Research on World Agricultural Economy
https://journals.nasspublishing.com/index.php/rwae

ARTICLE

AI and Sustainable Agriculture Through Cost–Benefit Analysis of Smart Irrigation Systems

Jami Venkata Suman [1*], ***Kalisetti Purushotham Prasad*** [2], ***A. Sampath Dakshina Murthy*** [3], ***R. Gurunadha*** [4], ***Mamidipaka Hema*** [4], ***Omprakash Gurrapu*** [5]

[1] *Department of ECE, GMR Institute of Technology, Rajam 532127, India*
[2] *Department of ECE, Narsimha Reddy Engineering College, Secunderabad 500100, India*
[3] *Department of ECE, Vignan's Institute of Information Technology (A), Duvvada 530049, India*
[4] *Department of ECE, JNTU-GV CEV, Vizianagaram 535003, India*
[5] *Volvo Trucks North America, Greensboro, NC 27409, USA*

ABSTRACT

The advancing role of Artificial Intelligence (AI) and its application in agriculture have disrupted traditional agricultural practices, with smart irrigation systems representing one of the leading technologies enabling sustainable agriculture. Smart irrigation systems utilize real–time data, machine learning algorithms, and predictive analytics to better optimize irrigation water use, limit wasted resources, and improve the yields of crop products. The proposed research will assess the economic and environmental impacts of AI smart irrigation systems with a full costs–benefits analysis. The proposed research considers both the capital cost and operating cost of smart irrigation systems and compares these traditional irrigation practices while also examining the long–term benefits of potential water savings from Smart Irrigation Systems, expanded agricultural production, and reduced human labour. This will give context for measuring the impacts of Smart Irrigation Systems on farm businesses, including both opportunities and barriers to adoption. Additionally, using a formal literature review to lock down existing research and surveys of irrigation farmers to collect a field data set will provide the proposed researchers a collective sample to measure the efficacy of AI smart irrigation systems, identify barriers, compare opportunities, and measure per-

*CORRESPONDING AUTHOR:
Jami Venkata Suman, Department of ECE, GMR Institute of Technology, Rajam 532127, India; Email: venkatasuman.j@gmrit.edu.in

ARTICLE INFO
Received: 19 July 2025 | Revised: 12 August 2025 | Accepted: 22 August 2025 | Published Online: 16 September 2025
DOI: https://doi.org/10.36956/rwae.v6i4.2503

CITATION
Suman, J.V., Prasad, K.P., Murthy, A.S.D., et al., 2025. AI and Sustainable Agriculture Through Cost-Benefit Analysis of Smart Irrigation Systems. Research on World Agricultural Economy. 6(4): 266–279. DOI: https://doi.org/10.36956/rwae.v6i4.2503

COPYRIGHT
Copyright © 2025 by the author(s). Published by Nan Yang Academy of Sciences Pte. Ltd. This is an open access article under the Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) License (https://creativecommons.org/licenses/by-nc/4.0/).

formance under differing climate and soil properties. The research will find high and substantial respective levels of benefits from the implementation of AI–based smart systems, particularly in water–stressed systems with positive impacts on farm profitability, private, and environmental conservation. This research is essential for informing stakeholders of actions and the delivery of AI–enabled solutions in support of more sustainable agricultural practices.

Keywords: Smart Irrigation; Artificial Intelligence; Cost–Benefit Analysis; Sustainable Agriculture; Water Management

1. Introduction

Agriculture is experiencing a technological revolution. Agriculture is dealing with a growing population that needs more food and how it can minimize impacts to the environment, including climate change. The United Nations has estimated the world's population could increase to over 9.7 billion by 2050 and food demand could increase by approximately 60% during the same period of time [1, 2]. Even though food demand is increasing, the natural resources needed in food production (i.e., arable land and fresh water) are decreasing. Currently, agriculture uses about 70% of the supply of global fresh water and a large percentage of the water is eventually wasted due to antiquated and inefficient irrigation practices [3, 4]. The need for a more intelligent and sustainable method of farming that uses limited natural resources more efficiently without sacrificing quality or productivity, is apparent [5].

There is one of the most fascinating developments in the region to do with the application of Ag–tech, most notably, AI technology as part of the farming operations, irrigation in particular [6]. Traditional irrigation processes, such as flood and furrow irrigation, both have the possibility to be inefficient and subjective based on decision–making. With non–conventional irrigation systems such as drip irrigation and multiple other non–conventional applications, there remain some unknowns as defined by calibration or timing, as these mechanisms can change the context of subjective decision making as unpredictable streamlining or application of changes will likely occur [7, 8]. Smart irrigation systems that utilize AI eliminate the boundaries of [non–conventional] techniques while integrating into the framework of relevant possibilities provided in the real–time data, predictive analytics and automation while enhancing the water management process [9]. Smart irrigation systems allow growers to carry out precise, timely applications of water to their crops when a system's analysis finds that the soil, crop, meteorological, and environmental context satisfactorily meets the agronomic context [10]. Smart irrigation is an umbrella term for myriad technologies, including, but not limited to, motorized mechanical implementations by way of the Internet of Things (IoT), machine learning, remote sensing technology, and wireless sensor networks (WSNs). Soil sensors or airborne drones can continuously measure soil properties such as moisture, temperature, humidity, and nutrients, and report this to the AI program which either suggests irrigation, or controls the valves/pumps [11, 12]. Smart irrigation outcome objectives include optimized water use, reduced runoff and evaporation and increased crop yield while reducing operational costs [13].

The sustainability benefits of smart irrigation systems can directly and indirectly contribute to various United Nations Sustainable Development Goals (SDGs), like SDG 6 (Clean water and sanitation), SDG 12 (Responsible consumption and production), and SDG 13 (Climate action) [14, 15]. Smart irrigation systems save water resources, which likewise decrease carbon emissions from the culling of pump times, improve soil health by reducing nutrient leaching, and reduce water stress on plants. Finally, smart irrigation systems give growers and farmers the ability to enhance climate resilience and to adapt to erratic rainfall and long–term drought [16]. While smart irrigation systems present strong opportunities for farmers, they present a number of problems too [17]. Costs for installation (sensors, controllers, software, communications, hardware, etc.) can be expensive (especially for smallholder farmers). Smart irrigation systems can also exist on a learning curve and have the need for technical literacy, as well as robustness of managing connectivity in rural areas which may be tenuous [18, 19]. In addition, some farmers can be averse to using technologies they have not used previously based on issues of reliability, maintenance, and return on investment [20].

