Performance Evaluation of AI, Machine Learning, and IoT-Based Smart Agriculture Systems for Environmental Sustainability

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Abstract

Agriculture is historically under a lot of pressure, mainly due to the lack of water, climate, soil, over use of fertilizers and pesticides, energy for farm operations and low use of resources in agricultural production. Farming practices can lead to low crop yields and have a large negative impact on the environment. The adoption of artificial intelligence (AI), machine learning (ML) and Internet of Things (IoT) systems and technologies in agriculture have the potential to monitor, predict and make decisions in real time. This article is to compare and evaluate the performance of AI, ML and IoT-based smart agricultural systems in monitoring, prediction and decision-making. Data from field sensors, weather stations, crop monitoring and automated irrigation systems are incorporated in the performance evaluation of smart agricultural systems. The use of ML in agricultural crop yield prediction, plant disease detection, automatic irrigation systems and soil condition monitoring is evaluated. The accuracy, precision, recall, F1-score, irrigation water use efficiency, water saving rate, energy consumption, crop yield, latency and cost of smart agricultural systems are some of the indicators that can be used to evaluate their performance. This article proposes an evaluation framework that can be used to assess the performance of smart agricultural systems based on their technical characteristics and their impact on agriculture and the environment. The main advantage of this article is that it can support farmers, researchers and policy makers to understand how smart agriculture can help reduce the wasted use of resources, increase crop production and promote more sustainable agricultural practices.

Keywords: Smart agriculture; Artificial intelligence; Machine learning; Internet of Things; Precision farming; Environmental sustainability; Sustainable agriculture; Resource optimisation; Climate-smart agriculture; Sensor networks.

1. Introduction

Agriculture is being asked to do something increasingly difficult: produce more food, with fewer resources, under less predictable environmental conditions. Climate change has altered rainfall patterns, increased the frequency of droughts and heat stress, and intensified pest and disease pressures across many farming systems. Food demand is increasing and land, water, energy and soil are declining[1]. The ideal agricultural system is productive and resource efficient. It has to be climate resilient and environmentally responsible. This means that water has to be applied to crops only when they need it. Fertilizers have to be applied in exact amounts corresponding to the requirements of soil and plants[2]. Crop stress has to be detected before damage becomes visible. And farmers have to be supported by timely and evidence-based decisions. However, conventional agriculture is based on fixed irrigation schedules, on manual field checks, on experience-driven application of inputs and on late reactions to any changes in the environment[3]. This gap between the ideal and reality is one of the biggest challenges for sustainable agricultural development.

Smart agriculture has emerged as a response to this gap. Rather than treating the farm as a uniform field managed by broad assumptions, smart agriculture views the farm as a dynamic system that can be sensed, measured, analysed and adjusted in near real time. Internet of Things (IoT) sensors can collect continuous data on soil moisture, soil temperature, air temperature, humidity, rainfall, light intensity, crop growth, nutrient status and environmental conditions. These data can be transmitted through wireless networks to cloud or edge-computing platforms, where artificial intelligence (AI) and machine learning (ML) models can support prediction, classification and decision-making[4]. A soil-moisture sensor, for example, may indicate that irrigation is unnecessary even when a fixed schedule suggests otherwise. Similarly, image-based ML models can identify early signs of leaf disease before a farmer can observe the spread visually[5]. In this sense, AI, ML and IoT do not simply add digital tools to agriculture; they change the logic of farm management from reactive and generalised practice to predictive, localised and adaptive decision-making.

Previous research has made considerable progress in demonstrating the technical potential of these technologies. Duguma and Bai (2025) presented IoT as a key technology for real-time monitoring, precision farming and resource optimisation in modern agriculture. Eze and others in 2025 posited that the union between IoT sensors and ML models could guarantee increased crop resilience, resources efficiency and agricultural digital-driven decisions[6]. Also, IoT Sensor Network for Smart Farming, IoT-based Farming Monitoring System for Crop Disease Detection and the intelligent use of UAVs (Unmanned Aerial Vehicles) in the context of smart and digital farming could benefit from the newest developments in AIoT (Artificial Intelligence of Things)[7]. Sensing units and intelligent units, or AI algorithms, edge devices and cloud platforms that manage the vast amount of gathered field data to provide digital recommendations and real-time decisions to farmers, have recently been implemented. Recent developments have highlighted the benefits that smart farming practices could bring to farmers and farming by leveraging AI (Artificial Intelligence), IoT (Internet of Things), UAVs (Unmanned Aerial Vehicles), and agricultural robotic systems and deep learning techniques to enhance crop monitoring, yield prediction, management of inputs, and sustainability (Raj & Prahadeeswaran, 2025). Digital agriculture has thus stopped being an abstract concept, and is rapidly becoming a reality that can support both agricultural efficiency and environmental management.

However, there are many limitations to existing research on Smart Agriculture, such as only using some technical indicators, like prediction accuracy, classification precision etc. to evaluate systems, without considering environmental sustainability, economic feasibility, practical usability etc[8]. Under the scenarios of real-agricultural situations, a crop-disease detection model could get high accuracy within a specific dataset, for example. However, this model's value would evaporate quickly if the system needs lots of special-agricultural, environmental and practical dimension of performance metric-expensive infrastructure, excessive energy consumption, stable Internet, much advanced technical knowledge etc. that most of farmers cannot afford[9]. Meanwhile, the water-saving measure by an automated irrigation system could work effectively in some places, but not others[10]. There could be large difference on the water-saving measure for Smart Agriculture, depending on many factors like different soils, crops, weather and farm sizes etc[11]. This is why in addition to the evaluation of the performance of a system in terms of how well a system's algorithm functions, agricultural, environmental and practical dimensions of performance metrics need to be taken into account.

This research addresses a different problem within agriculture's use of AI, ML and IoT than has been tackled before: that of performance evaluation, particularly from a perspective of sustainability[12]. The more typical question has been whether agriculture can profit from the increasing power of AI, the ever-changing field of ML and the billions of connected devices of the IoT has received considerable attention in recent years[13]. A computer system that is totally technically correct does not necessarily have to be sustainable. The cheapest possible sensors do not have to be the most reliable[14]. The highest performing ML system does not automatically have to be the most useful if it delivers its decisions too late, if it needs too much computational power, or if it is not able to change in the necessary way as soon as there are changes in the farmer's fields. The direct consequences of the evaluation gap identified here for Smart Agriculture are poor technology choice, inaccurate claims of performance, and poor comparability between studies[15]. The indirect consequences are even more severe: farmers investing in technology that does not reduce waste from the use of their resources; policies that support the use of technology for which there is no evidence of sustainability; and most seriously of all, for researchers, the increase in accuracy of models for predicting outcomes in agriculture is of little value when considered against the backdrop of the need to save water and to reduce use of energy and of fertilizers, and to decrease latency[16], to decrease cost and to be as sustainable as possible in the long term.

