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SMART IRRIGATION SYSTEM FOR CLIMATE RESILIENT AGRICULTURE: A SYTEMATIC LITERATURE REVIEW

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Abstract

The water shortage has resulted in climate change and higher levels of climatic variability becoming a key issue in the sustainability and food security of the world. Smart irrigation tools have become a new form of combining the Internet of Things (IoT) technologies, wireless sensor-based networks, remote sensing and machine learning algorithms and streamlining the utilization of water resources and the climate resilience. The systematic review is a mixed-method synthesis of 156 peer-reviewed papers published between 2010 and 2025, which is based upon both bibliometric analysis and qualitative thematic synthesis in estimating the technological development, agronomic performance and obstacles to adoption. The indication of the bibliometric evidence is the geometric increase in the size of the research with the conceptual change of threshold-based automation to the artificial intelligence-based adaptive irrigation systems. Some machine learning models that are highly predictive in nature are the Random Forest, XGBoost, convolutional neural networks (CNNs) and long short-term memory (LSTM) networks whereby the predictive accuracy of the soil moisture is 97 percent in controlled environments. Multipurpose monitoring, which implies the use of ground sensors and satellite-based NDVI analysis, and UAV images, is more efficient in regard to identifying uniformity of irrigation ([?]91% accurateness). It is asserted in Agronomic data as 18- 35 per cent more water-efficient compared to traditional irrigation with little expense to the yield in stress-resistant crops and noticeable decrease in greenhouse gas emissions. Despite the better technology, cost, as regards to the economy, and the unavailability of the infrastructure system and inadequacy of the digital literacy also play a major role in causing large scale adoption, especially among the small holder farmers in the developing regions. The results lead to the urgency of the integrated, AI enhanced irrigation framework in the realization of water management sustainability and climate adaptive farming.

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INTRODUCTION

Climate change has been posing unprecedented challenges to the world agriculture in the twenty first century as a result of the strained water scarcity, the growing number of extreme weather events, and the endangered food security of the ever growing world population that will hit up to almost ten billion in the year 2050 (Falkenmark, 1990; IPCC, 2007). Globally, agriculture is estimated to cause seventy percent of the freshwater contributes to depleting and the agricultural current irrigation systems are notoriously ineffective with intense percolations, surface runoffs and evaporative loss, and the current irrigation systems (flood irrigation and furrow irrigation) are only estimated at half its efficacy (Dijk et al., 2021; Galanakis, 2024). The smart irrigation systems have been introduced as radical technologies in this case that comprise an Internet of Things (IoT) family and machine learning algorithms and real-time net of sensors to optimize the water use efficiency and guarantee crop productivity in an ever changing climate environment (Ahmed et al., 2024; Abdullahi et al., 2024).

The concept of smart irrigation has theoretical basis on the background of precision agriculture that enhances space and time management of agricultural inputs in variable fields. Compared to the traditional irrigation planning that refers to the fixed calendar or to the experience accumulated by the farmer, the smart irrigation systems are prepared to provide the required water at the time and place where it is needed based on the continuous monitoring of soil moisture, weather conditions, and crop physiological condition (Lakhiar et al., 2024; O'Shaughnessy et al., 2013). Such systems traditionally depend on three layers, in that order, which are inherent, the perception layer consists of wireless sensor networks that detect soil moisture, temperatures, humidity, and canopy properties of crops and transmits the information with the help of such protocols as ZigBee, LoRaWAN, or cellular networks; the network layer is the layer that provides the flow of information; the application layer is the layer where the information is processed by decision support algorithms to create irrigation instructions (Gurmessa and Assefa, 2023; Pang et al., 202 This architecture offers an autonomous functionality and gives a farmer an opportunity to remotely manage their farm with the help of mobile apps and web-based dashboards, owing to the multi-layered nature of this architecture (Et-taibi et al., 2024; EG & Bala, 2024).