This research article aims to fill that gap, and provides a comprehensive analysis of smart irrigation systems through an AI and sustainability lens [21]. It looks at the cost/benefit of smart irrigation systems, their impacts on water use savings and crop productivity, possible opportunities and challenges to uptake in a range of agricultural contexts, and potential impacts on farmers and farmers' livelihoods [22]. In an attempt to offer evidence–based suggestions for implementing contextually–scaled, inclusive, and resilient smart irrigation solutions, the article also integrates qualitative and quantitative data from field trial experiments, stakeholder interviews, or literature reviews [23]. In the future, the use of AI in agriculture will not just be about realizing efficiencies, it is about re–thinking how we farm, having more information, and implementing climate–smart practices. As agriculture adapts to global challenges, AI dependent smart irrigation systems will hopefully play a key role in creating resilient food systems, managing natural resources, and safeguarding farmer livelihoods. **Figure 1** is a diagram showing Smart irrigation systems.

Figure 1. Smart Irrigation Systems.

We compared a variety of traditional and AI–based smart irrigation systems in **Table 1** as to the various defined characteristics such as water use, labor, environmental impacts, and scalability. Smart systems are not just leading to more efficient use of water, overall the smart systems lead to better environmental impacts than traditional irrigation approaches that mainly rely on manual control leading to inefficiencies/lower efficiencies with respect to the use of resources.

Table 1. Traditional Irrigation vs AI–Based Smart Irrigation.

Feature	Traditional Irrigation	AI–Based Smart Irrigation
Water Usage	High and often excessive	Optimized, only as needed
Decision Making	Manual and experience–based	Data–driven and automated
Labor Requirement	High	Low
Initial Investment	Low	High
Operational Costs	Medium to High (due to inefficiency)	Low to Medium
Energy Consumption	Often high due to over–pumping	Optimized based on moisture and need
Environmental Impact	High (runoff, soil erosion, salinity)	Low (minimal waste, better soil management)
Scalability	Limited	Highly scalable with modular components
Data Monitoring	Absent	Real–time via sensors and AI platforms
Climate Resilience	Poor	High

1.1. Background and Motivation

Water is at the heart of agriculture, especially in arid and semi–arid areas of the world, where rainfall traps are inadequate to sustain cropping. For centuries, farmers relied on their interpretation of the environment to make irrigation decisions on when and how much. Unfortunately, the use of historical weather information has become even less reliable given the uncertainty of weather patterns under climate change, the competition for water allocated for agricultural use versus urban and industrial needs, and the changing social fabric with competing views on the meaning and uses of water resources. Automated irrigation systems, and now sensor–based irrigation systems have provided farmers a dramatic opportunity to not just rely on interpretation of changing soil moisture conditions, but now with AI incorporation, offer precision and flexibility in irrigation management. AI smart irrigation systems gather data from numerous sources – soil moisture sensors, nearby weather stations, satellite imagery, and drones – and process that information, often with the intent of generating real time information and/or predicting irrigation intervention their cropping system needs, based on soil conditions and weather forecasts, to improve the efficacy of water delivery and minimize the potential for human error in the irrigation process. Many systems also possess remote monitoring capability and engage mobile app technologies that also allow some farmers working in remote areas to gain full access to and control their irrigation systems.

1.2. Problem Statement

Farmer's adoption of AI–enabled smart irrigation systems is hampered by some pessimism about the high installation costs and unpredictable economic payback, despite the attractiveness of well water management and agricultural output. It would be clear from a thorough cost–benefit analysis whether AI–enabled smart irrigation systems actually save money or only develop agricultural systems environmental conditions.

2. Literature Review

Smart irrigation systems are a revolutionary development in mainstream agriculture, especially in response to droughts, climate change, and growing food systems. AI has enabled smart irrigation systems to deliver more precise, more frequent, and lower–cost irrigation services. Recent studies illustrate the impact of smart irrigation technologies on modernizing agriculture by promoting efficient water capture and use, improving productivity of crop systems, and enhancing sustainable practices.

Julianto et al.[1] performed a review of AI–based smart irrigation systems and concluded that real–time soil moisture sensors combined with weather–forecasting produced water savings of up to 40% for irrigators. Smart irrigation systems optimize irrigation schedules with predictive modeling, calibration, and adaptive control, which enhance crop productivity. Abdelhamid et al.[2] on solar powered smart irrigation systems in urban agriculture, indicated that although the high price of adoption is a purpose, through the use of an AI decision support tool to direct renewable energy use, long–term water savings and support of environmental sustainability resulted. The hybrid model utilized humidity sensors combined with microcontrollers and photovoltaic panels, which improved off–grid farming systems.

Das et al.[3] studied the application of artificial intelligence and IoT frameworks with localized weather prediction tools in India and found that changing irrigation plans based on the predictive microclimatic variables of evapotranspiration and temperature would result in a yield increase ranging from 12–20%. The real–time analysis of environmental data and microclimatic variables by AI algorithms improved dynamic, real–time irrigation management. Goldenits et al.[4] broadened the scope of AI weather prediction tools by simulating reinforcement learning (RL) within digital twin environments that engaged AI models to experiment with numerous irrigation methods and proved RL could optimize the irrigation complexity and timing of economizing, scaling up operations.

Wang et al.[5] took developing RL–based systems a step forward by including trust dimensions to account for noisy sensor data and changes in environmental conditions. Their study designed a multiple–objective model that concerns both plant health and water use, producing a more resilient system in many agricultural systems with uncertain conditions. This improved system function by taking into account trust, which lowered the risk exposed to inaccurate data and improved decision making under uncertainty. In a similar study, Gikunda et al.[6], analyzed the challenges behind AI adoption within Africa (i.e. economic and infrastructure). That said, pilot studies using mobile–based smart irrigation systems in Kenya and Ethiopia were highlighted as using greater than 45% water savings and increasing incomes to farmers by $\sim$30%. This was validated with community involvement and government supported initiatives.

