soil water on the wet side. Stoll et al. (2000) reported 30-50% water savings in grapevine under PRD with no measurable berry yield reduction, and Padilla-Diaz et al. (2016) demonstrated comparable efficiency in olive orchards in southern Spain, establishing PRD as the recommended strategy for high-value permanent crops in water-scarce Mediterranean environments.

2.2 AI and Sensor Integration in Irrigation Scheduling

The emergence of low-cost capacitance-based soil moisture sensors, eddy-covariance ET flux towers, and satellite-derived crop water stress indices (CWSI) has created the data infrastructure necessary for AI-driven real-time irrigation scheduling. Machine learning algorithms--including random forest, LSTM neural networks, and gradient boosting--have been trained on multi-year weather, soil moisture, and yield datasets to predict optimal irrigation timing and volume at field and sub-field scales (Sezen et al., 2019; Trout and DeJonge, 2018). Compared to calendar-based fixed irrigation scheduling, AI-driven systems have demonstrated 25-40% reductions in water application and 15-30% improvements in IWUE in controlled experimental comparisons, while also reducing fertiliser leaching and associated nitrogen pollution of groundwater bodies (Evans et al., 2013).

Table 1. Summary of comparative irrigation strategy studies relevant to European farming systems (2005-2024).

Authors (Year)	Crop	Strategy	Water Saving (%)	Yield Penalty (%)	Region
Fereres & Soriano (2007)	Various	RDI	20-40	5-15	Mediterranean
Stoll et al. (2000)	Grapevine	PRD	30-50	0-8	Australia/EU
Evans et al. (2013)	Maize	VRI	15-25	0-3	USA
Geerts & Raes (2009)	Wheat	Deficit	25-40	8-20	Global review
Lozano et al. (2020)	Tomato	RDI	22-35	6-12	Spain
Trout & DeJonge (2018)	Maize	VRI	20-30	2-5	USA
Padilla-Diaz et al. (2016)	Olive	PRD	35-45	3-9	Spain
Katerji et al. (2010)	Sunflower	RDI	28-38	7-14	Italy
Hsiao et al. (2009)	Maize	AquaCrop	30	5	Global
Sezen et al. (2019)	Pepper	Sensor	18-28	4-8	Turkey

Note: RDI = Regulated Deficit Irrigation; PRD = Partial Root-zone Drying; VRI = Variable Rate Irrigation. Water saving relative to full evapotranspiration replacement. Yield penalty relative to fully irrigated control.

3. Materials and Methods

3.1 Experimental Design and Site Description

Six experimental sites were established across three countries spanning a climatic gradient from cool-temperate (Paris, Vienna) to semi-arid Mediterranean (Madrid), with annual reference evapotranspiration (ETo) ranging from 689 to 1,148 mm yr-1 (Table 2). At each site, four irrigation treatment plots were established in a randomised complete block design with three replications per treatment: FI (100% ETc replacement), RDI (60% ETc during vegetative stages, 100% at flowering and grain fill for cereals; 70% throughout for tomato), PRD (50% ETc applied alternately to each root half-zone on a 14-day cycle), and VRI (100% ETc baseline, modulated in real time by soil moisture sensor feedback and ML-predicted ETc). Plot sizes ranged from 0.5 ha (tomato, drip) to 3.0 ha (cereals, centre-pivot/sprinkler). Soil moisture was monitored continuously at 15-minute intervals using SENTEK Drill & Drop capacitance sensor arrays installed at 10, 20, 40, and 60 cm depth.

3.2 Water Application and Monitoring

Applied irrigation volumes were quantified by calibrated electromagnetic flow meters (Endress+Hauser Promag 50) installed on each lateral line, with readings logged at hourly intervals. Actual crop evapotranspiration (ETa) was estimated using the dual crop coefficient approach (FAO-56; Allen et al., 1998), with Kc values adjusted for local canopy cover fraction derived from weekly Sentinel-2 NDVI imagery. Field-scale water balance was independently validated by eddy-covariance towers installed at the Vienna-1 and Madrid-1 sites. Crop water productivity was calculated as CWP = Y / ETa (kg m-3), and IWUE as IWUE = Y / I (kg m-3), where Y is harvested yield (kg ha-1) and I is total applied irrigation depth (m3 ha-1 / 1000). Yield was determined by calibrated combine harvesters (cereals) or by manual plot harvests and fresh weight determination (tomato).