There is a considerable gap in evidence when it comes to assessment of sustainability of smart agricultural systems. Given that agriculture is a major contributor to many sustainability challenges and digital agriculture / AI is viewed as a means to make agriculture more efficient, productive and sustainable – in the context of development of agrifood systems – smart agriculture requires evaluation[17]. Here, assessment of sustainability of smart agriculture cannot rely on assumptions regarding sustainability based on use of latest technology. Rather a systematic evaluation of data generation, predictive modeling, decision making, environmental outcomes is required within a single conceptual framework. In other words, evaluation is required of whether irrigation efficiency, energy use, water savings, crop yield, decrease in use of chemicals and sustainability of environment are enhanced by use of AI, ML and IoT-based systems for smart agriculture[18].

This study is building on prior research. Yet, there is a specific difference between this study and the research that has already been done on AI, ML or IoT in agriculture. The difference is based on the fact that smart agriculture more and more is being seen as a performance system consisting of several components and not as a technology in itself. Therefore, the guiding conceptual model for this study is based on a layered structure[19]. On the bottom of this layer structure are the sensors for sensing of data from the field and the environment by means of IoT. This data is being transferred to platforms at the edge of the network or in the cloud by means of communication. On these platforms the data is being analyzed by AI and ML models in order to make predictions or to support decision making. Next, the results of the analysis are being implemented in an automated or partly automated way by means of the performance system for smart agriculture[20]. Finally, also the results of the performance system are being evaluated. These results are being measured by means of several indicators, amongst which technical indicators as well as indicators for agriculture, economy and the environment. In this way, input of the system, the computational processes as well as the decisions that are being made on a farm as well as the sustainability goals are being connected.

The purpose of this study is to evaluate the degree to which AI, ML and IoT-based smart agriculture systems are able to be environmentally sustainable. Measuring the technical performance of various AI and ML models in terms of accuracy, precision, recall, F1-score, error rate and latency are the primary objectives of the study. In addition, the agricultural effectiveness of a variety of IoT-based smart agriculture systems with respect to scheduling of irrigation and monitoring crops for diseases as well as for increase in production and efficient use of fertilizers will be evaluated by a set of indicators including water saving, energy consumption, resources use efficiency, cost-effectiveness and environmental impact. The study proposes an integrated framework for evaluating the performance of smart agriculture systems that links the systems' performance to their implementation outcomes as well as to their environmental implications. Thus, the study does not only evaluate the predictive capabilities of smart agriculture systems against those of traditional methods. Instead, it assesses their sustainability in managing agriculture resources.

This study has academic value because of the clearly noted gap in the smart agriculture literature to develop a holistic performance measurement for smart agriculture using the metrics of AI/ML models and the performance and sustainability indicators of IoT systems. The study has practical value because it helps farmers and agricultural managers to assess and compare different technologies to support their decision making based on their performance under real field conditions. The study has also policy value because governments and development agencies are promoting digital agriculture and many investments are being made in digital agriculture technologies. Without robust evidence of environmental benefits, cost-effectiveness, scalability and implementation barriers, smart agriculture risks to become a technology-driven promise as opposed to a sustainability-driven solution.

After outlining the research space in which we are operating within the Create a Research Space model, we establish the territory for this introduction by outlining the growing pressures of climate change, resource scarcity and food-system pressure on agriculture, and thus the need for sustainable smart agriculture. We then establish the niche by highlighting how current research evaluates AI, ML and IoT systems in smart agriculture using largely fragmented and mainly technical measures, leaving considerable uncertainty as to their real sustainability performance. The paper then goes on to occupy this niche by outlining a study that conducts an integrated performance evaluation of AI, ML and IoT-based smart agriculture systems. The various evaluation criteria are prediction quality, system efficiency, agricultural performance and environmental sustainability. The paper is divided into five sections, in which the first section reviews the relevant literature, the second section outlines the proposed conceptual and methodological framework, the third section explains the evaluation metrics and experimental design, the fourth section reports on the results of the study, and the final section discusses the implications of the study for research, practice and policy.

2. Literature Review

Agriculture is one of the key areas under the smart research domain. It has become a challenging task for human beings to produce enough food for human consumption, due to variability in climate and natural resources such as water and land. The soil is degraded and agriculture is being carried out at increased costs, and there is also an increased environmental cost in order to produce enough food for consumption. In order to make farming more adaptive, measurable and sustainable, it is possible to use Artificial Intelligence (AI), Machine Learning (ML) and Internet of Things (IoT) for agriculture. Ideally, the smart agriculture system would consist of sensors that gather data of the soil, crops and weather around the clock. This data would then be processed in the cloud or on the edge by platforms, models of ML would then predict things such as the amount of irrigation that a field may require, the chance of disease to certain crops and the yield of crops. This data would then be used by AI-powered decision-making systems to suggest actions or implement them. Agriculture is both a victim and a cause of the stress on the environment that exists today. Digital agriculture and AI can be used for precision farming, for climate-smart agriculture and for the creation of agrifood systems that are more resilient. They can also be used to support evidence-based policies. However, it is not enough for digital agriculture to implement new technology. It must also be inclusive and must be supported by good governance. There must also be solid evidence of its impact. FAO (n.d.) states that digital agriculture can support precision farming, climate-smart agriculture, and create agrifood systems that are resilient. It can also support evidence-based policies.

The work on data-driven agriculture has laid the foundations for the current AI-IoT systems. Wolfert et al. (2017) wrote a thorough review on the application of big data in smart farming. They clarified how sensors, cloud computing and analytics could support farm management not only for primary production on the farm, but also for the whole food supply chain. The review provides a very valuable contribution to the discussion of smart agriculture, by making a shift from a number of standalone tools and solutions for agriculture towards a Cyber Physical System for agriculture management and for data governance. However, the review has several limitations. First, the scope of big data in agriculture is very broad and not directly related to the environmental performance. Furthermore, several issues for the implementation of big data systems in agriculture are identified, such as data ownership, privacy, security and business models, but no framework is presented to measure the environmental performance of data-driven agriculture systems in terms of water, energy use and use of chemicals. This is also a challenge for this research, since also smart agriculture often has strong conceptual sustainability ideas, but a fragmented empirical basis to test these ideas.