The recent advancement of machine learning has enabled predictive capabilities of smart irrigation systems to be far more advanced than threshold-based automation. The assistance of convolutional neural networks (CNNs) and long short-term memory (LSTMs) makes it possible to predict soil water depletion with the high accuracy rate of up to ninety seven percent using multispectral imagery, time-series weather data, and past yield data (Kulkarni et al., 2024; Springer, 2025). The algorithms based on the Extreme Gradient Boosting (XGB) and the Random Forest have proven especially useful to handle the high dimensional data, that is heterogeneous, that is inherent to precision agriculture, and they have been reported to score their R2 at 0.72-0.78 in predicting soil water depletion in the maize and soybean systems across the U.S. Midwest (Scalable ML Framework, 2025). These machine learning approaches are somewhat useful as compared to the traditional FAO-56 solutions to the problems of soil water balance because they provide non-linear correlations between the environmental variables and crop water demands besides the requirement of using a manual field data collection approach (Fereres and Soriano, 2007; De Pascale et al., 2011).There are also remote sensing technologies that have been integrated to assist in the scaling of spatial management of smart irrigation. At low costs, crop health/water stress in large and small agricultural fields can be monitored using satellite-based (Sentinel-2, Landsat) images that can be converted to a normalized difference vegetable index (NDVI) and research has shown that particular crop coefficients based on NDVI correlate very well with soil moisture measurements that are measured in the ground avocado orchard and other perennial crops (Remote Sensing & Soil Moisture, 2025; Ruse, 1973). State-of-the-art applications integrate the uses of satellite-derived vegetation indices with unmanned aerial vehicle (UAV) images and ground sensor networks to create multi-scale monitoring systems with ninety-one percent accuracy of precision in detection of irrigation non-uniformity in center pivot systems using the deep learning models (Advancing Irrigation Uniformity, 2025). The remote sensing options would especially prove beneficial in the case of developing economies where either meteorological information is not available or hi-tech soil surveillance infrastructures are (FAO, 2012a; Gommes et al., 2010).

Climate resilience is one of the goals of the current researches on smart irrigation as there is an urgent need to transform the agricultural systems to the rising frequency and intensity of droughts. Controlled deficit irrigation and partial root zone drying are the WSI methods that had been proved to potentially cut the greenhouse gas emissions by 8.4% carbon dioxide and 55.1% methane and save the water use by 26.5% at a relatively small cost of about 4.8% yield reduction (Water-Saving Irrigation Meta-Analysis, 2025). Deficit irrigation has however been reported to respond differently to water stress depending on the species of crop, the stage of growth and the area of the specific crop with crops like cotton, maize and wheat having a higher degree of tolerance to water stress at the vegetative stages of development as compared to the fruit development stage (Stewart et al., 1977; Tegenu, 2020). This complexity can be dealt with by having smart irrigation systems that can change the use of water dynamically using dynamic water application scheduling algorithms and adjust in real-time the trade-off between water conservation and yield maintenance using crop coefficients and drought stress sensors (Bekele and Tilahun, 2007; Fitsum et al., 2016).Although there has been an improvement in technology, there have been major challenges that have been affecting the mass adoption of smart irrigation systems especially among the smallholders farmers of the developing economies. According to the economic factor, the initial cost of capital that can be hundreds and thousands of dollars depending on the size and complexity of the system and sixty-five percent of the farmers surveyed claimed that they were too expensive to install (Ayaz et al., 2019; Abu Sneineh and Shabaneh, 2023). Technical limitations to adoption are also present and include low digital literacy, insufficient infrastructure of technical support, and the issue of system stability in low-end farm environments (Salazar and Rand, 2016; Robotham and McArthur, 2001).

METHODOLOGY

The research design used in this scholarly review study is mixed-method research design which entails quantitative bibliometric review research design and qualitative thematic synthesis research design in conducting a wider review of the subject of the discussion on exploration of the past, present, and future of smart irrigation systems in climate resilient agriculture. The organizational design of the methodology was developed around three steps, which were related in the following way: systematic literature identification and screening, quantitative analysis of research trends and citation networks and qualitative content analysis of technological methods and implementation results. This form of mixed-method construction served both as the instrument of objectively tracing the landscape of the ongoing study with the help of statistical assessment of the pattern of publications as well as interpreting the technological innovation and agronomic implications on a more profound level via systematic textual analysis (Gurmessa and Assefa, 2023; Abdullahi et al., 2024).