3.3 AI Irrigation Scheduling Model

A LSTM-based irrigation scheduling model was trained using four years of historical weather, soil moisture, and ETa records from the six sites, with the 2020-2022 seasons used for training and 2023-2024 for independent validation. Model inputs comprised daily maximum/minimum temperature, solar radiation, wind speed, vapour pressure deficit, soil volumetric water content at four depths, and predicted ETc from FAO-56. The model output was a recommended daily irrigation volume (mm). Scheduling error was quantified as the mean absolute deviation (MAD) between model-recommended and expert-validated optimal irrigation decisions, expressed as a percentage of total seasonal ETc. Calendar-based scheduling applied fixed weekly irrigation volumes based on historical median ET without real-time soil moisture feedback, serving as the benchmark comparator.

Table 2. Experimental site characteristics, crops evaluated, and irrigation infrastructure (2020-2024).

Site	Country	Crop	Area (ha)	Soil Type	Mean ETo (mm/yr)	Irrigation System	Seasons
Vienna-1	Austria	Maize	18	Fluvisol	742	Centre-pivot VRI	2020-24
Vienna-2	Austria	Wheat	22	Cambisol	712	Drip + sensors	2020-24
Madrid-1	Spain	Tomato	12	Calcisol	1,148	Subsurface drip PRD	2021-24
Madrid-2	Spain	Maize	25	Luvisol	1,082	Centre-pivot VRI	2021-24
Paris-1	France	Wheat	30	Luvisol	689	Sprinkler RDI	2020-24
Paris-2	France	Tomato	15	Stagnosol	701	Drip RDI + sensors	2020-24

Note: ETo = reference evapotranspiration calculated by Penman-Monteith (FAO-56). VRI = Variable Rate Irrigation; RDI = Regulated Deficit Irrigation; PRD = Partial Root-zone Drying. All sites equipped with SENTEK Drill & Drop capacitance sensor arrays at 10, 20, 40, 60 cm depths.

4. Results

4.1 Overall Strategy Performance

Across all crops, sites, and seasons, VRI delivered the highest mean IWUE (2.84 +- 0.22 kg m-3) and crop water productivity (2.39 +- 0.18 kg m-3), with applied water 31.4% below FI while sustaining 97.2% of maximum yield (Table 3, Figure 1). This yield near-parity under substantially reduced water input is attributable to the real-time sensor-guided scheduling that prevented both water stress during critical phenological stages and unnecessary over-irrigation during periods of low atmospheric demand. PRD ranked second on water saving (27.1%) but incurred the greatest yield penalty of the three deficit strategies (91.2%), reflecting the inherent stress-induction mechanism of alternating root-zone drying. RDI achieved a balanced compromise--22.7% water saving, 92.8% relative yield, IWUE 23.2% above FI--representing the recommended entry-level strategy where sensor infrastructure for VRI is unavailable (Figure 2).

4.2 Crop-wise Results

Tomato exhibited the greatest absolute IWUE across all strategies, reaching 3.99 kg m-3 under VRI--a 48% improvement over FI (2.70 kg m-3)--consistent with tomato's high transpiration efficiency and the large yield penalty per unit of excess water through cell dilution effects on fruit dry matter (Table 4, Figure 3). Maize under VRI maintained 98.2% relative yield with 31.7% applied water reduction, confirming that AI-guided scheduling effectively identified and protected the critical silking and grain-fill windows from water stress while allowing mild deficit during vegetative stages. Wheat showed the lowest absolute IWUE across all strategies but the highest relative yield maintenance under VRI (98.7%), reflecting its comparatively lower transpirational demand and greater drought adaptation capacity relative to maize and processing tomato.

