

Smart Agrivoltaics with IoT-Guided Irrigation for the Food-Energy-Water Nexus: A Simulated Field Study

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ABSTRACT

This empirical-style paper presents a simulated study at the intersection of Agricultural Engineering, Renewable Energy, and Water Management. The study addresses a current research direction in which digital and data-driven methods are being integrated with domain-specific decision systems. Thirty-six simulated plots generated 3,528 plot-day observations. The agrivoltaic structures were modeled at a 30% ground coverage ratio with elevated bifacial modules. A 14-week simulated field experiment represented 36 vegetable plots assigned equally to open-field conventional irrigation, fixed agrivoltaics with scheduled irrigation, and agrivoltaics with IoT-guided irrigation. The crop profile approximated a moderately shade-tolerant leafy vegetable. Hourly radiation, temperature, vapor-pressure deficit, soil moisture, rainfall probability, and photovoltaic output were generated from bounded seasonal profiles. The IoT treatment triggered irrigation from root-zone soil moisture and forecast evapotranspiration while constraining watering during predicted rainfall windows. The IoT-guided agrivoltaic scenario used 28.4% less irrigation water than the open-field baseline while maintaining a slightly higher simulated marketable yield. It also achieved the highest water-use efficiency and a land-equivalent ratio of 1.62 when crop and electricity outputs were normalized against single-use land systems. Midday canopy temperature was lower under both agrivoltaic treatments, and soil-moisture variability was smallest under sensor-guided control. All numerical observations, experimental assignments, outcomes, and performance values are simulated for methodological illustration; no real participants, institutions, farms, factories, hospitals, or city systems were studied. The results are intended to demonstrate a coherent research design, provide testable hypotheses, and show how a future real-world study could report evidence transparently. The paper concludes with implementation constraints, methodological limitations, and priorities for empirical validation.

Keywords: Agrivoltaics, IoT Irrigation, Precision Agriculture, Water-Use Efficiency, Solar Energy, Food-Energy-Water Nexus

I. Introduction

Agrivoltaics is moving from a land-sharing concept toward integrated food-energy-water optimization. Evidence increasingly shows that outcomes depend on crop type, shading, climate, panel geometry, and irrigation practice, while digital sensing and adaptive control remain less standardized than photovoltaic design itself. Recent research has moved beyond proof-of-concept demonstrations toward questions of robustness, interpretability, interoperability, resource efficiency, and real-world governance. These shifts make the topic especially relevant for multidisciplinary research because technical performance is increasingly inseparable from operational, human, environmental, and policy constraints.

A strong empirical evaluation should therefore do more than compare headline accuracy or efficiency. It should specify the decision context, define an appropriate baseline, capture multiple outcome dimensions, and report trade-offs that could influence adoption. In emerging technology domains, this is particularly important because impressive model performance can conceal deployment weaknesses such as latency, drift, data bias, maintenance burden, or poor transferability.

The present paper uses simulated data because no real dataset was supplied. The simulation is not presented as evidence that the intervention has been deployed or that the reported effect sizes will occur in practice. Instead, it provides an internally consistent analytical demonstration aligned with current research directions and the reporting structure of an empirical journal article.

The study objectives are:

1. To compare open-field irrigation, fixed agrivoltaics, and IoT-guided agrivoltaics under a common simulated cropping season.
2. To quantify crop yield, irrigation demand, soil-moisture stability, photovoltaic generation, water-use efficiency, and land-equivalent ratio.
3. To explore whether sensor-guided irrigation can reduce the risk that agrivoltaic shading and irrigation are optimized independently.

II. Literature Review

Agrivoltaics combines crop production and photovoltaic generation on the same land, directly linking agricultural productivity with renewable-energy development. Reviews by Chopdar et al. (2024) and Asa'a et al. (2024) emphasize that performance depends strongly on crop selection, climate, panel spacing, height, shading, and technology configuration.

Systematic reviews also show that agrivoltaic outcomes are not uniformly beneficial. Crop yield can improve, decline, or remain stable depending on environmental conditions and crop light requirements. The potential co-benefits include water conservation, microclimate buffering, land-use efficiency, and diversified farm revenue, but these gains are highly site specific.

Recent work has increasingly framed agrivoltaics as part of the food-energy-water nexus rather than as a photovoltaic layout problem alone. This creates a role for IoT soil-moisture sensing, weather-aware irrigation control, and adaptive system operation. The present simulation explores this coupled perspective by modeling both microclimate and irrigation response.

