

Automated Rice Farming: A Sensor-Fused AI-IoT Framework for Smart Water Management

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Abstract - *Water is a key subject to manage in rice agriculture, and especially in Karnataka, where farmers continue to rely on traditional farming methods. Many farmers establish a schedule for watering their rice crop, based on years of farming experience, however, the continual change in weather patterns means that this experience must be taken into consideration along with the changes in weather for the previous year (such as rainfall and temperature increases). The result is that many farmers risk either over-irrigating or under-irrigating their crops. These risks, depending on whether they are too much or too little water, will have negative consequences on their crop yield, the health of the soil, and their overall productivity.*

This paper describes the use of a smart irrigation system that utilizes IoT sensors and artificial intelligence to assist farmers with their irrigation practices. The smart irrigation system gathers information about the moisture in the soil, temperature, humidity, and water levels in real-time from the farmer's field and uses this information, combined with short term weather predictions from local weather stations, to develop a better understanding of the factors affecting the agricultural industry in that area and how they will continue to be affected.

The intelligent irrigation system's goal is not to replace the farmer but to provide the farmer with simple, practical suggestions to help him or her make more informed decisions. The overall objectives of the smart irrigation system are to reduce water usage, decrease the cost of irrigation and improve the efficiency of rice production in light of the changing climate.

I. INTRODUCTION

Karnataka is a major producer of rice in India, however, due to climate change, it is becoming increasingly difficult for farmers in Karnataka to manage the water

used for growing rice. Previously, farmers could depend on a consistent rainfall pattern during the monsoon season, however this is no longer the case. Over the past few years, there have been longer periods of time between rainy seasons, more days of unexpected rain, and temperatures have continued to increase. As a result of these changes, there are often times when there is not enough water available to irrigate crops when required so traditional methods of irrigation are becoming unreliable.

In addition to climate change, the way irrigation is used still lags behind technology by far. Many farmers in rural Karnataka rely on fixed schedules and personal experience when determining how to irrigate their crops. This worked well for many years; however, current growing conditions do not always align with past growing conditions and therefore these traditional methods for deciding when to irrigate frequently fail. For example, a farmer could have previously determined that his crops needed to be irrigated on May 30, but now this date occurs during May in a season where there is sufficient moisture for the crop's growth. Because many farmers lack access to real-time information about soil moisture levels and short-term weather forecasts, the decision of when to irrigate is often based solely on guesswork.

Due to a lack of access to real-time data, many farmers do not have the ability to know the right time for irrigation, resulting in not enough or too much water being applied to the land, which increases irrigation costs as well as soil conditions that are poor due to either too much water or not enough water. Improving the efficiency of agricultural water use is still a significant problem because of this lack of proper timing and proper use of irrigation.

Fortunately, inexpensive sensors, as well as advances in machine-learning algorithms, have improved our capacity for monitoring soil moisture and temperature, water levels, and relative humidity in a continuous

manner through the use of IOT sensors. By using AI models in combination with short-term weather forecasts, it is possible to make more accurate irrigation decisions with a proactive approach using predictive models; therefore, instead of reacting to crop stress and then applying irrigating as a reaction, it will be possible to use predictive models and take action beforehand.

The research study proposes a framework based on AI-IOT sensor systems for the purpose of providing timely irrigation guidance and for improving the overall water management system through predictive models in the area of paddy production in Karnataka.

II. OBJECTIVES OF THE STUDY

1. To examine the challenges related to irrigation and water management in rice cultivation in Karnataka.
2. To design a smart irrigation framework that integrates IoT sensors for monitoring soil moisture, water level, and weather conditions.
3. To apply Artificial Intelligence models to analyse field data and support accurate irrigation decision-making.
4. To study how the proposed system can help reduce water wastage and improve overall farming efficiency.

III. LITERATURE REVIEW

Author & Year	Study Focus	Key Findings	Relevance to This Study
Bowden et al., 2023	Machine learning analysis of monsoon variability and rice yield	Showed that rainfall patterns can be analysed using ML to predict crop performance.	Demonstrates how climate data can improve irrigation planning.
Venkatesh et al., 2022	Rainfall variability and crop water stress in Karnataka	Found that irregular rainfall patterns directly	Highlights the need for better irrigation decision systems in

		affect crop water stress.	Karnataka .
Parikh & Sharma, 2025	ML-based irrigation prediction	Developed models to estimate crop water requirements using historical weather data.	Supports the use of machine learning for irrigation forecasting.
Preite & Vignali, 2023	AI-based irrigation optimisation	Predictive algorithms reduced water usage while maintaining crop productivity.	Shows how AI can optimise irrigation efficiency.
Singh & Meena, 2024	ML integrated with IoT irrigation monitoring	Demonstrated improved irrigation decisions using sensor data and ML models.	Validates combining IoT sensors with AI models.
Binayao et al., 2024	IoT sensor network for rice irrigation	Continuous monitoring of soil moisture and temperature improved field management.	Shows the practical value of IoT sensors in rice farming.
Kumar et al., 2024	Adoption of IoT and AI in	Sensor-based systems	Supports technology adoption