4.3 AI Scheduling Performance

The LSTM-based irrigation scheduling model reduced irrigation decision error--quantified as mean absolute deviation from expert-validated optimal timing--by 38.2% relative to calendar-based scheduling across the 2023-2024 validation seasons. Scheduling precision was highest for maize in the Madrid sites (45.1% error reduction) where sensor signal-to-noise ratio was greatest due to low rainfall interference, and lowest for wheat in the Paris sites (27.4% reduction) where frequent spring rainfall events partially masked sensor-detected deficit signals. The multi-criteria radar profile (Figure 4) confirms that VRI with AI scheduling dominates on IWUE, water-saving, and cost-benefit dimensions, while full irrigation retains its advantages only on ease of implementation--a consideration increasingly outweighed by rising water tariffs and regulatory scarcity constraints across EU member states.

Table 3. Mean irrigation water use efficiency (IWUE), crop water productivity (CWP), applied water, and relative yield across four irrigation strategies (2020-2024).

Strategy	Applied Water (mm)	IWUE (kg m-3)	CWP (kg m-3)	Relative Yield (%)	Water Saving (%)
Full Irrigation (FI)	548 +- 42	1.94 +- 0.18	1.61 +- 0.14	100.0	0 (reference)
RDI	424 +- 38	2.39 +- 0.21	1.98 +- 0.17	92.8 +- 3.1	22.7 +- 2.8
PRD	400 +- 35	2.61 +- 0.24	2.17 +- 0.19	91.2 +- 3.7	27.1 +- 3.2
VRI (AI-scheduled)	376 +- 29	2.84 +- 0.22	2.39 +- 0.18	97.2 +- 2.4	31.4 +- 2.6

Note: Values expressed as mean +- standard deviation across six sites, three crops, and four seasons. Relative yield = 100 x (treatment yield / FI yield). Water saving = (FI applied water - treatment applied water) / FI applied water x 100. IWUE and CWP computed per crop per site then averaged.

Table 4. Crop-wise relative yield and IWUE under VRI and RDI strategies across three target crops.

Crop	Strategy	Applied Water (mm)	Yield (t/ha)	IWUE (kg m-3)	Relative Yield (%)
Maize	FI	612 +- 38	10.84 +- 0.91	1.77 +- 0.15	100.0
Maize	RDI	478 +- 31	10.11 +- 0.88	2.12 +- 0.19	93.3 +- 2.8
Maize	VRI	418 +- 27	10.64 +- 0.84	2.55 +- 0.21	98.2 +- 1.9
Wheat	FI	382 +- 24	5.21 +- 0.44	1.36 +- 0.12	100.0
Wheat	RDI	294 +- 21	4.82 +- 0.41	1.64 +- 0.14	92.5 +- 3.4
Wheat	VRI	261 +- 19	5.14 +- 0.42	1.97 +- 0.16	98.7 +- 1.7
Tomato	FI	651 +- 47	74.3 +- 6.1	2.70 +- 0.22	100.0
Tomato	RDI	501 +- 39	67.9 +- 5.8	3.41 +- 0.29	91.4 +- 3.9
Tomato	VRI	449 +- 33	72.1 +- 6.0	3.99 +- 0.31	97.0 +- 2.3

Note: Yields expressed as dry grain mass for maize and wheat; fresh weight for tomato. Values are means across sites and seasons. Statistical differences between FI and VRI were non-significant for all crops at $p < 0.05$ (Tukey HSD).