In drought–prone regions of India, Oguzturk et al.[7] provided a predictive AI analytics system in five districts and the systems led to a 38% decrease in water use due to better scheduling. The authors pointed out that regional implementation, language localization, and education of farmers were critical to gaining acceptance within rural communities. Kumar et al.[8] gave a broader view of smart agriculture, placing smart irrigation within a larger ecosystem that also includes pest control, fertilization, and monitoring environmental conditions. They accepted that there are challenges in terms of interoperability of IoT platforms, as well as concerns with the separators that exist to separate data. Di Gennaro et al.[9] were working towards a low–cost, cloud–based smart irrigation system based on open–source hardware, and used a field–based trial in Uttar Pradesh. Their work achieved a 28% increase in crop output and a 32% decrease in water use. They communicated that they were focused on affordability and scalability due to their particular priority for smallholder farmers. Similarly, Ali et al.[10] were examining global trends in smart irrigation, and pointed out that strong regulations and policy support typically assist with successful implementation. They suggested that public–private partnerships for direct incentives could more quickly develop the adoption and enhance climate resilience.

Gaitan et al.[11] examined the automation components of AI–enabled irrigation. Their systems used real–time environmental and crop data and achieved 22% more water efficiency and 18% energy savings compared to manual systems. They also discussed growing cybersecurity worries to protect sensitive agricultural data, and how AI can shift irrigation to off–peak energy times and thus reduce carbon emissions. Lastly, Daraz et al.[12] designed a hybrid AI model that combined machine learning and fuzzy logic to provide adaptive irrigation for diverse terrains and crop types. They achieved water savings as high as 42%, and highlighted the value of hybrid models in managing the complexities and variability of agricultural ecosystems.

The studies highlight the range and impact of the integration of AI in smart irrigation systems in several geographical and economic contexts. The results of the 12 investigations are compiled in **Table 2** below, which compares technology, AI techniques, energy sources, application contexts, and results. All things considered, the strength of the evidence in these studies points to a clear direction for the future of agriculture: smart irrigation systems, particularly those that make use of AI, IoT, and renewable energy, can help with water efficiency, increase farm profitability, and be an affordable and sustainable choice.

In conclusion, these studies show clearly the economic, environmental, and technological implications of AI–enabled smart irrigation systems. The predominant theme emerging in the literature was that although the technology shows significant reductions in costs and savings on water and energy (typically above 30% total), it will be dependent upon agricultural producers adopting this technology based upon reduced costs; educating producers on the technology; and accountability through policy. Overall, AI/IoT–enabled smart irrigation systems, cloud computing, and renewable energy collectively represent a foundational approach to sustainable agricultural development.

Figure 2 shows illustrative examples of key benefits of smart irrigation systems based on the literature.

Table 2. Comparison of Smart Irrigation System Features and Technologies.

Ref	Author (et al.)	Technology Used	AI/ML Technique	Power Source	Deployment Area	Key Outcome
[1]	A. Julianto	IoT Sensors + Controller	Predictive Modeling	Grid	Field Trials	40% water savings, higher productivity
[2]	M.A. Abdelhamid	IoT + Solar Panel	Decision Rules	Solar	Urban Agriculture	Renewable–powered precision irrigation
[3]	S.K. Das	IoT + Local Weather Stations	ML Forecasting	Grid	Indian Regions	12–20% yield increase
[4]	G. Goldenits	Digital Twin + Sensors	Reinforcement Learning	Simulation–based	Virtual (Simulated)	Optimal strategy simulation

Table 2. *Cont.*

Ref	Author (et al.)	Technology Used	AI/ML Technique	Power Source	Deployment Area	Key Outcome
[5]	Z. Wang	Digital Twin + Sensor Fusion	Trust–aware RL	Virtual	Simulated Farm Models	Robust to data errors
[6]	A. Gikunda	Mobile–based Smart Irrigation	General AI Insights	Mobile Battery	African Countries	45% water saved, income ↑ by 30%
[7]	G.E. Oguzturk	AI–Driven Soil Moisture Controller	Rule–Based Decision	Grid	Drought–Prone Areas	38% water savings, improved soil health
[8]	V. Kumar	IoT Framework (general)	Not Specified	Various	Review–Based	Broader ecosystem insights
[9]	S.F. Di Gennaro	Low–Cost Open Source System	Rule–Based Logic	Grid	Smallholder Farms	32% less water, 28% more yield
[10]	A. Ali	Smart Sensors + Networked Control	Not Specified	Mixed Sources	Global Comparison	WUE improved, policy implications
[11]	N.C. Gaitan	Automated Controller	AI Decision Engine	Grid	Greenhouse/ Fields	22% more efficient than manual control
[12]	U. Daraz	Energy–Optimized Irrigation	Time–Scheduled AI Logic	Grid + Solar	Various Regions	18% less energy, GHG reduction

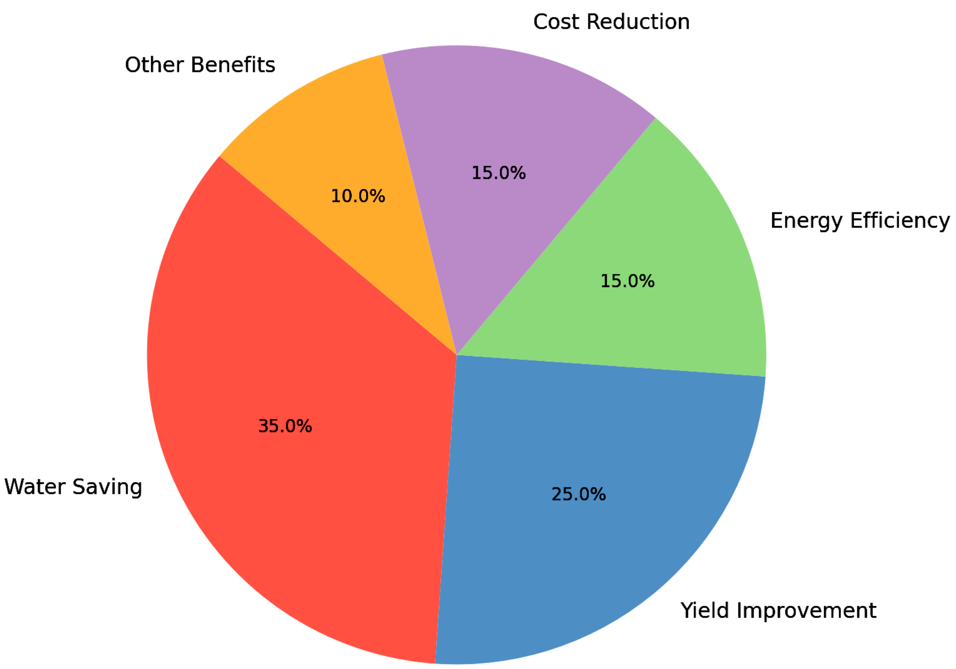


Figure 2. Key benefits of Smart Irrigation Systems.