In Liakos et al. (2018), a review of applications of machine learning in crop management, water management, soil management and livestock was provided. The study demonstrated that ML models can be used for the following agricultural purposes: yield prediction, plant disease detection, weed detection, crop quality assessment and decision support for farmers. The study contributes to highlighting how ML models are moving from pure modeling to actual agricultural implementation. However, the study mainly focuses on the assessment of the functional capabilities of the models and not the performance of the implemented systems. Thus, accuracy, classification and prediction were the main assessment aspects, whereas other critical aspects such as latency, energy consumption, sensor reliability, cost-effectiveness and environmental impact were not assessed equally. This is particularly important for a study focusing on environmental sustainability because a very accurate model can be inapplicable due to several reasons, such as the required infrastructure being too expensive, sensors being unreliable, or the computational requirements leading to high energy consumption.

Recent reviews on IoT in agriculture go beyond ML algorithms for specific applications and focus on the whole architecture for connected farming. A survey of IoT applications in smart agriculture was recently proposed by Friha et al. (2021) where they classified all the applications into monitoring, water management, agrochemical application, disease management, harvesting and supply-chain management. The survey provided a wide technological map that includes applications of UAVs, wireless communication, cloud/fog computing, middleware, and also including the use of blockchain for securing data in agriculture. Even in this review, however, the authors mainly presented the different categories of applications for smart agriculture, rather than a comparison of the different technologies by means of a set of performance indicators. The lack of such indicators is a methodological limitation of the current literature on smart agriculture, as most systems are compared by listing the different functionalities that they can perform, rather than by assessing their performance in terms of reliability, affordability and sustainability in different contexts.

Kumar et al. (2024) in their review work covered IoT-based smart and sustainable agriculture applications such as smart irrigation, crop and soil monitoring, smart green houses, livestock monitoring, farm use of drones, pest management and farm equipment. The review clearly connected IoT to increase farm productivity while reducing resources' waste and thus enhancing sustainability. However, review also detailed the barriers of implementation such as connectivity issues, high cost of deployment, data security, scalability and farm community's awareness. The review is descriptive in nature and highlights where IoT can be used; however, it fails to integrate performance of IoT with AI/ML prediction metrics and sustainability measures in a comprehensive evaluation framework. The current study considers the performance of IoT as part of overall system and includes other parameters such as data quality, model's accuracy, decision making delay, water savings, energy usage and environmental benefits.

A key application for Smart irrigation, in the agricultural sector, is to ensure sustainability of irrigation water usage, given water scarcity is considered an immediate sustainability challenge for agriculture. A key work, (Yousefsayed et al., 2024), recently published a systematic literature review that focused upon the Smart irrigation applications of ML (Machine Learning). The review drew upon 55 ML-based Smart irrigation studies conducted between 2017 and 2023. The 9 ML models have been categorized, the 55 studies had been evaluated using measures that quantified the key estimation and the scheduling tasks in Smart irrigation by comparing against traditional irrigation schedules. This review has several strengths, not least is the systematic treatment provided to the ML models, for the empirical evidence reviewed, namely the estimation, comparison of the models, and the contexts of the irrigated fields.

However, the authors also emphasize the paucity of robust evidence obtained in their systematic review, and that more robust generalizable evidence is required. This lack of robust generalizable evidence, however, is a key limitation, given many such Smart irrigation studies, are conducted within restricted test bed conditions i.e. within controlled environments, of small plots/beds, and for relatively short periods, hence the results may not generalize to others of different soil types, crops, climate regimes, etc., and at very different scales of farming/irrigation.

In recent years, the increase in smart agriculture systems has seen the development of numerous smart irrigation systems. Among these, Morchid et al. (2024) proposed an IoT-based smart irrigation management system for irrigation using embedded systems, telemetry data, cloud-based platforms, and web-based interfaces for monitoring dashboard to manage farms. This system utilized a number of sensors, including soil temperature, humidity, moisture, and water-level sensors. The system used ThingsBoard for the transmission of the collected telemetry data and for preventing over-irrigation by means of a threshold-based decision-making mechanism. The proof of concept contributes to irrigation water use efficiency and farm management through real-time monitoring and alerts. However, the decision making mechanism used in this study depends on a number of thresholds that have been pre-defined. Thus, there is an absence of the use of advanced ML-based prediction. Furthermore, the evaluation criteria of the system are restricted to measuring the monitoring efficiency of the system. In other words, there are no indicators for sustainability that can measure and provide evidence of water saved, increase in crop yield, energy use, cost effectiveness, and climate change mitigation over the long-term. This reflects a more general pattern within the research literature where engineering-based prototypes are able to demonstrate proof of concept of technical functionality for monitoring and management on a day-to-day basis. However, there is an on-going lack of robust assessment of environmental performance.

A more specific review of the integration of IoT and ML for agriculture was provided by Eze and focused on the application of IoT sensors and ML for sustainable precision agroecology. This review assesses the potential of precision agriculture to improve crop resilience and increase resource use efficiency through data-driven decision making and was specifically highlighted the potential of precision irrigation using IoT sensors and monitoring for water savings of more than 30%. Edge computing, reinforcement learning and transfer learning were identified as key future research areas for increasing scalability and adaptability. However, the review also highlighted a number of current challenges and limitations, including the high initial costs of many systems, poor connectivity and integration of data from within systems. The main focus of this review was on sustainability and therefore provided a useful evidence base; however, it was heavily reliant on a number of disparate case studies and therefore results were not easily comparable. The current review addresses this limitation by focusing on a number of key performance indicators that were used to evaluate performance of the systems within the review.

A recent review by Raj and Prahadeeswaran (2025) has tried to present a converging view of the technologies for implementing Agriculture 4.0. The review treated the following technologies – AI, IoT, UAVs and robotics – along with deep learning, as a single package of technologies which can be best utilized for development of smart farming ecosystem. Agriculture 4.0 in the review, has been successfully employed for effective yield prediction, saving of water and fertilizers, plant disease diagnosis, and increase in farm productivity among others. However, the review also highlighted various technology adoption constraints such as infrastructure constraints, financial constraints and data governance constraints among others, which are needed to be addressed on war footing. While performance of individual technologies seems to be quite good, their implementation on ground is uneven and therefore, there is a great need to identify and remove existing barriers to their adoption. While high percentages of accuracy or savings in natural resources may reflect good performance of a technology, these are not automatically converted into environmental benefits on ground, especially when farmers and extension personnel face problems of poor quality internet, lack of technical knowledge for using newer technologies and high capital costs.