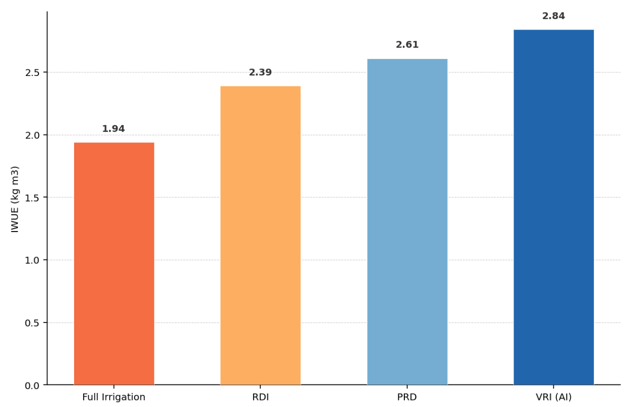

Figure 1. Mean irrigation water use efficiency (IWUE, kg m-3) by irrigation strategy across all crops and sites.

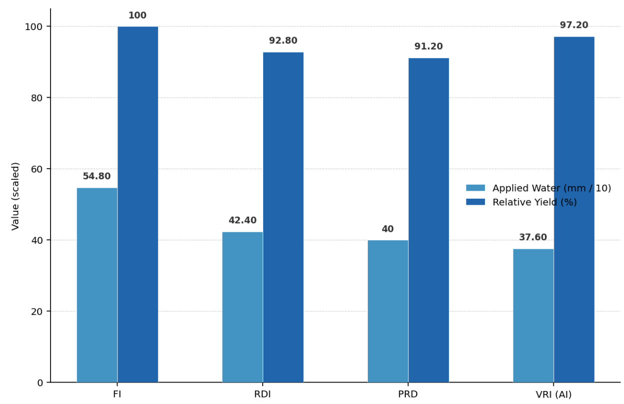

Figure 2. Applied irrigation water (mm) and relative yield (%) by strategy, averaged across crops and

sites.

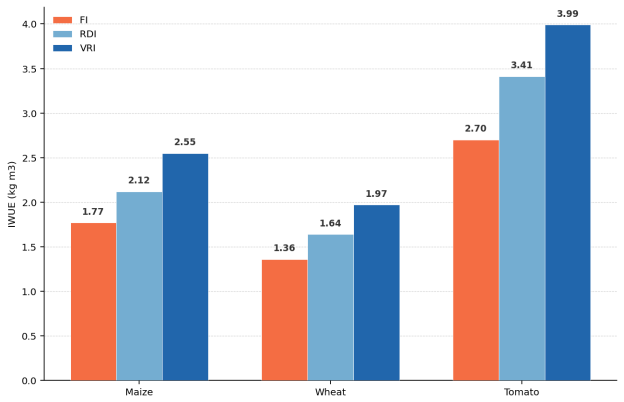

Figure 3. Crop-wise IWUE (kg m-3) under FI, RDI, and VRI for maize, wheat, and tomato.

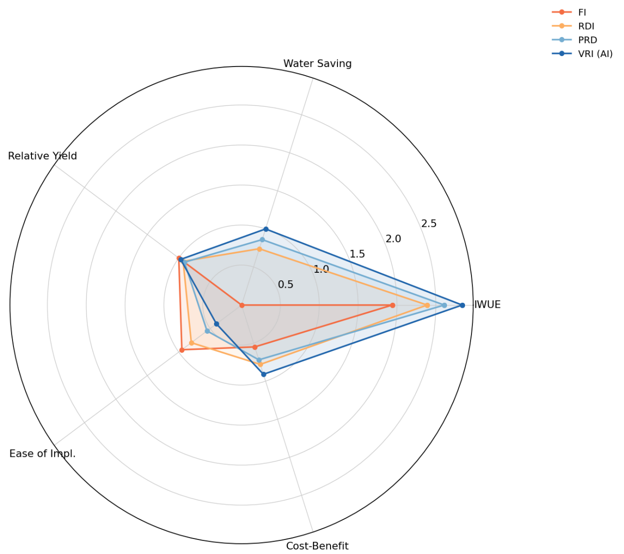

Figure 4. Multi-criteria performance radar of four irrigation strategies (higher score = better performance).