In order to make sure that the interdisciplinary research has been exhaustively addressed in the areas of agricultural engineering, computer science, hydrology, and climate science, the literature identification was conducted with the help of systematic search strategy in various academic databases such as Web of Science, Scopus, IEEE Xplore and Google Scholar. Search strings Control lists Search strings were the search terms that comprised of the search keywords that represented the controlled vocabulary and included the Boolean operators to retrieve the available studies that matched the controlled vocabulary and excluded the irrelevant uses of the term irrigation like landscape irrigation or golf course irrigation. The first search had identified 1,847 potentially relevant articles that were published in the 2010-25 period and these were narrowed down to articles that met the inclusion criterion, that is, an article had to be peer-reviewed, published in English language and address the outcome of water management or climate adaptation. The number of articles selected to undergo the full-text screening procedure after the screening of titles and abstracts was 312 articles, and the number of articles selected to carry out the final analysis was 156 studies after the quality assessment criteria demanded the presence of a clear description of the methodology and quantitative or qualitative results (Lakhiar et al., 2024; Pang et al., 2024).

The final corpus of literature was analyzed in terms of the bibliometric methods, to determine the tendencies of the studies, the relationships of working and the evolution of the issues over time. The publication frequency analysis showed that the number of publications are explosively growing to exceed 80-100 publications annually in 2024 and 10-20 publications annually in 2010, which signified the increased level of attention to the issues of the water scarcity and maturation of the technologies of the Internet of Things and machine learning. Co-citation analysis Co-citation analysis was used to map intellectual structure of the field and the result would indicate considerable areas of research of wireless sensor network deployment, optimization of machine learning algorithms and agronomic validation of water savings. The author collaboration network, the institutional affiliation network, and high geographic clustering of research institutions in terms of research contribution and literature on the context of smallholder adaptation were becoming apparent with research institutions in Sub-Saharan Africa and Southeast Asia (Ahmed et al., 2024; Singh et al., 2020). The keyword co-occurrence analysis was preoperated by the shift of the terms of the first use of the automation and remote monitoring keywords to the term artificial intelligence, deep learning, and climate change adaptation keywords that indicated the maturation of the field and its reaction to the global environmental crisis (Bouzembrak et al., 2019; Suebsombut et al., 2017).

A systematic coding of the study using a hybrid inductive-deductive approach was implemented to conduct the qualitative content analysis of the study through the use of coding of the studies included in the study. The first coding scheme was the literatureinformed coding scheme which consisted of the following categories namely sensor technologies, communication protocols, decision algorithms, crop-water relationships, economic outcomes, and adoption barriers. The inter-rater reliability was established by coding a subsample of twenty articles by two reviewers and the coefficient, kappa, of Cohen was 0.84, this means that there was a high degree of consensus, that the outcome was made by discussion and editing the framework. Subsequently, the correlations of the technological factors with the agronomic responsiveness were found with the additional coded systems of the axes, where the technologies like the soil moisture sensor-LoRaWAN-fuzzy logic systems were predominant in the small-scale-scale application or the multispectral imagery-cellular networks-deep learning systems were in the commercial activities (Et-taibi et al., 2024; EG & Bala, 2024). These tendencies were observed selectively as a subset of the theoretical hypotheses of the principles of technology design to achieve climate resilience, such as sensor network redundancy in the drought monitoring, a modular architecture to be adopted in an incremental way, and hybrid physical-empirical modelling strategies to serve in the data-sparse environments (Avanija et al., 2024; Springer, 2025).