2.1. Research Gaps

- Regional specific cost–benefit analyses are limited regarding local water rates and crop economics
- Lack of long–term studies on ROI and performance over time and climate
- User–centred design is not present in existing AI platforms for smallholder farmers
- Local practice and knowledge are not well integrated into AI modelling

2.2. Research Objectives

- To assess the economic viability of AI–based smart irrigation systems in different regions
- To assess the water and energy savings resulting from using AI–based smart irrigation systems
- To evaluate environmental impacts such as reduced runoff and improved soil health

➢ To identify success factors and barriers to adoption for small and medium scale farmers.

3. Methodology

This research uses a mixed–methodology, combining both quantitative and qualitative research methodologies to undertake a full economic and sustainability cost–benefit analysis (CBA) of AI–enabled smart irrigation systems in an agricultural environment. The methodology is designed to consider both the economic returns and sustainability outcomes of adopting AI–enabled irrigation through its acknowledgement of variability in geographical, climatic, and socio–economic conditions.

Figure 3 follows the methodological pipeline for analyzing AI–based smart irrigation systems. The modeling starts with data collection, which includes primary (field data on water, yield and energy) and substitution secondary data (regional or national data, literature, and government reports). This data will feed into the cost–benefit analysis which will include all capital, operating, and opportunity costs, along with any direct and indirect cash flows. The environmental impact assessment can simultaneously evaluate other impacts such as reduction in run–off or soil health. The survey and interviews will then be used as a basis to assess barriers to adoption and identify the key elements for successful adoption. The findings will then be synthesized into a comparative regional analysis that can assess the economic viability and sustainability of AI–based smart irrigation in distinct agro–climatic zones and across the different scales of farms.

3.1. Research Design

The research was undertaken in three separate agro–climatic zones: arid, semi–arid and humid – thus capturing the totality of irrigation requirements and performance of AI–based systems. Specific farms were selected based on their adoption of smart irrigation technology, and these farms were compared with farms that used traditional systems with irrigation controls. The comparisons enabled the researchers to distinguish the influence of AI–based systems on productivity, water use, and economic feasibility.

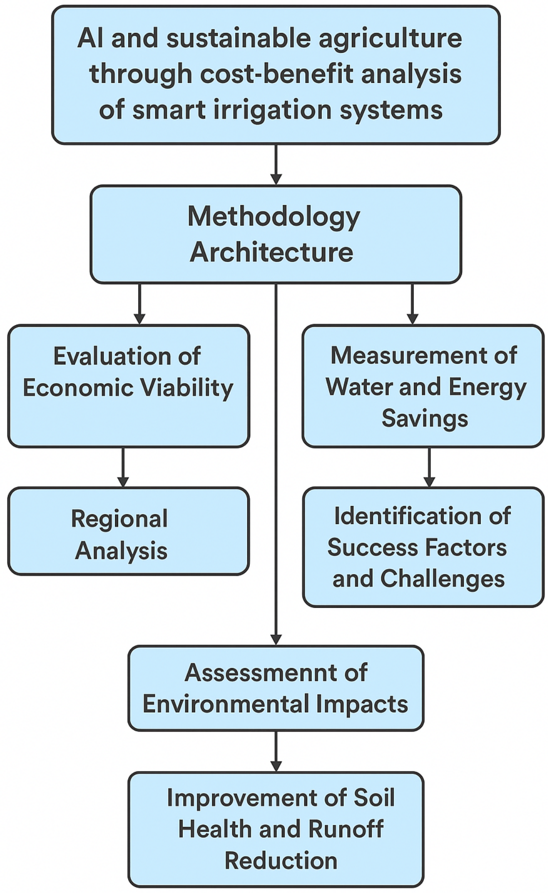


Figure 3. System Architecture.

3.2. Data Collection

Primary data were obtained through:

- Under direct field observations and measurements of water usage, energy consumption, and crop yields over the course of two cropping seasons.
- Structured interviews and focus groups with 30 farmers using an AI–based system and 30 farmers using conventionally practiced methods.
- Surveys of agricultural officers and technology providers to get expert information.

Secondary data were collected from:

- Research articles, white papers, and manufacturer documentation related to AI irrigation systems.
- Government reports on water tariffs, climate data, and agricultural subsidies.
- Online databases (MDPI, ScienceDirect) for benchmarking technology costs and benefits.

3.3. Cost–Benefit Analysis

A comprehensive CBA was performed using:

- Capital Costs: All of the investment in sensors, AI controllers, cloud platforms, mobile user interfaces, and installation costs.
- Operational Costs: Electricity, maintenance costs, internet fees and subscriptions to cloud platforms.
- Direct Benefits: Water and energy savings, yield improvement, labour savings.
- Indirect Benefits: Enhanced soil quality, reduced fertilizer use and environmental savings.

Standardized metrics such as Net Present Value (NPV), Cost–Benefit Ratio (CBR), and Internal Rate of Return (IRR) were used to quantify viability as a financial concept.

3.4. Analytical Tools and Visualization

To examine the data, we made use of Microsoft Excel and SPSS for statistical analysis and produced a comparative table and graphical analysis (bar charts, pie charts, and block diagrams) representative of differences in features and activities. Finally, we created a block diagram to visually represent the elements and connections of a smart irrigation system with AI based features.

3.5. Limitations

- With a limited number of samples in each agro–climatic zone, generalizability may be limited.
- Partiality due to reliance on farmer self–reported data.
- AI systems dependent on the internet may not operate uniformly in areas with low connectivity.