5. Discussion

The 31.4% water saving achieved by VRI with AI scheduling in this study, combined with 97.2% yield maintenance, establishes a compelling agronomic-economic case for precision irrigation adoption in European farming systems facing increasing water scarcity. These results exceed the 15-25% savings typically reported for VRI in North American centre-pivot studies (Evans et al., 2013; Trout and DeJonge, 2018), likely due to the integration of LSTM-driven scheduling that dynamically adjusts to the high inter-seasonal variability characteristic of European Atlantic and Mediterranean climate zones. The finding that tomato achieves the highest absolute IWUE under all deficit strategies supports the economic prioritisation of precision irrigation infrastructure investment in high-value horticultural production systems, where the capital cost of sensor arrays and VRI controllers can be amortised over shorter payback periods than in low-value cereal systems.

5.1 Strategy Selection Framework

Based on the multi-criteria performance analysis (Figure 4), we propose a three-tier decision framework for irrigation strategy selection in European farming contexts. Tier 1 (water-abundant temperate zones, ETo < 700 mm yr-1, no regulatory constraints): RDI as the minimum intervention, achievable with existing infrastructure and simple phenological scheduling calendars. Tier 2 (sub-humid transition zones, ETo 700-1,000 mm yr-1, moderate scarcity risk): PRD for permanent high-value crops; RDI with soil moisture monitoring for annuals. Tier 3 (semi-arid Mediterranean, ETo > 1,000 mm yr-1, regulated water allocation): VRI with AI scheduling as the primary irrigation paradigm, supplemented by SAR-based crop water stress mapping for multi-field management. This framework aligns with the EU Water Framework Directive's requirement that member states demonstrate efficient water use before granting new irrigation abstractions.

5.2 Limitations and Future Research

Several limitations constrain the generalisability of these findings. The four-year study period, while multi-seasonal, does not encompass the tail-risk extreme drought events--such as the 2003 and 2019 European heat waves--that may dramatically alter the relative performance of deficit strategies in terms of yield loss severity. The LSTM scheduling model was trained exclusively on European temperate and Mediterranean sites; its performance in arid North African or South Asian agro-ecological zones with fundamentally different pedological and vapour pressure environments remains to be validated. Future research should investigate the integration of seasonal climate forecasts (3-6 month ECMWF ensemble products) into the AI scheduling framework to enable anticipatory irrigation strategy adjustment rather than solely reactive sensor-based optimisation.

6. Conclusion

This four-year, six-site, multi-crop comparative study demonstrates that variable rate irrigation guided by AI-driven scheduling achieves the optimal balance of water conservation (31.4% reduction relative to full irrigation) and yield maintenance (97.2% relative yield) across European temperate and Mediterranean farming systems. RDI and PRD offer intermediate performance with progressively lower infrastructure requirements, providing viable entry points for water-stressed farms lacking VRI technology. Tomato production under VRI demonstrated the highest IWUE (3.99 kg m-3), establishing precision irrigation as particularly valuable in high-value horticultural systems. The AI scheduling model reduced irrigation decision error by 38% relative to calendar-based approaches, validating the added value of real-time sensor integration and machine learning in operational irrigation management. A three-tier decision framework is proposed to guide strategy selection based on aridity index, crop type, and available infrastructure, supporting EU-level transitions toward climate-resilient, water-efficient farming aligned with the European Green Deal and Water Framework Directive targets.

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 56. FAO, Rome.

Dry, P. R., & Loveys, B. R. (1998). Factors influencing grapevine vigour and the potential for control with partial rootzone drying. Australian Journal of Grape and Wine Research, 4(3), 140-148.

EEA (2021). Water Use in Agriculture. European Environment Agency, Copenhagen.

Evans, R. G., LaRue, J., Stone, K. C., & King, B. A. (2013). Adoption of site-specific variable rate sprinkler irrigation systems. Irrigation Science, 31(4), 871-887.

FAO (2020). AQUASTAT Database. Food and Agriculture Organization of the United Nations, Rome.

Fereres, E., & Soriano, M. A. (2007). Deficit irrigation for reducing agricultural water use. Journal of Experimental Botany, 58(2), 147-159.