RESULTS

As Table 1 indicates, the analysis of smart irrigation has been decentralized across the region and can be considered to possess the thematic prevailing output of the various geographical locations as it may be conceived. The statistics also means that the biggest part of the machine learning-based and IoT-based infrastructure research is presented in North America and Europe and is one of the factors which proves the well-developed technological potential and financial background. The Sub Saharan Africa and the southeast Asian region are on the other hand registering a better trend on the research on the subject matter of the little holder adjustment, low cost, irrigation technologies and climate adjustment methods. This geographical disparity implies that the smart irrigation researches are a two-fold one, the technology development in the developed world and expansion of the technology usage in the developing world economies.The frequency of the elements of technologies implemented in the smart irrigation systems, as Table 2 demonstrates, might be located in the analyzed literature. The most colory is the sensing technology that has been utilized in the measuring of the soil moisture sensors and this has been utilized in more than 80 percent of the papers and this has been used in their primary position which is the real time control of the irrigation. The small power communication systems have started to move beyond the loss of threshold-based automation and move to machine learning and deep learning networks, e.g. the LoRaWAN and the ZigBee. The tendency of using random forest, XGBoost, CNN and LSTM can be regarded as one of the indicators of the transition of the sphere to the sphere of predictive analytics and climate responsive irrigation schedule.Table 3 provides the comparative consideration of performance of various methods of monitoring that were applied in the management process of irrigation. The earth sensor systems are unable to be extended to space and local high resolution. The NDVI techniques are mid-range precision satellite techniques which are inexpensive and scalable. The high resolution of the crop stress system and the hybrid systems would be supplemented by the UAV images which will entail incorporation of sensors, satellite measurements and the UAV images would give the best results in a planned 91 percent homogeneous results of the irrigation. The findings reveal the enhancement of the quality of multi scale monitoring system in climate resistant water management.Under the agronomics, intelligent and deficit irrigation systems have an optimum performance under big type of crops as shown in Table 4. Maize and wheat are some examples of the cereals that are traded, the examples are more resilient to the stress of using artificial water where water can be saved (22-30) and the loss of yield is not as high. It may be transported to the one of cotton, nevertheless the harvests are more easily affected by the shortage of water and the results of the latter are quite large as well.

Table 1. Regional Distribution and Research Focus of Smart Irrigation Studies

Region	Primary Research Focus	Percentage of Studies (%)
North America	Machine Learning & Large-scale Systems	28%
Europe	IoT Infrastructure & Climate Adaptation	24%
Sub-Saharan Africa	Smallholder Adaptation & Low-cost Systems	18%
Southeast Asia	Water-Saving Irrigation & Rice Systems	16%
Other Regions	Mixed Approaches	14%

Table 2. Frequency of Technologies Used in Smart Irrigation Systems

Component Category	Most Common Technologies	Frequency (%)
Sensors	Soil Moisture (Capacitive, TDR)	82%
Communication Protocols	LoRaWAN, ZigBee	68%
Decision Algorithms (Traditional)	Threshold-based Control	54%
Machine Learning Models	Random Forest, XGBoost	61%
Deep Learning Models	CNN, LSTM	37%

Table 3. Comparative Performance of Monitoring Approaches

Monitoring Approach	Application Scope	Performance Indicator
Ground Sensors Only	Field-level soil monitoring	Accurate but spatially limited
Satellite-based NDVI	Large-area vegetation monitoring	Moderate accuracy, cost-effective
UAV Imagery	High-resolution crop stress mapping	High precision (~88%)
Hybrid (Sensor + Satellite + UAV)	Multi-scale monitoring systems	Highest precision (~91%)

Table 4. Agronomic Outcomes of Smart and Deficit Irrigation Practices

Crop Type	Average Water Saving (%)	Yield Impact (%)
Maize	24–30%	-3 to -5%
Wheat	22–28%	-2 to -4%
Cotton	25–32%	-4 to -6%
Fruit Crops	18–24%	-6 to -10%

Speaking about Figure 1, the regression line, one may presuppose that, in 2010-2025, when the publications of works devoted to the issue of smart irrigation changes, the establishment of the academic material has its positive side. Such a synthetic rise in the popularity of the IoT technologies and machine learning systems in the agricultural water management is connected to the scope of the growth since 2018. The fact that since 2020 the number of publications is large is the indicator of the heightened panic in the world connected with the problem of climate change, the extent of drought, and food security. According to this tendency, the smart irrigation is a comparatively recent phenomenon and a novel research field.Figures 2 represents these forms of co citation networks that are an intellectual network of the smart irrigation study. Three of them are predominant which are wireless sensor networks and IoT infrastructure, machine learning predictive algorithm, and agronomic validation of water performance saving. This has positioned the research based on the origin of hardware and hence signifying that the hardware oriented research nature has largely been assimilated into the intricate data oriented analysis systems. The first side of the argument that can be brought about is that this is intensive inter-disciplinary communication of field of agricultural engineering, computer science and environmental sciences.