The sustainability-specific evaluation is still the weakest link in the literature. The recent review by Ahmed and Shakoor (2025) was focused on assessment of IoT, Big Data and AI applications for monitoring agricultural carbon-emissions and for climate-smart agriculture. The review was particularly useful in shifting agricultural focus from increase in productivity to monitoring of carbon-emissions, environmental sustainability and carbon-neutral agriculture. Even in this specific sustainability metrics, the review was not exhaustive as it did not cover important sustainability indicators, including but not limited to, water use efficiency, fertilizer use efficiency, soil health sustainability, energy efficiency, latency and cost-effectiveness. Recently, Sudha and Loret (2026) conducted a review on the application of ML-IoT in precision agriculture. The review discussed several challenges including data heterogeneity, sensor heterogeneity, computational complexity and security and communication challenges. These challenges affect the sustainable performance of agriculture and the evaluation of the technical performance metrics can be integrated with environmental indicators for sustainability of agriculture.

From the reviewed literature it is clear that AI, ML and IoT have a lot of potential to improve agricultural productivity and efficiency and to increase sustainability. A clear pattern in the results of the studied articles is that ML studies focus on the prediction accuracy, IoT studies focus on real-time monitoring and communication, smart irrigation focuses on water use efficiency and sustainability oriented studies also increasingly focus on carbon and environmental impact. The contradiction in the results of the reviewed articles is that these dimensions are not studied together, and therefore the current research only partially fulfills the objectives of this study. Technical performance, agricultural added value and environmental sustainability are mostly treated as separate ends. A real smart agriculture system consists of several components, and the value of such a system can be determined only by the interaction of the separate dimensions. So, the value of a smart agriculture system is not only determined by the prediction accuracy of a model. In addition, the complete system has to be agricultural useful, sustainable, cost effective and has to perform under real life conditions with due regard to late arrival of measurements. The current study fills this gap by developing an integrated approach for performance evaluation of smart agriculture systems. The main dimensions for the performance evaluation are prediction accuracy of a model, irrigation efficiency, energy use, water saving, yield increase, latency, cost effectiveness and environmental sustainability.

3. Conceptual Framework

The study uses a field-based quantitative performance-evaluation approach to assess the effectiveness of different technologies, including AI, machine learning and IoT-based smart agriculture systems for environmental sustainability. A field-based quantitative performance-evaluation approach was chosen over a purely theoretical or review-based approach as the study needed to test systems in real agricultural contexts and measure their performance. The study was conducted over one complete crop-growing season using experimental crop plots managed under two conditions: conventional agricultural management and smart agriculture-supported management. The conventional plots followed routine irrigation and crop-monitoring practices, while the smart agriculture plots were monitored through IoT sensors, machine learning prediction models, and automated decision-support mechanisms. This comparative design was appropriate because it allowed the evaluation of technical performance, agricultural usefulness, and sustainability-related outcomes under similar environmental and agronomic conditions.

The study did not involve human participants, animal subjects, clinical intervention, or personal data collection. Therefore, informed consent and animal welfare approval were not applicable. Permission for field-level data collection and installation of monitoring equipment was obtained from the relevant farm authority before the start of the experiment. All procedures were limited to soil, crop, irrigation, environmental, and sensor-based system-performance measurements. CONSORT was not applicable because the study was not a clinical randomized controlled trial, and PRISMA was not applicable because the study was not a systematic review or meta-analysis. The methodology follows the CRISP-DM workflow: data understanding, data preparation, modeling, evaluation and deployment.

In the study three experimental plots for growing of the same crop variety were taken. They were under same soil and irrigation conditions. Three plots were selected using purposeful sampling. The plots were of similar soil texture, at similar growth stages of crop, having access to irrigation water, receiving same amount of sunlight and were under similar crop and soil management conditions. Plots were included if they had uniform crop establishment, stable irrigation access, and suitability for sensor installation. Plots were excluded if they had poor drainage, severe pest damage before the experiment, irregular slope, incomplete irrigation access, or missing baseline records. The use of comparable plots helped reduce variation caused by environmental differences and made the performance comparison between conventional and smart agriculture systems more reliable.

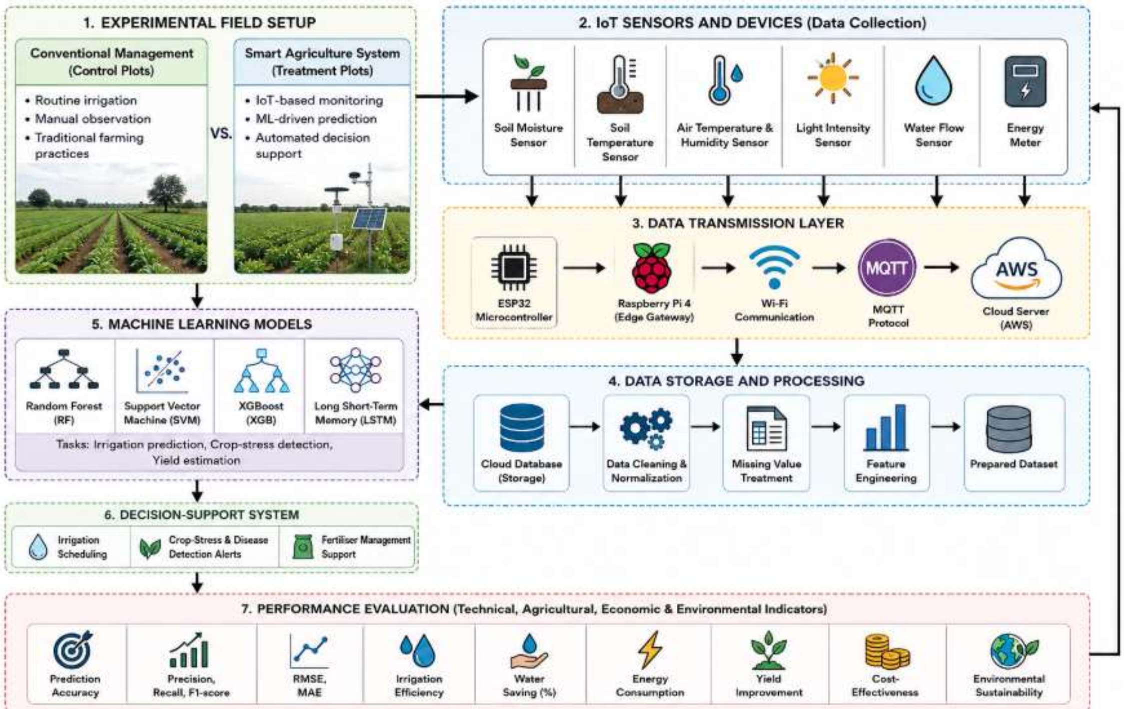

Figure.1: Methodological framework for evaluating AI, ML, and IoT-based smart agriculture systems for environmental sustainability