	South Indian agriculture	can translate real-time field data into irrigation guidance.	in regional farming practices.
Gaitan et al., 2025	Fully automated AI-IoT irrigation system	AI predictions triggered irrigation actuators automatically.	Demonstrates the potential of automated irrigation systems.
MDPI Agriculture, 2022	Precision irrigation using ML models	Integrated smart agriculture framework improved water-use efficiency.	Supports AI-based irrigation optimisation.
Springer Smart Agriculture Journal, 2025	Smart agriculture systems	Unified frameworks perform better than single-function irrigation systems.	Justifies the integrated system design used in this study.
MDPI Sensors, 2023	Review of sensor technologies for agriculture	Summarised available technologies for soil and water monitoring.	Shows sensor monitoring is important for smart irrigation.
Remote Sensing Study, 2025	Satellite monitoring of rice irrigation	Remote sensing can analyse water management	Provides broader monitoring insights.

		practices at large scale.	
CNN Water Monitoring Study, 2024	Computer vision for water level detection	CNN models can estimate paddy water levels using images.	Suggests alternative monitoring technologies.
FAO, 2021	Penman–Monteith evapotranspiration method	Standard approach for estimating crop water requirements.	Provides scientific foundation for irrigation models.
IRRI, 2022	Alternate Wetting and Drying (AWD) technique	Demonstrated up to 30% water savings in rice farming.	Supports efficient irrigation practices.
Jagannathan & Ramakrishnan, 2023	Climate-smart irrigation in India	Identified challenges and opportunities for irrigation technologies.	Provides regional context for irrigation improvements.
Mishra & Patil, 2023	Water resource management in Karnataka	Documented irrigation challenges in the region.	The need for improved water management systems.

IV. METHODOLOGY

1. Research Methodology

A conceptual but design-oriented research method was employed for this study, which did not attempt to create a fully functioning system but create a framework that

could be implemented under real-world conditions for agricultural purposes. This framework's primary purpose was to establish if the implementation of IoT monitoring and AI modelling would improve irrigation implementations prior to the full rollout of the established system.

The conceptual framework was informed by prior research, practical problems in Karnataka's rice production systems and the known capabilities of both the machine learning model and the sensor system.

2. Framework for System Design

The system is divided into four main layers: sensor, edge, cloud/AI, and irrigation control.

• Sensor Block

Data is collected from the field (i.e., soil moisture, water level and basic weather information such as temperature, humidity and rainfall) through three types of sensors. This data provides an understanding of current field conditions.

• Edge Block

The edge device processes the data through a microcontroller (ESP32 / Raspberry Pi). It filters out unnecessary data (noise), stores data temporarily and continues to work without a reliable internet connection.

• Cloud/AI Block

The collected data is analysed based on existing AI modelling (i.e., XGBoost). XGBoost will predict the amount of rain and air temperature, and LSTM will allow for a historical assessment of soil moisture trends and, as a result, enable better irrigation decision-making.

• Irrigation Control Block

This block will execute an irrigation command based on the output of the AI modelling, with preset safety limits to prevent over-irrigation of crops.