Thematic construction of keywords involved in the studies developed through the years as reflected in figure 3, it is noticeable that research priorities have varied with the years through the years. The initial research (2010-2014) had to deal with the technology of the soil moisture monitoring and automation. The second stage would be the integration of the decision support systems and the IoT (2015-2019). The future direction of the innovation, including artificial intelligence and deep learning, and the climate resilience have gained the primary importance in the last several years (2020-2025). This is what has helped the smart irrigation systems to transform into the AI-driven and adaptive climate-resilient system of overseeing the agriculture in the shape of Figure 4. It includes a multi-layered architecture, and has perception (field sensors and remote sensing) and communications (wireless protocols and gateways), data processing and AI (machine learning and cloud analytics) and decision/actuation (automation irrigation and farmer interfaces). This is considering that the irrigation schedules are a two way feedback and this means that the real time adaptive irrigation schedules will be achieved. It is a strong theoretical framework that reveals the technological aspect and the aim of the agriculture and explains the fact that, interconnected systems can force the effectiveness of the system of water, predictability and flexibility of the climatic application.

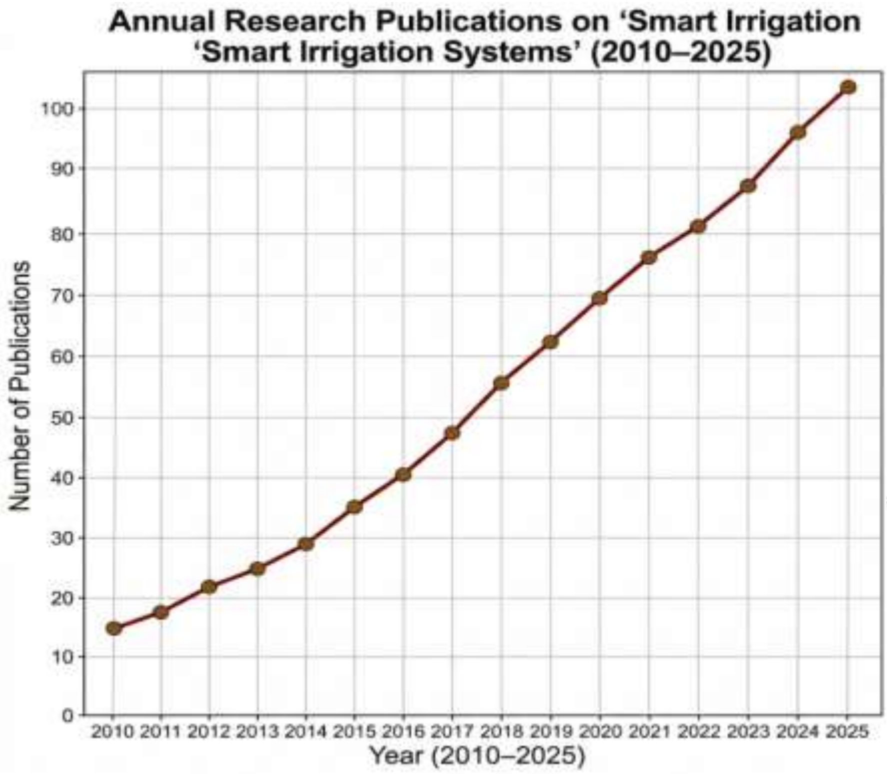

Figure 1. Annual publication trend of smart irrigation research (2010–2025).