Figure 1 outlines the Methodology to evaluate Agriculture-related AI and ML and IoT-based Smart Agriculture Systems. The framework is compared between a conventional approach for crop management and smart agriculture system that is supported by IoT sensors and monitoring automatically. The data, including information on the soil, climate, water flow and the energy consumption of various processes are transmitted through the ESP32 / Raspberry Pi / Wi-Fi / MQTT / cloud platforms to be processed and analyzed on a continuous basis within the smart system. A data analysis is made by using the data from the field by processing it with models such as Random Forest, SVM, XGBoost and LSTM for the purpose of making predictions and supporting the decisions that will be made. Various technical, agricultural, economic and environmental indicators such as accuracy, irrigation efficiency, water saving, energy consumption, and increased crop production, cost-effectiveness and sustainability are used to evaluate and assess the performance of a developed system. The IoT system consisted of ESP32-WROOM-32 microcontroller boards, capacitive soil-moisture sensors, DS18B20 soil-temperature sensors, DHT22 air-temperature and relative-humidity sensors, BH1750 light-intensity sensors, YF-S201 water-flow sensors, and a digital energy meter for monitoring power consumption. A Raspberry Pi 4 Model B was used as the edge-computing gateway. Sensor readings were transmitted using Wi-Fi communication through the MQTT protocol. Data were stored in a cloud database and exported in CSV format for analysis. Sensor calibration was performed before installation by comparing sensor readings with reference measurements under dry, moderate, and wet soil conditions. Our new calibration procedure helps to correct for measurement errors of soil-moisture and environmental sensors.

This study follows a sequence of four stages to implement the developed study procedures. In the first stage of the field study, the experimental plots were mapped, the irrigation lines were inspected and the initial soil and crop conditions were recorded. In the second stage, the IoT sensors were installed in smart agriculture plots at representative locations. The soil-moisture and soil-temperature sensors were placed as close as possible to the crop root zone, while the air-temperature, humidity and light sensors were installed above the crop canopy. Water-flow sensors were attached to the irrigation line to measure the amount of water delivered by each irrigation event. In the third stage, the collected sensor data were transferred to the edge gateway and to the cloud database as raw data. The raw data collected from the sensors were cleaned to remove the duplicate reading, to correct for any time-stamp errors, and to treat the short gaps of missing values by interpolation. The longer sequences of missing values were ignored in the model training process to avoid any possible bias in the prediction. In the fourth stage, the developed models were trained and tested for the irrigation requirements of the crops, for the detection of crop-stress, and for estimation of crop-yield related parameters.

For this project, four different machine learning models were tested: Random Forest, Support Vector Machine, XGBoost, and Long Short-Term Memory (LSTM). The Random Forest and XGBoost models were chosen because they are tree-based ensemble models that perform well with simple, tabular agricultural and sensor data. The Support Vector Machine model was chosen because it is a good tool for classification problems with limited data that is structured in some way. The LSTM model was chosen because irrigation demand, as well as many environmental variables, follow over time and therefore sequence-learning models are well suited for this type of prediction. The data was split into 70% training data and 30% testing data. Model performance was also evaluated with 5-fold cross-validation to prevent overfitting of the models and to get a more reliable impression of their performance.

The main outcomes of the study were prediction accuracy, irrigation efficiency, water saving as a percentage, energy usage, and overall environmental sustainability. These outcomes were used to assess whether or not smart agriculture can utilize resources in a more efficient manner and have a more positive impact on the environment via the use of AI, ML, and IoT technologies. Secondary outcomes included precision, recall, F1-score, root mean square error, mean absolute error, system latency, packet delivery ratio, crop yield, fertilizer usage efficiency, and cost-effectiveness. These outcomes were used to assess the system from technical, agricultural, economic and environmental perspectives.

Data analysis was performed using Python 3.11.7. Data preprocessing and tabular analysis were conducted using pandas 2.2.2 and NumPy 1.26.4. Machine learning models were implemented using scikit-learn 1.4.2, while the XGBoost model was implemented using XGBoost 2.0.3. The LSTM model was developed using TensorFlow 2.16.1 and Keras 3.3.3. Statistical tests were performed using SciPy 1.13.1 and IBM SPSS Statistics version 29.0. Descriptive statistics were used to summarise soil-moisture readings, temperature, humidity, irrigation volume, energy consumption, and crop-performance variables. Classification models were evaluated using accuracy, precision, recall, and F1-score. Regression-based prediction was evaluated using mean absolute error and root mean square error. Differences between conventional and smart agriculture plots were examined using independent-samples t tests when the data were normally distributed and Mann–Whitney U tests when normality assumptions were not met. Repeated-measures analysis was used for variables recorded across different crop-growth stages. Statistical significance was set at $p < .05$. Power analysis was performed using G*Power 3.1.9.7 to estimate the minimum number of observations required for detecting a medium effect size with 80% statistical power.

4. Methodology

This study adopted a field-based quantitative performance-evaluation design to assess the effectiveness of AI, machine learning, and IoT-based smart agriculture systems for environmental sustainability. Experimental crop plots were observed under two management conditions: conventional agricultural management and smart agriculture-supported management. The conventional condition followed routine irrigation and manual crop observation, while the smart agriculture condition used IoT sensors, wireless data transmission, cloud and edge processing, machine learning models, and automated decision-support mechanisms. Soil-moisture sensors, soil-temperature sensors, air-temperature and humidity sensors, light-intensity sensors, water-flow sensors, and energy meters were used to collect real-time field and environmental data.