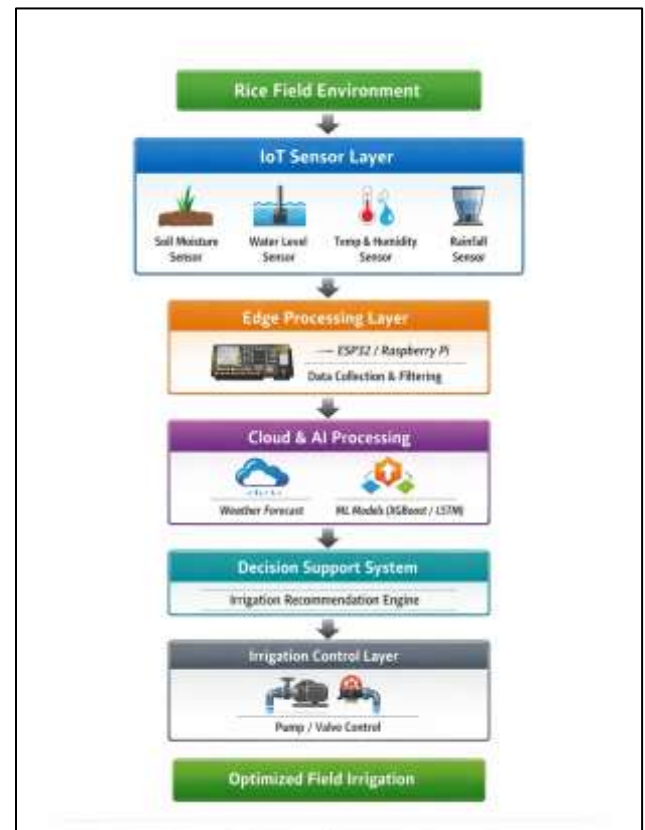


Figure 1. Architecture of the Proposed AI-IoT Smart Irrigation System

3. Data Collection and Processing

The AI models in the system rely on two forms of input: sensor-based data that are coming in real-time from the field as well as short-term weather forecast data. Sensor data consists of key data points including water level, soil moisture at multiple depths, temperature and humidity levels as well as rainfall fall data. This conceptual study was designed using simulated environmental conditions found in Karnataka rice-growing regions derived from existing research and climate datasets.

Before using the data for predictive modelling, it will go through several processing steps within the cloud layer first. First, the raw sensor readings are cleaned from noise or errors allowing the final data to be properly organized. In addition to this, calculations will be performed on some of these sensor readings to improve overall model performance (for example calculating the change in water levels over a period of time, accumulating the total amount of rainfall over specified time frames and computing soil moisture deficit according to crop requirements) before the models use the data to make their predictions.

These calculated values give the models better trend understanding since they do not only have to rely on today's value of a particular set of data but also have the

benefit of knowing the historical data used as a comparison/reference point. In short, the system leverages both present conditions and nearterm changes in its irrigation management decision process.

4. Predictive Modelling

The system utilizes two modeling techniques for prediction purposes: XGBoost and LSTM (Long Short-Term Memory). XGBoost is the preferred choice for predicting both temperature and short-term rain due to its ability to efficiently process structured data using more complex patterns of data without requiring an excess of statistical samples. In contrast, LSTM is preferred for predicting soil moisture based on its dependence on historical data regarding factors such as rain and irrigation; thus LSTM provides an efficient means for modeling (or defining) the temporal dependency of soil moisture on previous events.

Both methodologies run concurrently with their respective outputs combined to produce a risk score that will be used when determining whether to irrigate in the next decision layer (irrigation).

5. Irrigation Decision Logic

The irrigation decision layer uses the outputs from the two methodologies and available sensor readings to produce a set of actionable feasibility as to when to irrigate. The decision layer relies on fixed rules or artificial intelligence (AI) predictions and focuses primarily on avoiding flooding, reducing crop stress, reducing unnecessary water usage, and helping to improve the timing of irrigation.

Thus, depending on the conditions associated with the respective risk score produced for each of the two modeling methodologies, users will receive guidance as to whether or not they need to irrigate: i.e., begin irrigation immediately; implement a shorter irrigation frequency; and/or delay irrigation due to anticipated rainfall. Moreover, safety thresholds will be placed on the amount of irrigation applied to mitigate flooding and maintain appropriate moisture levels in crops.

6. Assessment Process

Because the concept of the system has not yet been realized in the form of an operational application within its actual environment, evaluation will take place through two approaches. The first will be explored via internal consistency to verify that all layers of the system work in conjunction without error. Second, existing studies have been reviewed to determine if other systems similar to the one proposed achieve benefits under the same conditions as proposed.

This form of evaluation is appropriate for the current stage of development because it helps establish if the proposed design is practical and sound based on logic. Testing the system in field locations will occur during future phases.

7. Farmer Interaction Component

Having a system that provides adequate technical performance does not guarantee success for the system. If farmers do not comprehend or have confidence in the system, it is probable that they will not use it. This is why the next phase of the study will include analyzing farmer interaction with the proposed system.

The data obtained from this assessment will consist of a survey conducted during field testing to determine how farmers currently irrigate, the challenges they face, and their experience using digital tools. In addition, the survey will investigate how receptive farmers are to following the system's recommendations. The information derived from this evaluation will assist with designing a simple and functional user interface for those using the system.