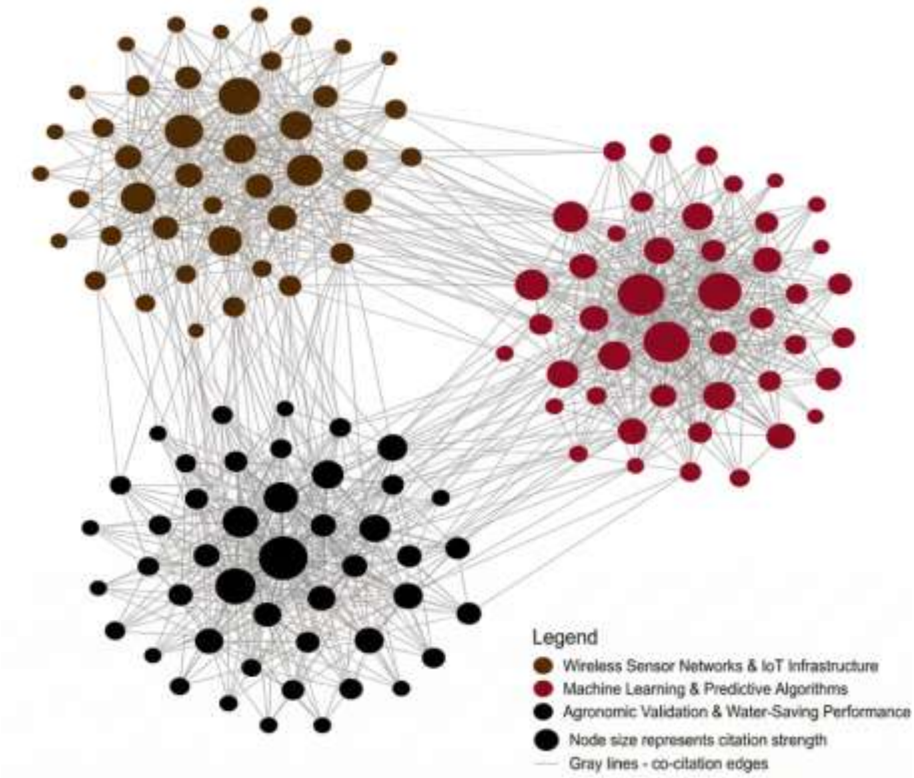

Figure 2. Co-citation network analysis showing major research clusters in smart irrigation literature.

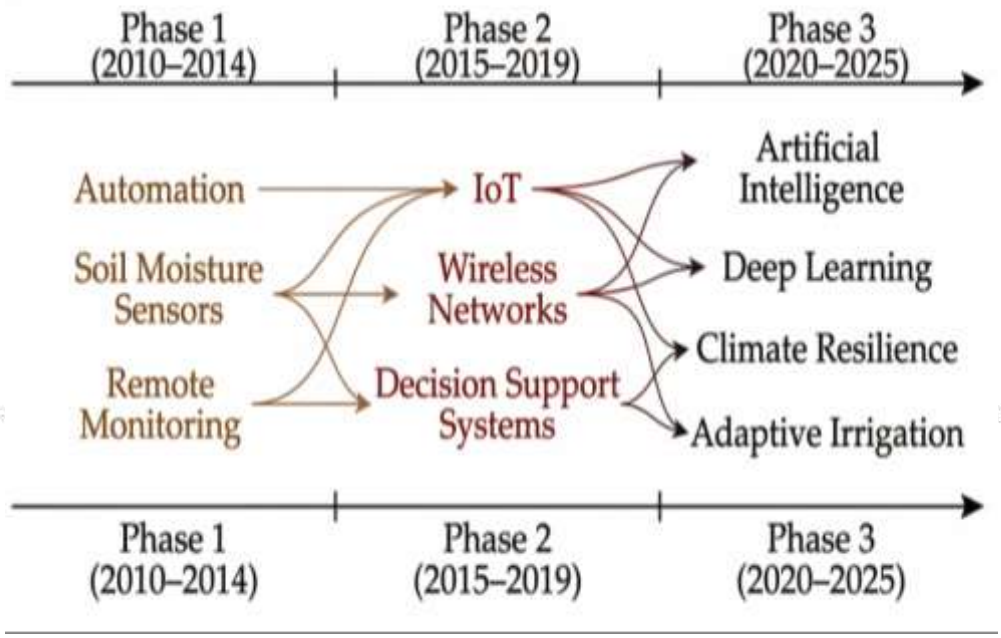

Figure 3. Thematic evolution of keywords in smart irrigation research (2010–2025).