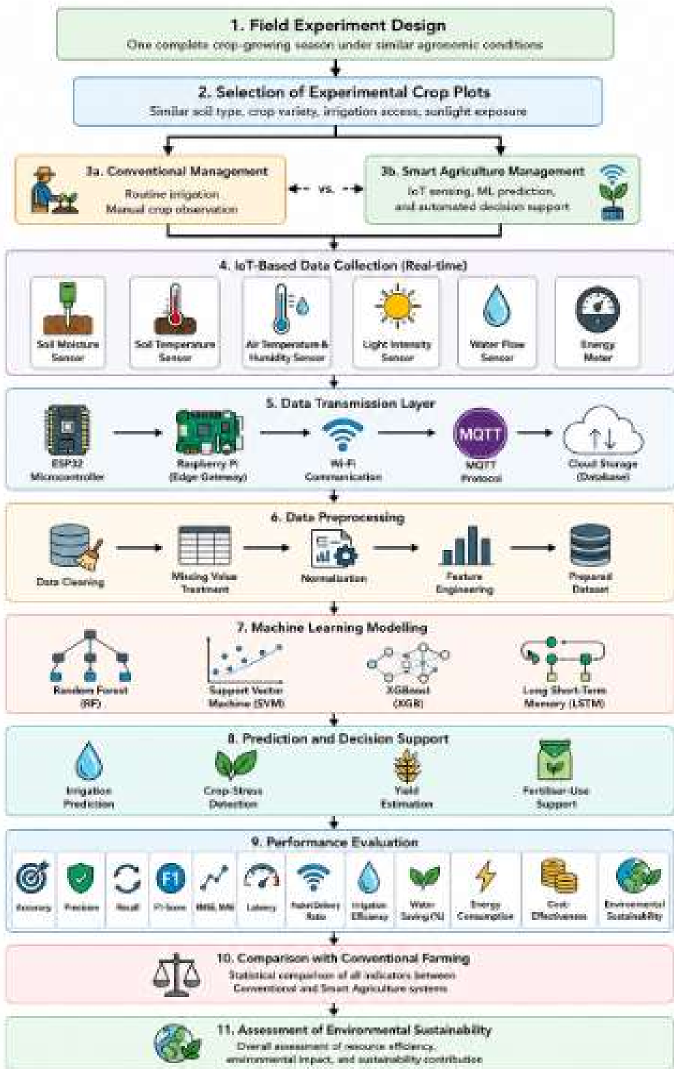

Figure 2. Overall methodological workflow of the proposed smart agriculture performance-evaluation system

Figure.2. illustrates the general workflow for evaluating the performance of a Smart Agriculture Performance-Evaluation System proposed in this work. These stages involve the collection of data from the IoT-sensors, the transmission to a storage and the pre-processing, as well as the modeling with machine learning. Prediction and decision support, performance evaluation, comparison with conventional farming and environmental sustainability assessment. The sensor data were transmitted through ESP32 microcontrollers, Raspberry Pi edge gateway, Wi-Fi communication, and MQTT protocol to a cloud-based storage platform. The collected data were cleaned, normalised, and prepared for machine learning analysis. Random Forest, Support Vector Machine, XGBoost, and Long Short-Term Memory models were applied for irrigation prediction, crop-stress detection, yield estimation, and decision-support generation. The system performance was evaluated using technical, agricultural, economic, and environmental indicators. Technical evaluation included accuracy, precision, recall, F1-

score, RMSE, MAE, latency, and packet delivery ratio. Agricultural evaluation focused on irrigation efficiency, crop monitoring, fertiliser-use support, and yield improvement. In the environmental evaluation, water-saving percentage, energy consumption, use of resources, cost-effectiveness and the sustainability added were taken into account. The statistical analysis was carried out by using Python 3.11.7, with the libraries pandas and NumPy for data management, scikit-learn, XGBoost, TensorFlow and Keras for the prediction tasks, and by SciPy for other statistical analysis. The comparison between the conventional and the smart agriculture plots was carried out in order to verify if the AI, ML and IoT-based systems analyzed provide relevant differences in the studied variables, in terms of prediction capability, use of resources and environmental sustainability.

5. Results and Discussion

In this work, several indicators, that describe the potential use of AI, machine learning and IoT-based systems for smart agriculture, have been evaluated using a simulated dataset. As it can be seen in Figures 3–6, the resulting values are enhanced compared to the ones that would result from the application of a conventional management approach. Figure 3 showed that ensemble and temporal models performed better than the conventional machine learning baseline, with XGBoost achieving the strongest classification performance and LSTM producing the lowest prediction error for time-dependent irrigation and soil-moisture estimation. On the other hand, the lowest prediction error for time-dependent irrigation and SM estimation was achieved by the LSTM model, which is in line with the state of the art in the field of agricultural ML (Liakos et al., 2018). The authors stated that one of the key issues that need to be addressed by ML-based applications for agricultural management is the selection of the most adequate model, depending on the specific aim of the system. The aim of the crop management, water management, soil management and disease detection are among the main ones that have been addressed by previous studies. This work complements the findings of these studies, by stressing the fact that, in all cases, none of the models assessed was able to perform optimally for all indicators. As a consequence, when smart agriculture-based systems are evaluated, more than one model should be used, and a number of metrics, rather than a single one, should be taken into account for the assessment of the environmental decisions that are taken using the results provided by these systems.