8. Summary

The proposed system's methodology contains specifically defined steps for design, data collection from the field, data processing and its use to support irrigation decisions (i.e. how each piece of the system is used from sensor deployment to training an AI model), the critical need for farmers' input in the decision-making process (very important factor will be usability and farmer acceptance), and sufficient detail to facilitate actual implementation. Also, although the methodology is clear enough for implementation of the framework, real-world testing of the framework will fully validate its value.

V. RESULTS AND DISCUSSION

Results Summary

As this research was entirely theoretical, results were generated through simulated environments reflecting 'normal' climatic conditions for the state of Karnataka. Simulations have been carried out to evaluate how an AI-IoT irrigation system will behave in practical agricultural applications

Sensor/Data Trends

Changing patterns of soil moisture content, water level (in the irrigation channel), and temperature measured throughout time all reflected expected outcomes in the

simulated environment. For instance, when rain occurred, the level of water increased, and was buffered by evaporation during drier periods. This backs up the idea that ongoing observations are critical to effective water management. Also, these findings demonstrate that using the proposed sensor package will yield useful, realistic agricultural field data under actual practices.

Model Validation

Models were found to be suitable for making reliable predictions under simulation, particularly in short-term predictions. Rainfall predictions assisted the system in determining if irrigation could be postponed; while predictions of impending soil moisture deficits indicated when plants would exhibit signs of water deficiency prior to actual water loss. Therefore, despite the results being based upon computer-generated simulation data, the results show that the models will provide better irrigation decision-making capabilities and improve the conservation of water through efficient irrigation.

Irrigation Decision Making Based on Irrigation System Decision Rules

The decision rules contained within the irrigation management system responded appropriately to changes in the conditions of the field during simulation testing, e.g., The decision rules for your irrigation system are effective in changing the irrigation strategy, responsive to a drop in required irrigation levels and therefore initiated irrigation when irrigation levels dropped too low or planned to stop irrigation just prior to anticipated rainfall. This allows for eliminating wasteful irrigation and demonstrates how the irrigation management system can significantly increase the efficiency of water use while at the same time reducing the cost of pumping water.

Practical Insights

By utilizing the irrigation management system to make irrigation decisions, farmers in real world situations will be able to conserve water through proper irrigation scheduling. The irrigation management system will also improve decision-making capabilities under unknown weather conditions. The actual performance of the irrigation management system in real fields will be determined by factors such as the accuracy of plant water use sensors, the availability of reliable data connections, and adjustments made to accommodate local soil and environmental conditions.

Summary of Discussed Results

The potential for improved irrigation management through the integration of AI & IoT technologies is

significant based upon these findings. The discussion results of this study have only been confirmed by simulating the performance of these technologies, with future testing needed to establish how well these systems will perform in actual on-the-hill conditions.

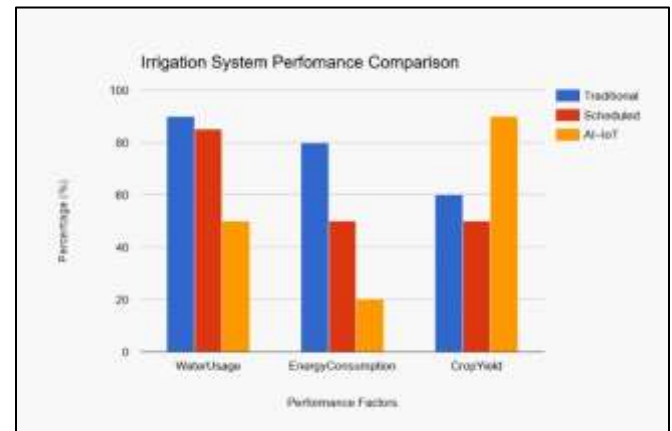


Figure 2: Irrigation System Performance Comparison

VI. SUSTAINABILITY & FUTURE SCOPE

Sustainability in the context of this framework operates on two levels. At the environmental level, the system's most direct contribution is the reduction of unnecessary irrigation, which conserves groundwater, reduces soil salinisation from over-watering, and lowers the carbon footprint associated with diesel or electric pump operation. In a region where groundwater depletion is a growing concern, even modest reductions in irrigation frequency can have meaningful long-term effects on aquifer levels. The framework also supports the adoption of water-saving practices like Alternate Wetting and Drying, by providing the precise soil moisture monitoring that AWD requires but that most farmers currently lack the tools to perform.