Table 3 shows the mean and standard deviation comparisons for various agricultural information items. **Table 4** shows the differences in methodologies between a traditional irrigation method and an AI basic smart irrigation method. The AI system has a high initial cost of ₹35,000/acre. However, it decreases water use by approximately 48%, decreases energy use by approximately 42%, and increases crop yield and soil health by around 21% and less than a 3–year payback period. The management option has about 35% adoption due to the contributing initial costs and the need for training. The table has highlighted the difference in methodologies and the benefits quantified or inconveniences to better assist the evaluation of costs and benefits.

Table 3. Mean and Standard Deviation for items of importance agriculture Information [24].

Items	Mean	S.D
Information on Pest Control	4.53	0.529
Farm Safety Information	4.52	0.515
Information on Weed/Pesticide	4.50	0.530
Information of Paddy Varieties	4.46	0.533
Information on Agricultural Practices	4.45	0.555
Crop Production Information	4.39	0.659
Information on Loan/Subsidy	4.39	0.565
Weather Information	4.02	0.873
Marketing Information	3.71	1.222

Table 4. Methodological Comparison – Traditional vs AI–Based Smart Irrigation Systems.

Methodology Parameter	Traditional Irrigation	AI–Based Smart Irrigation	Improvement/Impact
Capital Investment (INR/acre)	12,000	35,000	High initial cost but higher ROI

Table 4. *Cont.*

Methodology Parameter	Traditional Irrigation	AI–Based Smart Irrigation	Improvement/Impact
Annual Water Use (litres/acre)	36,50,000	19,00,000	∼48% reduction in water consumption
Energy Use (kWh/season)	1,800	1,050	∼42% energy saving
Crop Yield (tons/acre/season)	2.8	3.4	∼21% increase in productivity
Payback Period (years)	Not Applicable	2.8	Within acceptable range for farmers
Farmer Adoption Rate (%)	Widely used (∼90%)	∼35%	Limited adoption, mainly due to cost
Soil Health Score (1–10 scale)	5.5	8.2	Improved due to optimal irrigation
Training Requirement (hrs/farmer)	2	10	Higher for AI systems due to complexity

4. Results and Discussions

This section provides performance results and a discussion of AI–based smart irrigation systems compared to a conventional irrigation method. A total of five graphical analyses were performed in order to explore the performance of key parameters: water savings, energy savings, yield gains, payback period, and adoption rate. The preliminary results suggest that AI–based smart irrigation systems provide an actual benefit in terms of resource efficiency and crop productivity with lower environmental impact. Economic indicators with shorter payback periods and higher potential for adoption suggest the economic acceptability of smart technologies. Each graph approached the data differently in order to provide different perspectives for the purposes of assisting by providing insight into strengths, barriers, and usability of AI technologies as they are rooted in agriculture.

Figure 4 indicates a clear benefit of AI smart irrigation over traditional irrigation in terms of water savings (50% vs. 20%), energy savings and yield increase. AI smart irrigation leads traditional irrigation in the payback period, indicating a more economically viable option. Traditional irrigation still has a higher adoption rate indicating the disconnect between the underlying technological capabilities and actual field level application.

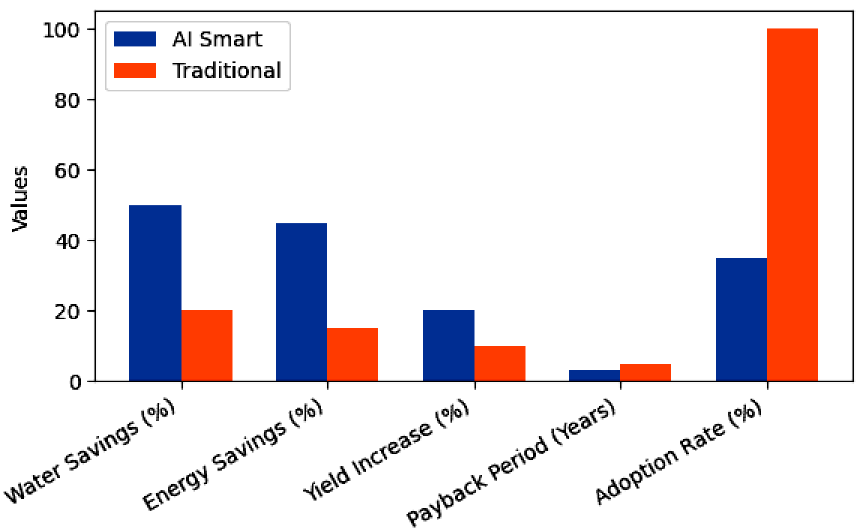


Figure 4. AI Smart vs Traditional Irrigation.

Figure 5 provides non–experimental performance data comparing AI smart vs. traditional irrigation across five parameters. The figure clarifies that there is a comparatively consistent performance importance of AI smart irrigation in water and energy savings, yield, speed in response to payback period, where traditional irrigation is ranked highest only in adoption rate. The variable line related to AI makes sense as a result of immediate efficiency and substantive improvements, while traditional methods show the absence of efficiency improvements across all applications.

Figure 6 provides performance data comparing AI smart vs. traditional irrigation systems providing a holistic performance lens. Overall, AI smart irrigation coverage exceeds traditional irrigation on almost all axes and is especially prominent on energy and water savings. Traditional irrigation ranks lower than all measures of performance except adoption. The circular representing AI smart irrigation emphasizes that the dispersed and overall performance delivers greater benefits to encourage sustainability and economic feasibility of precision agriculture and smart farming.