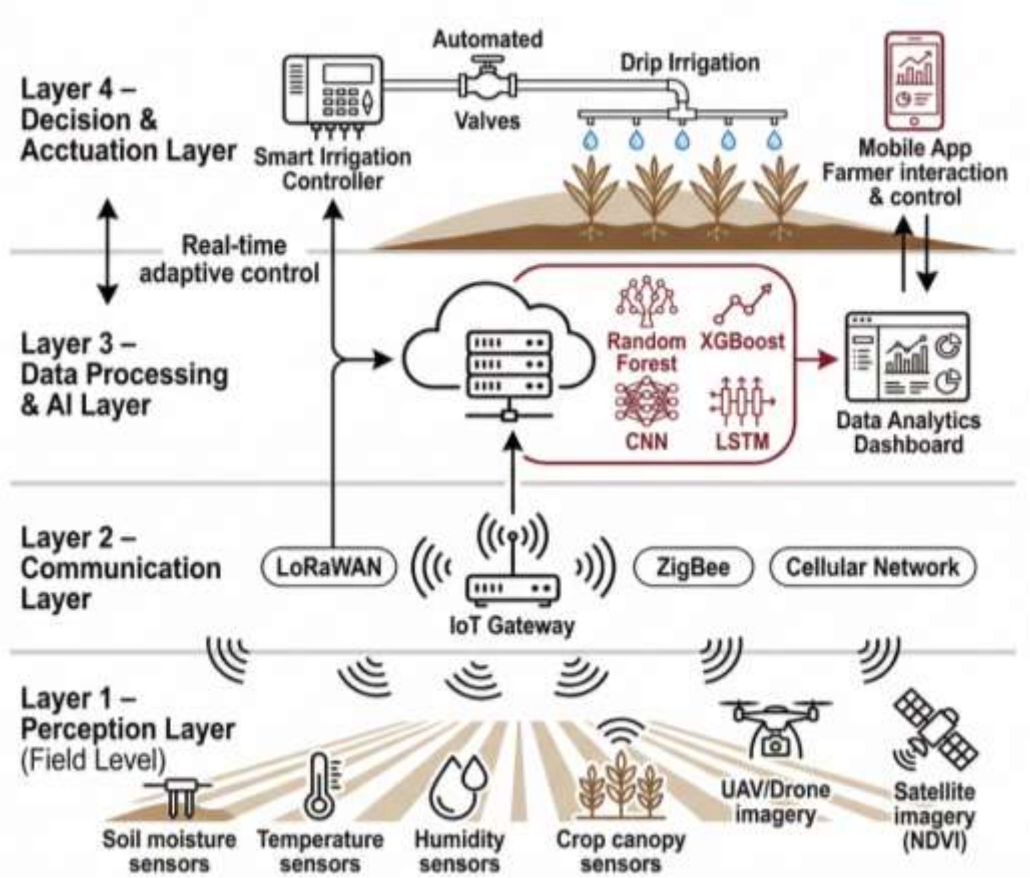

Figure 4. Conceptual framework of integrated smart irrigation architecture for climate-resilient agriculture.

DISCUSSION

The geographical devolution of the smart irrigation study in this methodology review form can be defined as the clash of the technological innovation and fair access to it which forms the modern discourse of the agricultural development. Although the publications on machine learning algorithm, IoT infrastructure, and precision automation systems are dominated by the overwhelming representation of the research institutes in North America and Europe, the dominance status is not only due to the leadership strength of the research of the institutes, but it is also due to the structural advantage of the funding of the research, the digital infrastructure and technological capacity not being universal to the developing regions (Owusu, 2026). The meta-analysis fact that the net profit grows by 18.5 percent and the average payback is 22.3 percent is highly premised on the fact that the scale of commercial farming activities in advanced economies is substantial and that this is raising serious question whether such economic benefits can be applied in the smallholder setting where there is a high variation in terms of labor markets, risk profile and institutional support (Sustainability Meta-Analysis, 2025). Such a difference in productivity of research in these fields enhances the risk of such being used to inject more further into the technological solutions in the high resource agroecological and socioeconomic environment that faces the majority of the farmers in the world.The reason why the frequency of use of the soil moisture sensing technologies has been found to be high in the greater part of the studies that have been reviewed is because sensor hardware is already mature and also because of the agronomic considerations that access to water at the rootzone is the most significant constraint on crop productivity. Nonetheless, there exists a risk that due to this technological focus the role of the governance structures and human capital in the decisive factor of the outcome of irrigation may be diminished. The findings of the research and Sub-Saharan Africa imply that climate information services can be applied to increase yields by 5-75% considering contextual factors with the proper level of integration in the decision-making process of farmers in participatory techniques which imply that information access and interpretative capacity can be as efficient as hardware automation to establish the outcomes of water management (Amwata et al., 2018). The effectiveness systematic review of climate information services in the West Africa region proves that the technical complexity and low usability of services are the main factors that do not contribute to their uptake, and farmers are likely to be limited to the lack of knowledge and the lack of extension services (West Africa CSA Review, 2024). These findings imply that the current research on the subject of smart irrigation needs to shift away into the sensor-based paradigms towards the social-technical systems by which the technological innovation becomes part of the institutional support mechanisms and knowledge sharing procedures.