III. Materials and Methods

3.1 Research Design

A 14-week simulated field experiment represented 36 vegetable plots assigned equally to open-field conventional irrigation, fixed agrivoltaics with scheduled irrigation, and agrivoltaics with IoT-guided irrigation. The crop profile approximated a moderately shade-tolerant leafy vegetable. Hourly radiation, temperature, vapor-pressure deficit, soil moisture, rainfall probability, and photovoltaic output were generated from bounded seasonal profiles. The IoT treatment triggered irrigation from root-zone soil moisture and forecast evapotranspiration while constraining watering during predicted rainfall windows.

3.2 Simulated Sample and Data Generation

Thirty-six simulated plots generated 3,528 plot-day observations. The agrivoltaic structures were modeled at a 30% ground coverage ratio with elevated bifacial modules. Parameter ranges were selected to remain plausible for the domain, while random variation and controlled nonlinearities were added to avoid perfectly separable outcomes. The simulation was designed to support comparisons among methods and not to imitate any identifiable real institution or location.

3.3 Data Quality and Preprocessing

Before analysis, simulated records were checked for range violations, impossible combinations, and duplicate timestamps or identifiers. Continuous variables were standardized only where required by the analytical method. Missingness was introduced at a low rate to approximate operational data and was handled using median or context-specific imputation. Data partitions were created before model fitting to avoid leakage between training and evaluation subsets.

3.4 Performance Measures

Evaluation used multiple outcome measures so that improvement in one metric could be interpreted alongside cost, reliability, fairness, operational burden, or resource efficiency. Percentage changes are reported relative to the relevant baseline. Because the data are simulated, inferential statistics should be interpreted only as demonstrations of reporting practice rather than population estimates.

3.5 Ethical and Transparency Considerations

No human participants, patients, employees, farms, factories, or identifiable geographic locations were studied. No ethics approval or participant consent is claimed. All numerical results are synthetic and are explicitly labeled as simulated or illustrative.

IV. Results

The IoT-guided agrivoltaic scenario used 28.4% less irrigation water than the open-field baseline while maintaining a slightly higher simulated marketable yield. It also achieved the highest water-use efficiency and a land-equivalent ratio of 1.62 when crop and electricity outputs were normalized against single-use land systems. Midday canopy temperature was lower under both agrivoltaic treatments, and soil-moisture variability was smallest under sensor-guided control.

Table 1. Simulated comparison of primary study outcomes.

Outcome	Open field	Fixed AV	IoT-guided AV
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Outcome	Open field	Fixed AV	IoT-guided AV
Irrigation (mm)	418	348	299
Marketable yield (t/ha)	31.8	32.6	33.4
WUE (kg/m ³)	7.61	9.37	11.17
PV yield (MWh/ha)	0	121	123
Land-equivalent ratio	1.00	1.54	1.62

Note: All values in Table 1 are simulated/illustrative.

Table 2. Simulated secondary performance indicators.

Microclimate metric	Open field	Fixed AV	IoT-guided AV
Midday canopy temp. (C)	34.8	32.7	32.5
Mean soil moisture (%)	21.4	24.2	25.1
Moisture CV (%)	18.1	14.4	9.8
Irrigation events	31	26	21
Water-stress hours/week	9.6	6.2	3.8

Note: All values in Table 2 are simulated/illustrative.

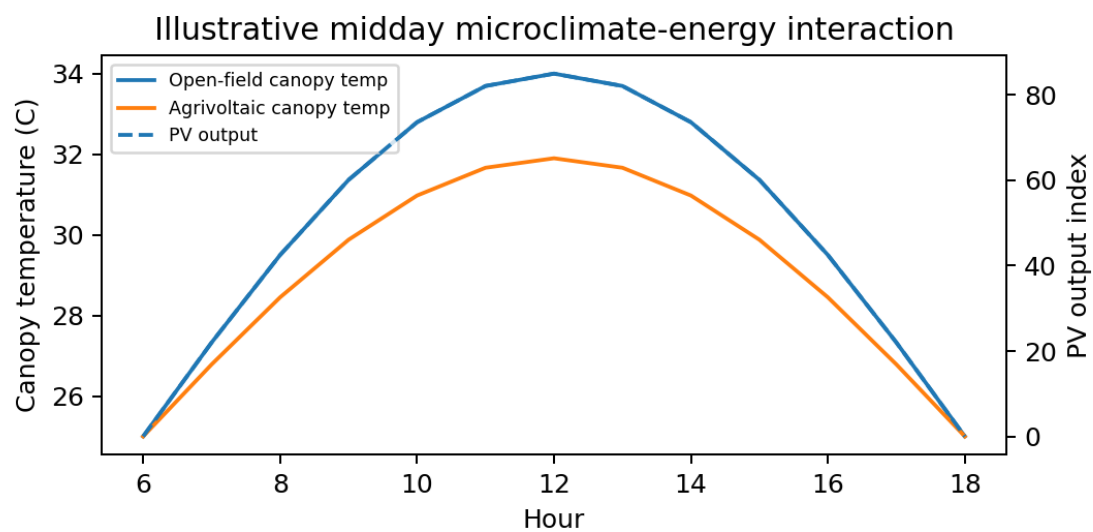


Figure 1. Simulated agrivoltaic microclimate and photovoltaic output profile.