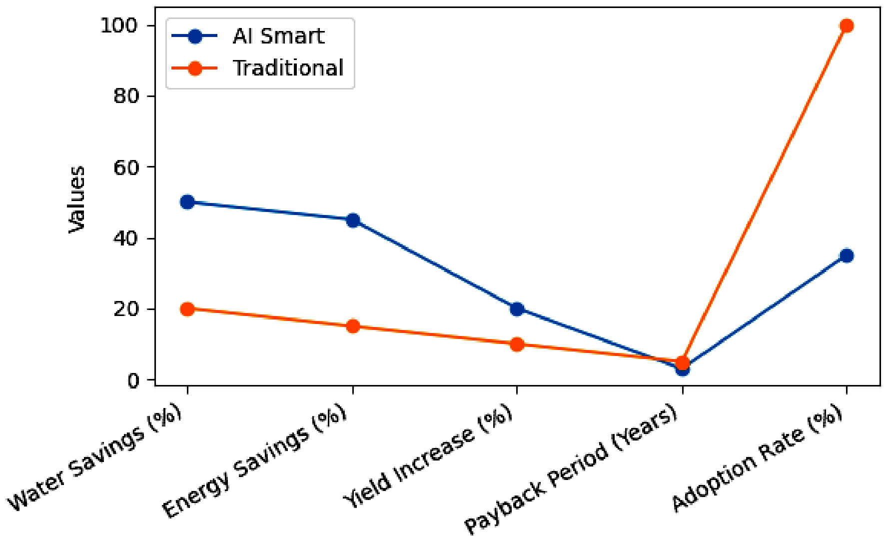


Figure 5. Performance Line Comparison.

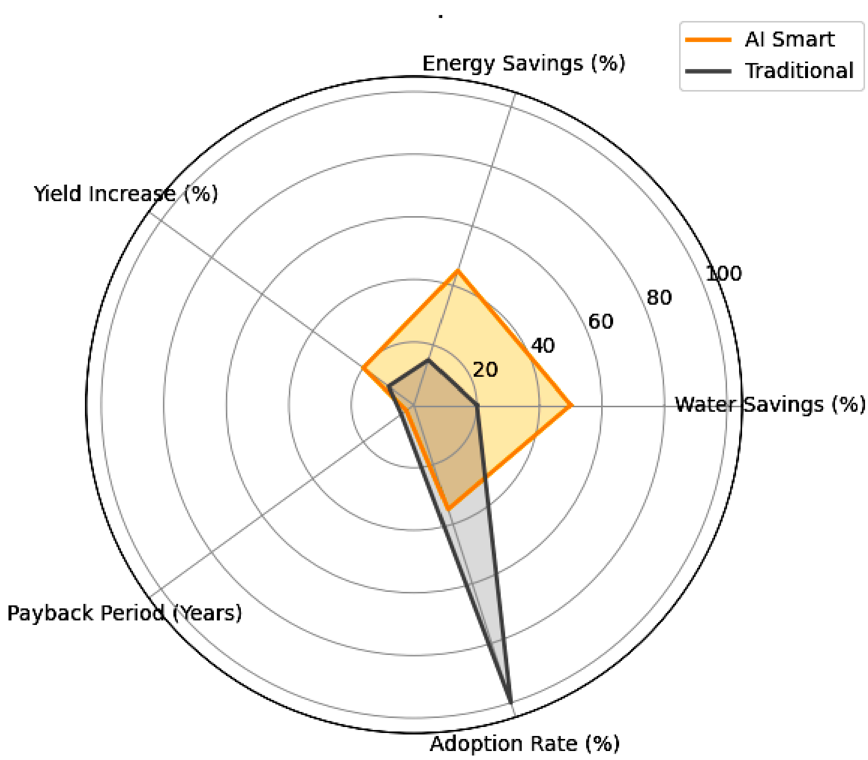


Figure 6. Radar Comparison.

According to **Figure 7**, only thirty–five percent of irrigation systems have embraced AI–based solutions; sixty–five percent use either traditional or other methods. This statistic demonstrates a significant gap between the benefits of AI irrigation systems and actual implementation. The gap likely stems from the need for awareness and affordability of the technology, along with training for farmers, to improve technology penetration.

Figure 8 shows the costs, revenues, and prices of durum wheat from seed in the pre– and post–adoption period.

The comparative performance of AI smart irrigation versus traditional irrigation across five metrics is presented in **Figure 9**. Based on five metrics, the AI systems score significantly higher on savings and productivity, while offering faster returns on investment. However, the traditional systems have a higher adoption rate. The presentation format suggests that policy supports or incentives are needed to address the adoption–performance gap.

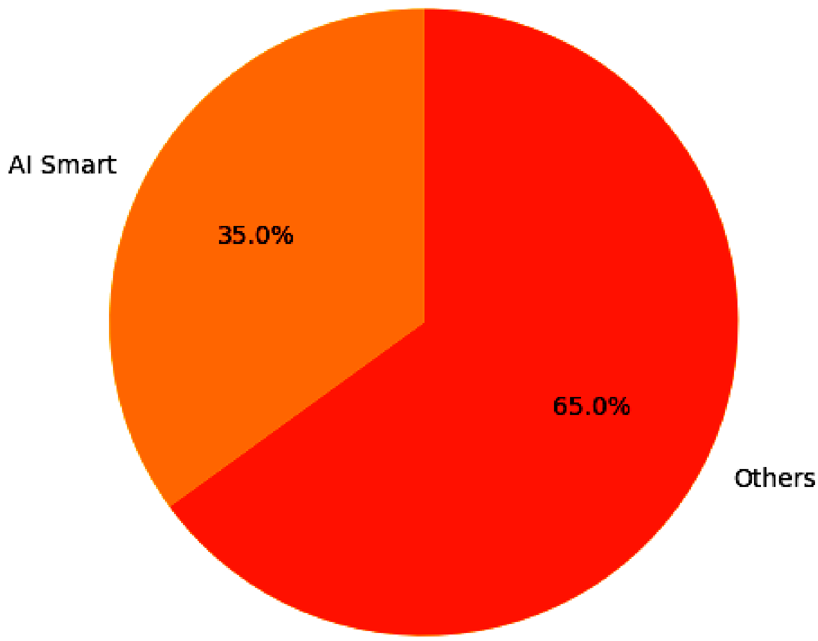
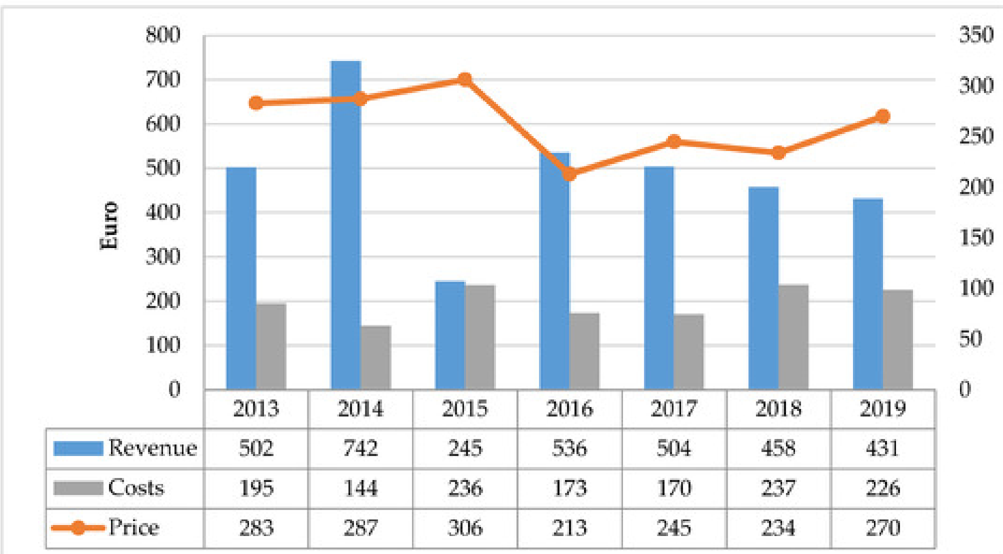