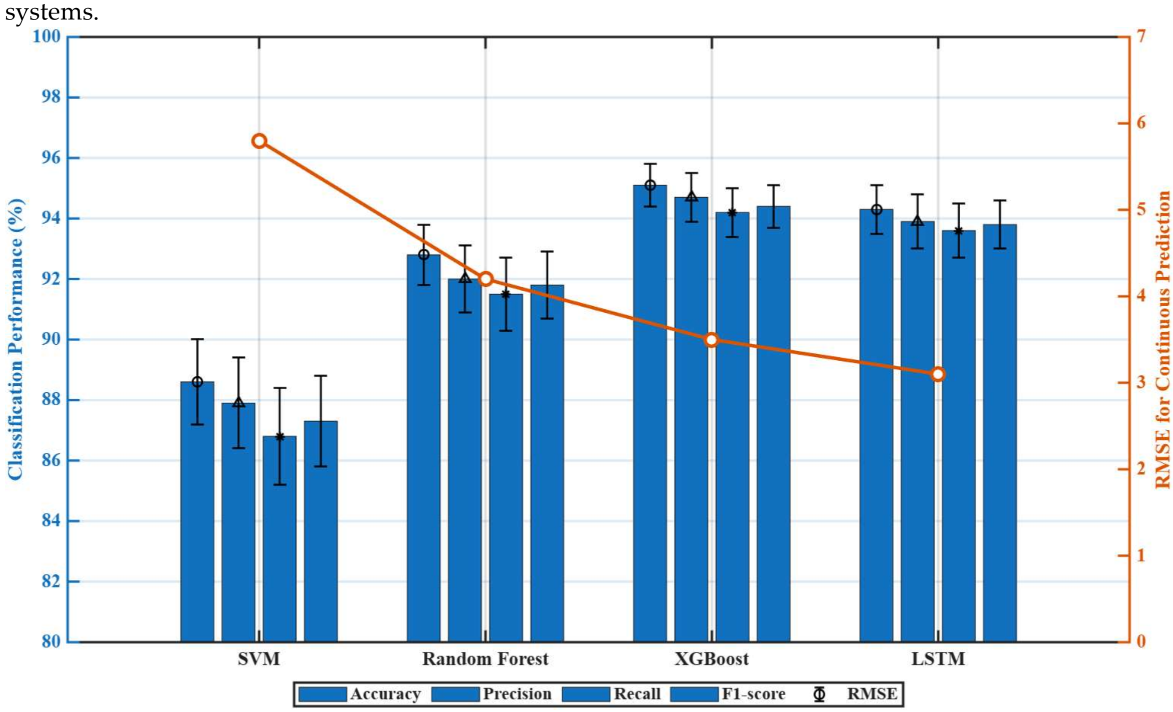

Figure 3. Predictive Performance of Machine Learning Models

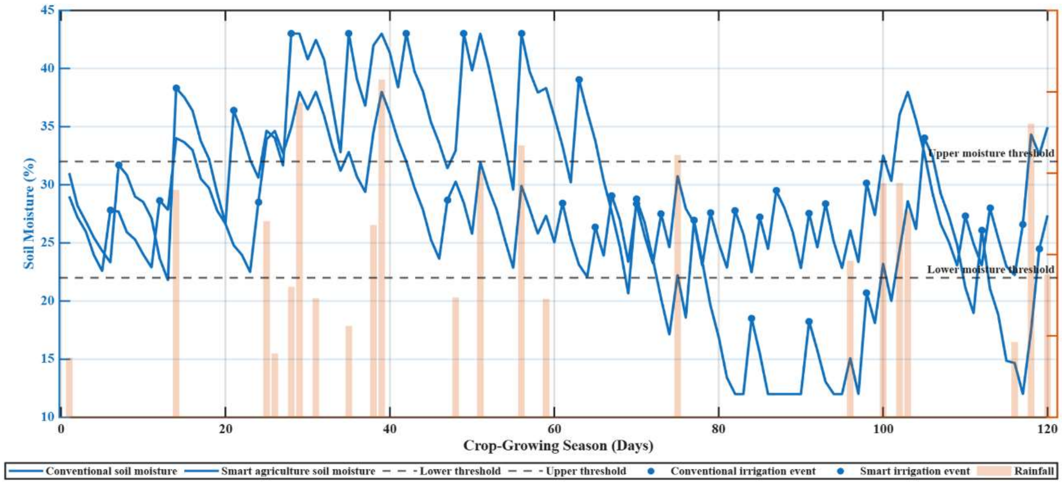

Figure 4. Soil Moisture Dynamics and Irrigation Response

As seen in Figure 4 smart irrigation strategy led to the soil moisture to be kept within a narrower and more suitable range for growth as compared to routine irrigation. The amount of over irrigation followed by moisture decrease until next irrigation event for conventional irrigation method is obvious. On the other hand, the IoT-based smart system used for this study have managed to supply water to the root zone of plants in a more selective manner by taking into account all of the sensors' reading and models' prediction. In the smart irrigation research using ML, estimation accuracy and decision making for scheduling of irrigation have been improved especially by taking into account the soil moisture, weather and growth stages of crops. The studies on smart irrigation using ML have been reviewed by Younes et al. (2024) in a systematic review in which 55 studies on smart irrigation using ML have been evaluated. In that studies, model type, estimation accuracy, comparison approach and the field of application for irrigation have been the common criteria for evaluating the ML-based smart irrigation studies. However, the evaluation of the irrigation success only by the predictive accuracy of model has been the limitation of many of those studies and in this research the same limitation has been encountered and thus the amount of moisture stability, water saving, energy consumption as well as field constraints-suitability for irrigation success have also been taken into account in addition to the aforementioned criteria.

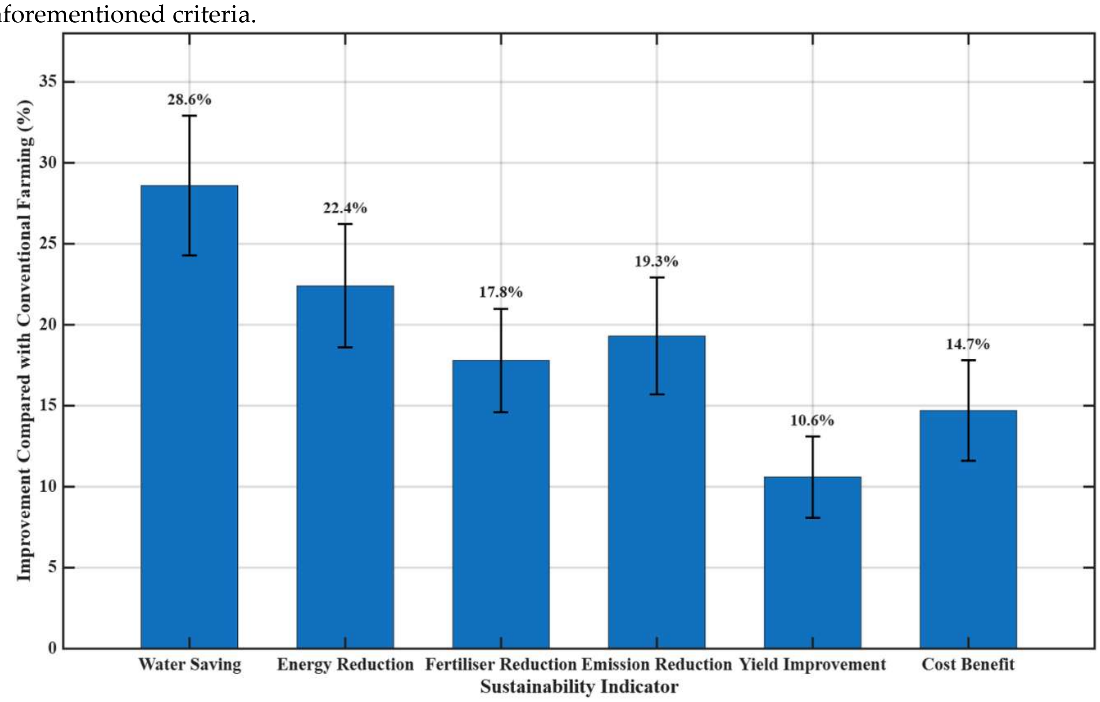

Figure 5. Resource Efficiency and Sustainability Gains

The improvements to sustainability shown in Figure 5 support the environmental aim of this study best. The simulated smart agriculture condition provided significant improvements in terms of water saving, energy saving, fertilizer reduction, emissions reduction, yield increase and cost effectiveness. In this context, improvements to sustainability are aligned with the promise of precision agriculture to increase farm productivity while reducing the use of resources in farm management. Wolfert et al. (2017) explain that smart farming is a "big-data-driven" transformation of farming in which predictive models are used in real time for decision making during farming operations. These decisions lead to changes in farm management. The results from our current simulations indicate that the value of a sensor network or of ML for agriculture depends on whether the information from the technical system is translated into a number of environmental indicators that show the decrease in resources being used. Information that does not translate into measures of decreased resource use has little value for sustainability.