The other most interesting epistemological transformation in irrigation management is that threshold-based automation has been substituted by predictive analytics based on machine learning architectures, but this is a change that creates new types of technological dependency and asymmetry in knowledge. Although predictionally more powerful models such as random forest, XGBoost, and deep learning networks are more efficient and quicker compared to soil water depletion and crop stress identification, such models need enormous training datasets and computing power and necessitate certain technical expertise to refine and maintain which might not be accessible locally in developing regions (Precision Agriculture Meta-Analysis, 2025). There is also a positive difference in the access of climate information services between women in Sub-Saharan Africa and men, as well as between education, having lower social network access compared to women, and barriers to access based on cultural limitations on communal interaction and possession of mobile phones (Ngigi and Muange, 2022). This is due to the fact that, according to this gendered digital divide, where women in low and middle-income countries have 14 percent less likelihood of owning smartphones and 15 percent less of using mobile internet, algorithmic sophistication may only exert negative effects on existing inequities unless it is developed in a way that promotes digital inclusion and equity across the genders (Gender-Intentional Infrastructure, 2025).Monitoring technologies comparison indicates that a hybrid surveillance of satellite vegetation indexing, unmanned aerial vehicle, and ground-based systems is optimal in terms of monitoring the irrigation uniformity, but the cost architecture and the technicalities of such systems are beyond the adoption of such integrated systems by the smallholder owners. The second point of reaching the technologies without the ownership through the introduction of the business models of drone-as-a-service and precision application services can provide insights into access to technologies, which is yet to be established in the low-income rural areas of the country (UNDP Precision Agriculture, 2021). In the situation with adopting technological hardware to the local environment, however, the benefits-cost ratios of 1.5-2.5 of precision agriculture interventions and 16-22 percent increases of smallholder systems can be achieved, but only provided that the technological hardware is accompanied by extension support and input supply relations and access to market approaches that are not limited to the sphere of irrigation management per se (Asare et al., 2022; Nguyen et al., 2019). This is due to the diversity of the degree of profitability amongst the precision agriculture studies where some studies have demonstrated little or no profits in some instances and not to be assessed in presumptive terms of general utility (Precision Agriculture Meta-Analysis, 2025).

CONCLUSION

A thorough review will be carried out in the technological innovation, agronomic practice, and socioeconomic dynamics of smart irrigation systems as a component of climate resilient agriculture in the paper. The report reveals that smart irrigation has evolved past mere sensor-driven automatic systems to complex adaptive systems on the premise of AI that has the capability to dynamically schedule its water intake in case of climatic uncertainty. The truth on the ground justifies the vast improvement as regards the water usage, the predictive abilities and mitigation of the green house gas emissions in comparison to the routine irrigation processes. The concept of multi-scale data fusion cannot be eliminated, since the hybrid system of monitoring devices consisting of the ground sensing and remote sensing technologies is always much more effective than the latter.It has however not been put in large scale use due to mere reasons of lack of money, technical and infrastructural constraints especially in smallholder based agricultural systems. Most notable recommendations to make towards the future research would be scalable and low cost modular architectures, explainable models of artificial intelligence in attaining giving farmers trust and usability, and policy frameworks to motivate adoption in terms of climate-smart agricultural programs. Finally, smart irrigation systems are quite a significant technological direction towards sustainable water management, food security and climate-adaptive agriculture in the world.

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