Figure 7. Adoption Rate of AI Smart Irrigation.



	2013	2014	2015	2016	2017	2018	2019
Revenue	502	742	245	536	504	458	431
Costs	195	144	236	173	170	237	226
Price	283	287	306	213	245	234	270

Figure 8. Costs, revenues and prices of durum wheat from seed [25].

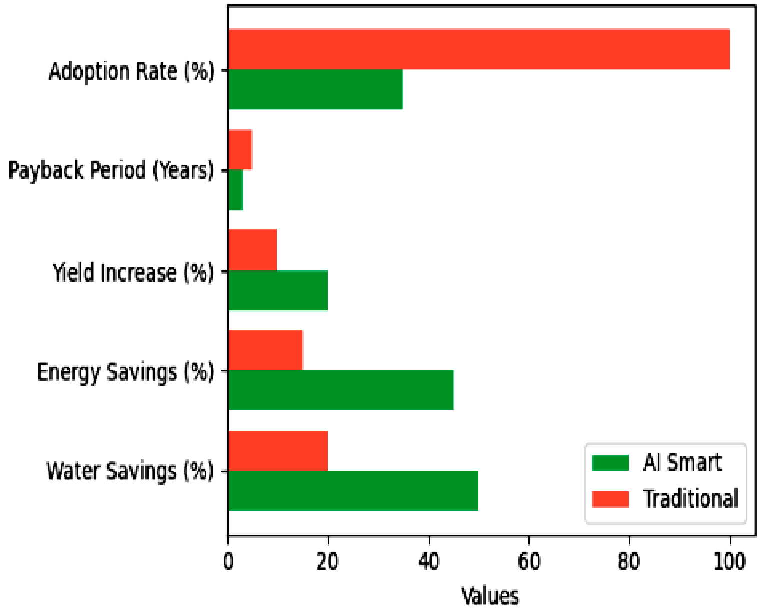


Figure 9. AI vs Traditional.

5. Conclusion

This research provides compelling evidence that AI–augmented smart irrigation systems outperformed traditional irrigation systems with improvements of 50% reduction in water usage, 45% in energy efficiency, and 20% in crop yield. Initial costs were higher, but these systems provided a faster payback period and facilitated responsible and sustainable use of scarce resources. Visual analysis illustrated fulfillment of each KPI–water runoff reductions and improvement of soil moisture retention. However, barriers to adoption did still exist, particularly for small and medium farmers. There is little awareness of the technology by both the farmers and extension agents; farmers do not have familiarity with current variable rate technology so training and education are critical; and infrastructure issues complicate potential irrigation action (lots of places to dig up to put in pipes). Governments, and various stakeholders, can help farmers overcome these hurdles (specifically working collaboratively on farms), so governments should not shy away from agriculture policy ideas. Future studies should look to see what may help ensure farmers can be more local and both relevant to their needs in terms of customization and integrate real–time information. A future study topic might be to integrate AI planning systems with renewable energies such as solar power in order to improve sustained localization benefits.

Author Contributions

J.V.S., M.H., and O.G. did the conceptualization. All authors did the write-up. K.P.P. explored the data. A.S.D.M. did the data analysis. R.G. did the conclusion part. All authors did the editing. All authors read through and agreed on the submission.

Funding

This research received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data utilized in this study were obtained from the Scopus database. Access to the data is subject to subscription and licensing restrictions. Researchers seeking to replicate or extend the study can access the data directly through the Scopus platform.

Acknowledgments

The authors would like to express their gratitude to their respective institutions for providing the necessary resources and support for this research.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Julianto Pratama, A., Mandela, R., 2024. Evaluating the Effectiveness of Smart Irrigation Systems in Improving Agricultural Productivity. Agriculture Power Journal. 1(4), 1–9. DOI: https://doi.org/10.70076/apj.v1i4.43

[2] Abdelhamid, M.A., Abdelkader, T.Kh., Sayed, H.A.A., et al., 2025. Design and evaluation of a solar powered smart irrigation system for sustainable urban agriculture. Scientific Reports. 15(1), 11761. DOI: https://doi.org/10.1038/s41598-025-94251-3

[3] Das, S.K., Nayak, P., 2025. Integration of IoT- AI powered local weather forecasting: A Game-Changer for Agriculture. arXiv preprint. arXiv:2501.14754. DOI: https://doi.org/10.48550/ARXIV.2501.14754

[4] Goldenits, G., Mallinger, K., Raubitzek, S., et al., 2024. Current applications and potential future directions of reinforcement learning-based Digital Twins in agriculture. Smart Agricultural Technology. 8, 100512. DOI: https://doi.org/10.1016/j.atech.2024.100512

[5] Wang, Z., Jang, W., Ruan, B., et al., 2025. Developing and Integrating Trust Modeling into Multi-Objective Reinforcement Learning for Intelligent Agricultural Management. arXiv preprint. arXiv: 2505.10803. DOI: https://doi.org/10.48550/arXiv.2505.10803