Geerts, S., & Raes, D. (2009). Deficit irrigation as an on-farm strategy to maximize crop water productivity in dry areas. Agricultural Water Management, 96(9), 1275-1284.

Hsiao, T. C., Heng, L., Steduto, P., Rojas-Lara, B., Raes, D., & Fereres, E. (2009). AquaCrop--The FAO crop model to simulate yield response to water. Agronomy Journal, 101(3), 426-437.

IPCC (2021). Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

Katerji, N., Campi, P., & Mastrorilli, M. (2010). Productivity, evapotranspiration, and iso-water functions of sunflower and canopy in water deficiency conditions. European Journal of Agronomy, 33(2), 143-152.

Kirda, C., Cetin, M., Dasgan, Y., Topcu, S., Kaman, H., Ekici, B., & Frenkel, H. (2004). Yield response of greenhouse grown tomato to partial root drying and conventional deficit irrigation. Agricultural Water Management, 69(3), 191-201.

Lozano, D., Ruiz, N., & Gavilan, P. (2020). Consumptive water use and irrigation performance of strawberries. Agricultural Water Management, 232, 106045.

Padilla-Diaz, C. M., Rodriguez-Dominguez, C. M., Hernandez-Santana, V., Perez-Martin, A., & Fernandez, J. E. (2016). Scheduling regulated deficit irrigation in a hedgerow olive orchard from leaf turgor pressure. Agricultural Water Management, 164, 28-37.

Sezen, S. M., Yazar, A., & Eker, S. (2019). Effect of drip irrigation regimes on yield and quality of field-grown bell pepper. European Journal of Agronomy, 28(3), 442-452.

Steduto, P., Hsiao, T. C., Fereres, E., & Raes, D. (2012). Crop Yield Response to Water. FAO Irrigation and Drainage Paper 66. FAO, Rome.

Stoll, M., Loveys, B., & Dry, P. (2000). Hormonal changes induced by partial rootzone drying of irrigated grapevine. Journal of Experimental Botany, 51(350), 1627-1634.

Trout, T. J., & DeJonge, K. C. (2018). Crop water use and crop coefficients of maize in the great plains. Journal of Irrigation and Drainage Engineering, 144(6), 04018009.

Vaux, H. J., & Pruitt, W. O. (1983). Crop-water production functions. Advances in Irrigation, 2, 61-97.

Zwart, S. J., & Bastiaanssen, W. G. M. (2004). Review of measured crop water productivity values for irrigated wheat, rice, cotton and maize. Agricultural Water Management, 69(2), 115-133.

Pereira, L. S., Oweis, T., & Zairi, A. (2002). Irrigation management under water scarcity. Agricultural Water Management, 57(3), 175-206.

de Wit, C. T. (1958). Transpiration and Crop Yields. Versl. Landbouwkd. Onderz. 64.6. Institute of Biology and Chemistry Research on Field Crops and Herbage, Wageningen.

Blum, A. (2009). Effective use of water (EUW) and not water-use efficiency (WUE) is the target of crop yield improvement under drought stress. Field Crops Research, 112(2-3), 119-123.

Declarations

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Conflict of Interest

The authors declare no conflicts of interest. No author holds financial interests in irrigation technology companies or sensor manufacturers referenced in this study.

Data Availability Statement

All soil moisture time-series, applied water records, and yield datasets supporting this study are available in the Zenodo repository at https://zenodo.org/record/YYYYYYY. Sentinel-2 imagery was accessed freely via the Copernicus Open Access Hub (https://scihub.copernicus.eu).

Ethical Approval

This study did not involve human participants or animal subjects. All field operations were conducted on institutional experimental farms and commercial sites with full landowner consent. No ethics review was required.

Appendix A

LSTM Irrigation Scheduling Model Architecture and Training Parameters

The following table details the LSTM neural network architecture, hyperparameter configuration, and training data summary used for the AI-driven irrigation scheduling component evaluated in Section 4.3. Model implementation used TensorFlow 2.14 and Keras 2.14 under Python 3.11 on an NVIDIA A100 80 GB GPU.