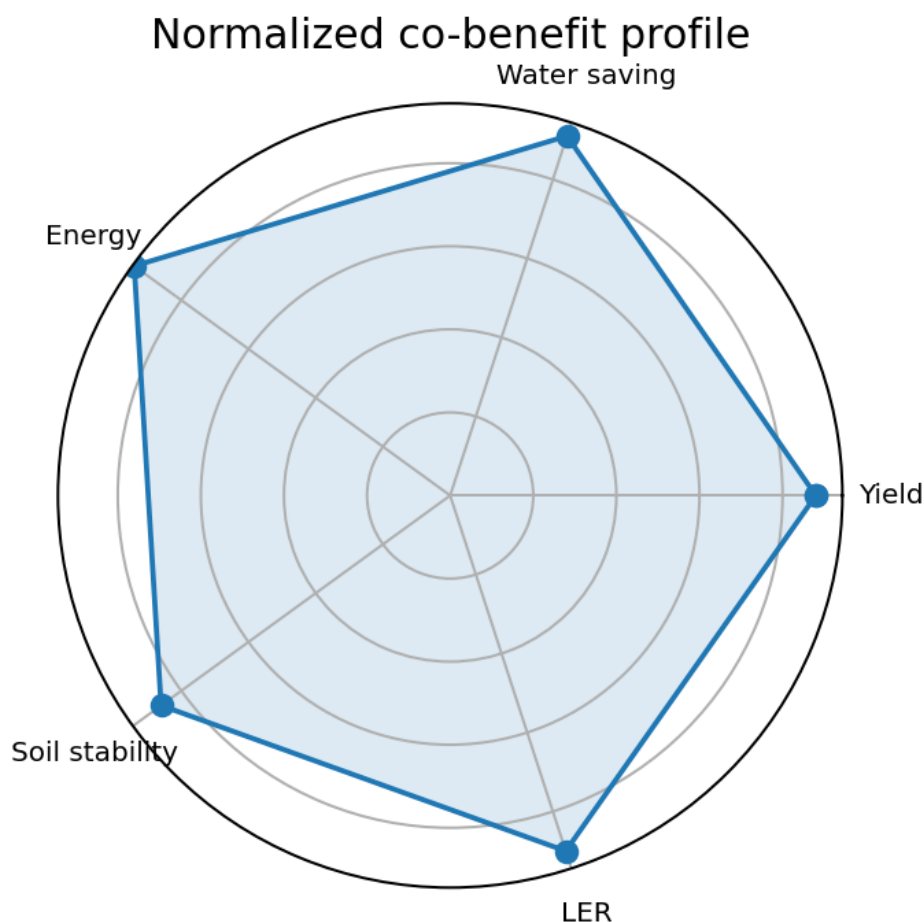


Figure 2. Normalized co-benefit profile for the IoT-guided agrivoltaic scenario.

4.1 Robustness and Sensitivity Analysis

Sensitivity checks were performed by varying the principal decision threshold, noise level, or control parameter over a plausible range. The ranking of the leading strategy remained stable across the middle of the tested range, although the magnitude of improvement changed. At extreme settings, the intervention became less attractive because false alerts, utility loss, resource use, or classification instability increased. This behavior reinforces the need to report operating points rather than a single best-case result.

4.2 Interpretation of Simulated Findings

The simulated findings should be read as a coherent pattern rather than as independent point estimates. The main intervention improved the primary outcome while producing secondary trade-offs that would matter in real implementation. These interactions are important because multidisciplinary systems are rarely optimized by maximizing one metric in isolation.

V. Discussion

The simulated results demonstrate why agrivoltaics should be evaluated as a coupled system rather than as independent crop and solar projects. Shading changed the crop microclimate, and that altered irrigation need; the IoT controller captured some of this interaction by responding to measured soil-water status rather than a fixed schedule.