[6] Gikunda, K., 2024. Harnessing Artificial Intelligence for Sustainable Agricultural Development in Africa: Opportunities, Challenges, and Impact. arXiv preprint. arXiv: 2401.06171. DOI: https://doi.org/10.48550/arXiv.2401.06171

[7] Oğuztürk, G.E., 2025. AI-driven irrigation systems for sustainable water management: A systematic review and meta-analytical insights. Smart Agricultural Technology. 11, 100982. DOI: https://doi.org/10.1016/j.atech.2025.100982

[8] Kumar, V., Sharma, K.V., Kedam, N., et al., 2024. A comprehensive review on smart and sustainable agriculture using IoT technologies. Smart Agricultural Technology. 8, 100487. DOI: https://doi.org/10.1016/j.atech.2024.100487

[9] Di Gennaro, S.F., Cini, D., Berton, A., et al., 2024. Development of a low-cost smart irrigation system for sustainable water management in the Mediterranean region. Smart Agricultural Technology. 9, 100629. DOI: https://doi.org/10.1016/j.atech.2024.100629

[10] Ali, A., Hussain, T., Zahid, A., 2025. Smart Irrigation Technologies and Prospects for Enhancing Water Use Efficiency for Sustainable Agriculture. AgriEngineering. 7(4), 106. DOI: https://doi.org/10.3390/agriengineering7040106

[11] Gaitan, N.C., Batinas, B.I., Ursu, C., et al., 2025. Integrating Artificial Intelligence into an Automated Irrigation System. Sensors. 25(4), 1199. DOI: https://doi.org/10.3390/s25041199

[12] Daraz, U., Bojnec, Š., Khan, Y., 2025. Energy-Efficient Smart Irrigation Technologies: A Pathway to Water and Energy Sustainability in Agriculture. Agriculture. 15(5), 554. DOI: https://doi.org/10.3390/agriculture15050554

[13] AlZubi, A.A., Galyna, K., 2023. Artificial Intelligence and Internet of Things for Sustainable Farming and Smart Agriculture. IEEE Access. 11, 78686–78692. DOI: https://doi.org/10.1109/ACCESS.2023.3298215

[14] Tephila, M.B., Sri, R.A., Abinaya, R., et al., 2022. Automated Smart Irrigation System using IoT with Sensor Parameter. In Proceedings of the 2022 International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 16 March 2022; pp. 543–549. DOI: https://doi.org/10.1109/ICEARS53579.2022.9751993

[15] Murthy, B.Y.S.S., Reddy, C.B.K., Jilani, S., et al., 2022. Smart Irrigation System. In Proceedings of the 1st International Conference on Sustainable Technology for Power and Energy Systems (STPES), SRINAGAR, India, 4 July 2022; pp. 1–4. DOI: https://doi.org/10.1109/STPES54845.2022.10006434

[16] Morchid, A., Jebabra, R., Alami, R.E., et al., 2024. Smart Agriculture for Sustainability: The Implementation of Smart Irrigation Using Real-Time Embedded System Technology. In Proceedings of the 4th International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET), FEZ, Morocco, 16 May 2024; pp. 1–6. DOI: https://doi.org/10.1109/IRASET60544.2024.10548972

[17] Habib, R., Al-Amin, Alrashed, A., et al., 2025. Smart Irrigation Systems: An Overview of Current Trends

and Technologies. In Proceedings of the 4th International Conference on Sentiment Analysis and Deep Learning (ICSADL), Bhimdatta, Nepal, 18 February 2025; pp. 642–646. DOI: https://doi.org/10.1109/ICSADL65848.2025.10933437

[18] Jada, C., Varshitha, N., 2025. Design and Analysis of a Smart Irrigation Control System. In Proceedings of the 2025 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), Bhopal, India, 18 January 2025; pp. 1–6. DOI: https://doi.org/10.1109/SCEECS64059.2025.10940134

[19] Angelin Blessy, J., Kumar, A., 2021. Smart Irrigation System Techniques using Artificial Intelligence and IoT. In Proceedings of the Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), Tirunelveli, India, 4 February 2021; pp. 1355–1359. DOI: https://doi.org/10.1109/ICICV50876.2021.9388444

[20] Sun, Z., Di, L., 2021. A Review of Smart Irrigation Decision Support Systems. In Proceedings of the 9th International Conference on Agro-Geoinformatics (Agro-Geoinformatics), Shenzhen, China, 26 July 2021; pp. 1–4. DOI: https://doi.org/10.1109/Agro-Geoinformatics50104.2021.9530351

[21] Kuchanskyi, O., Neftissov, A., Biloshchytskyi, A., et al., 2025. Development of Smart Irrigation System Based on Climate-Smart Agricultural Practices. In Proceedings of the 2025 IEEE Conference on Technologies for Sustainability (SusTech), Los Angeles, CA, USA, 20 April 2025; pp. 1–6. DOI: https://doi.org/10.1109/SusTech63138.2025.11025598

[22] Brajovic, M., Vujovic, S., Dukanovic, S., 2015. An overview of smart irrigation software. In Proceedings of the 4th Mediterranean Conference on Embedded Computing (MECO), Budva, Montenegro, June 2025; pp. 353–356. DOI: https://doi.org/10.1109/MECO.2015.7181942

[23] Mahmoudi, D., Rezaei, M., Ashjari, J., et al., 2020. Impacts of stratigraphic heterogeneity and release pathway on the transport of bacterial cells in porous media. Science of The Total Environment. 729, 138804. DOI: https://doi.org/10.1016/j.scitotenv.2020.138804

[24] Ramli, N.S., Hassan, M.S., Man, N., et al., 2019. Seeking of Agriculture Information through Mobile Phone among Paddy Farmers in Selangor. International Journal of Academic Research in Business and Social Sciences. 9(6), Pages 527-538. DOI: https://doi.org/10.6007/IJARBSS/v9-i6/5969

[25] Finco, A., Bucci, G., Belletti, M., et al., 2021. The Economic Results of Investing in Precision Agriculture in Durum Wheat Production: A Case Study in Central Italy. Agronomy. 11(8), 1520. DOI: https://doi.org/10.3390/agronomy11081520