At the economic level, the benefits are equally real but will take longer to materialise. Lower pumping costs are the most immediate and quantifiable gain. Over a full growing season, avoiding unnecessary irrigation cycles translates directly into reduced electricity or diesel expenditure, a meaningful saving for farmers operating on thin margins. More reliable crop water management also reduces the risk of stress-induced yield losses, which in turn contributes to more predictable farm income. For the framework to deliver these benefits at scale, however, the upfront hardware costs of sensor deployment need to remain affordable, and this is an important design constraint that future implementation work must take seriously.

Looking ahead, several directions are worth pursuing beyond the field pilot. Integration with government irrigation infrastructure and water management schemes operating across Karnataka's river basins could extend the framework's impact beyond individual farms to watershed-level water allocation. Federated learning approaches could allow models trained on data from multiple farms to improve without centralising sensitive farm data, which matters for farmer trust and privacy. Edge AI hardware, as it becomes more capable and affordable, could eventually shift more of the computational burden from the cloud layer to the field controller, making the system functional even in areas with very limited connectivity. Each of these directions is a natural extension of the foundation this study has laid.

VII. REFERENCES

1. Binayao, R. P., Mantua, P. V., Namocatcat, H. R. M., & et al. (2024). *Smart water irrigation for rice farming through the Internet of Things*. International Journal of Computing Sciences Research, 8, 2550–2563.
 2. Bowden, C., et al. (2023). *Identifying links between monsoon variability and rice production variability using machine learning*. Scientific Reports.
 3. Parikh, R., & Sharma, D. (2025). *A machine-learning approach to optimise the water consumption for irrigation of rice crop*. Conference Proceedings on Sustainable Agriculture and AI.
 4. Preite, L., & Vignali, G. (2023). *Artificial intelligence to optimise water consumption in agriculture: A predictive algorithm-based irrigation management system*. Environmental Modelling & Software.
 5. Gaitan, N. C., et al. (2025). *Integrating artificial intelligence into an automated IoT-based irrigation system*. Sensors, 25(4), 1199.
 6. *AI-Driven optimisation of agricultural water management for sustainable farming systems*. (2024). Nature Scientific Reports.
 7. *Remote sensing reveals adoption of sustainable rice water management practices at scale in Punjab, India*. (2025). arXiv Preprint.
 8. *IoT-enabled intelligent irrigation system with machine learning for rice agriculture*. (2024). International Journal of Intelligent Systems and Applications in Engineering (IJISAE).
 9. *IoT and AI for smart agriculture in resource-constrained environments*. (2025). Springer Smart Agriculture Journal.
 10. *Precision irrigation management using machine learning models*. (2022). MDPI Agriculture.
 11. *Sensors and IoT-based irrigation management: A systematic review*. (2023). MDPI Sensors, 25(7), 2291.
 12. *Accurate water-level monitoring in AWD rice cultivation using CNN + attention mechanisms*. Li, X., & Wang, H. (2024). arXiv Preprint.
- ### Supporting and Contextual References (for Methods)
13. Food and Agriculture Organization (FAO). (2021). *FAO Penman-Monteith equation for reference evapotranspiration*. FAO Irrigation and Drainage Paper 56.
 14. International Rice Research Institute (IRRI). (2022). *Water-saving technologies for rice: Alternate Wetting and Drying (AWD) guidelines*. Los Baños, Philippines.
 15. Jagannathan, P., & Ramakrishnan, M. (2023). *Climate-smart irrigation systems for Indian rice ecosystems: Opportunities and challenges*. Indian Journal of Agronomy, 68(4), 412–421.
 16. Kumar, S., et al. (2024). *Adoption of IoT and AI-based smart irrigation in South Indian paddy cultivation*. Journal of Agricultural Informatics, 15(1), 22–35.
 17. Mishra, R., & Patil, P. (2023). *Water resource management strategies in Karnataka's rice-growing regions*. Current Science, 125(8), 1321–1329.
 18. Singh, A., & Meena, K. (2024). *Integration of machine learning and IoT for precision rice irrigation under monsoon variability*. Computers and Electronics in Agriculture, 213, 108187.
 19. Venkatesh, B., et al. (2022). *Rainfall variability and crop water stress in Karnataka: An analytical review*. Journal of Water and Climate Change, 13(5), 1829–1841.
 20. Zhao, L., & Chen, T. (2025). *Edge-cloud collaboration for intelligent irrigation control*. IEEE Internet of Things Journal, 12(6), 5432–5445.