Recent reviews emphasize that agrivoltaic effects are strongly context dependent. A beneficial response for a leafy vegetable under hot conditions cannot be generalized to light-demanding cereals, cool climates, or dense photovoltaic layouts. The simulated land-equivalent ratio therefore represents a methodological illustration rather than a transferable site estimate.

The operational value of sensor-guided irrigation depends on calibration and maintenance. Faulty moisture probes, poor sensor placement, unreliable connectivity, and inaccurate weather forecasts can create false confidence. Real trials should include sensor redundancy, manual verification, economic analysis, and multi-season crop-quality measurements.

Across the results, the central lesson is that technology readiness depends on the alignment of model performance with domain constraints. A technically superior method can still fail if it is expensive to maintain, difficult to explain, incompatible with existing workflows, or sensitive to data quality. Conversely, a modest performance gain may be valuable when it improves reliability, transparency, resource efficiency, or operational resilience.

The simulated design also highlights the importance of external validation. Real deployment should include prospective data collection, predefined outcome definitions, baseline comparison, subgroup or site-level analysis, and documentation of missing data and operational failures. Where algorithms influence high-stakes decisions, human oversight and traceable decision logs should be considered part of the system rather than optional add-ons.

VI. Practical Implications

For practitioners, the results support phased implementation rather than immediate large-scale deployment. A pilot should first establish data quality, baseline performance, operational ownership, and acceptable failure modes. Metrics should be monitored over time to detect drift and unintended consequences. Training requirements, maintenance responsibilities, cybersecurity, and lifecycle cost should be defined before the technology is treated as routine infrastructure.

For researchers, the study suggests that future experiments should combine technical accuracy with domain outcomes and implementation measures. Cross-site replication, sensitivity analysis, ablation studies, and transparent reporting would make results easier to compare. Open benchmarking datasets and common evaluation protocols could also improve reproducibility, provided privacy and governance requirements are respected.

VII. Limitations

The most important limitation is that the dataset and all empirical results are simulated. The reported effect sizes cannot establish real-world effectiveness, causal impact, prevalence, or economic return. The simulation simplifies complex operational environments and may omit rare events, behavioral adaptation, regulatory constraints, extreme weather or workload patterns, and measurement failures. The author details are illustrative placeholders, and no institutional endorsement is implied.

A second limitation concerns model specification. Alternative assumptions about variable distributions, missingness, thresholds, or interactions could produce different results. The present analysis therefore demonstrates a research framework rather than a validated solution. Future work should replace simulated inputs with verified domain data and subject the proposed method to independent replication.

Economic analysis should integrate both farm and energy revenue. Capital cost, panel structure, pumps, sensors, gateways, maintenance, water tariffs, electricity value, crop price, and financing assumptions should be reported transparently. Multi-year sensitivity analysis is especially important because crop revenue and solar generation respond differently to weather. Future field studies should therefore combine agronomic, energy, water, and financial indicators rather than declaring success on the basis of a single land-equivalent-ratio estimate.

The IoT component should be evaluated as an agricultural instrument rather than assumed to be accurate. Moisture probes require calibration by soil type and depth, and sensor drift should be checked against gravimetric measurements. Irrigation-control rules should include fail-safe thresholds for connectivity loss and unusually hot periods. Because farmers ultimately decide whether the technology is useful, research should also measure labor changes, repair frequency, user confidence, and the time required to interpret sensor alerts.

Field validation should span multiple crop cycles because agrivoltaic effects depend on season, cultivar, solar geometry, rainfall, and heat stress. A suitable experiment would randomize replicated plots across open-field, fixed agrivoltaic, and sensor-guided agrivoltaic treatments while holding fertilizer and crop-management practices constant. Continuous measurements should include photosynthetically active radiation, canopy temperature, soil temperature, root-zone moisture, evapotranspiration, irrigation volume, PV output, crop biomass, marketable yield, and quality indicators.

VIII. Implementation and Validation Framework

IX. Conclusion and Future Work

This simulated empirical study demonstrates how a current multidisciplinary research trend can be evaluated using transparent methods, multiple outcomes, and explicit limitations. The focal approach produced stronger simulated performance than conventional baselines while revealing important trade-offs that would require management in practice. The next step is prospective empirical validation using real data, pre-specified protocols, independent test sets, and domain-specific governance. Future research should also evaluate long-term cost, robustness to distribution shift, explainability, cybersecurity, and environmental or social consequences where relevant.

Declarations

Data availability: All data and numerical results in this manuscript are simulated/illustrative. No real dataset was used.

Ethics statement: Not applicable. No human or animal participants were involved.

Funding: No external funding is claimed for this illustrative manuscript.

Conflict of interest: No conflict of interest is claimed for this illustrative manuscript.

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