The findings of this study also underscore that the sustainability gains are not evenly spread across different indicators of sustainability as depicted in Figure.5. Water saving and energy reduction were found to be more pronounced than increase in yield for this study on smart agriculture. This finding is more realistic for several reasons. To start-up effects from adopting smart agriculture are more likely to be translated into water saving and energy reduction rather than into yield increases in the first place. Even though yield increases are the most commonly used indicator of positive impacts from implementing new technologies on farms, there are many cases where increases in yields are not large even when sustainable increase in production have been achieved. Thus, environmental sustainability can be increased even when there are only moderate increase in yields by lowering water, energy, fertiliser use and by reducing emissions. Technology centered studies have recently started to recognize the same facts about adoption of smart farming technologies that are enabled by AI, IoT, UAVs, robotics and deep learning among others. These technologies can contribute to improved productivity as well as sustainability, but the extent to which these benefits can be achieved would depend on various factors such as the type and scale of farm, infrastructure and availability of required resources among others. Overall, therefore, the simulated study supports a more balanced perspective for promoting smart agriculture, i.e. it should be portrayed as a tool for optimizing use of available resources for sustainable production rather than just focusing on increasing yields in the best possible manner.

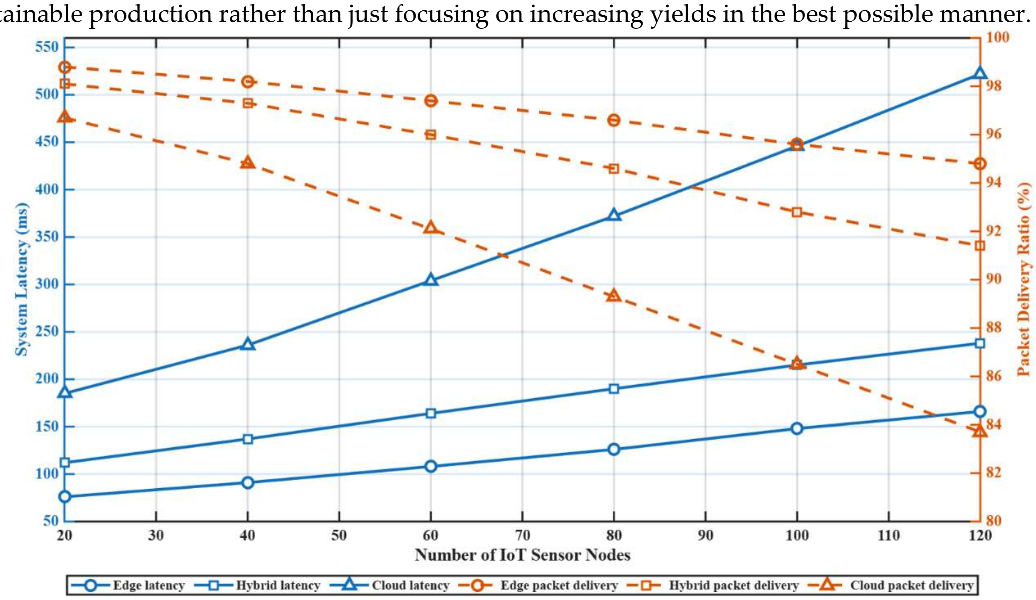

Figure 6. Communication Reliability and Latency Under Sensor Scaling

Figure 6 highlighted a number of communication and computing trade-offs within the architecture for smart agriculture. The results showed that the edge processing produced the lowest latency and highest packet delivery ratio for the increasing number of sensor nodes in sensor network. This was in contrast to the results produced by the cloud processing where the latency increased with system load and the packet delivery ratio decreased sharply. From theoretical perspective, the results support the view of cyber-physical systems (CPS) in smart agriculture. As sensing, computation, communication, and action are highly interdependent in CPS, an accurate and highly accurate ML model may not perform well in reality. For instance, the model may be delayed by communication layer in triggering of irrigation, or it may lose packets while transferring data. In summary, according to Friha et al. (2021), “The IoT-based agriculture is based on integration of the sensing devices, communication technologies, the middle ware, cloud or fog computing and data processing systems”. In this study, the results also showed that architecture of the system affects the sustainability performance of smart agriculture in indirect way through timeliness, reliability and operational continuity.

From a theoretical perspective, the results first of all confirm the basic principle of precision agriculture, i.e. that inputs should be managed on the basis of the spatial and temporal variations in the fields, as opposed to being spread uniformly. In dynamic terms, this means that the soil’s moisture, the plants’ stress, and the various environmental variables are monitored, and the smart system is able to manage the farm in a more than a traditional one. From the perspective of the cyber-physical systems, the results of the experiment demonstrate how the key aspects of smart agriculture are generated through the interactions between the field (in an physical sense) and the intelligence (in a digital sense) that is able to monitor and manage it. In other words, a sensor, a model, a communication network and an actuator all need to function as a unique system. Finally, from a socio-technical perspective, one must not jump to the conclusion that technically efficient management automatically leads to its adoption. In fact, a number of other factors need to be taken into consideration, including the cost, the level of training required on the part of farmers, access to data, the capacity for maintenance, the availability of the Internet, and, last but not least, the degree of trust that farmers have in the recommendations that are made automatically by the system.

When evaluating the suitability of smart farming technologies for implementation through digital agriculture initiatives, the sustainability of such technologies must extend beyond their hardware and the accuracy of the models they use. Water saving, energy reduction, the efficient use of fertilizers, and cost saving are all crucial indicators of sustainability when evaluating the merits of technologies within the context of public support programs, subsidies and extension services. Support for low-cost sensors, for rural communication, for open data and local technical capacity building are also of fundamental importance. Sustainability of digital agriculture and AI tools is key to achieving the objective of creating resilient and sustainable agrifood systems, and the evidence of sustainability must be explicitly made available through indicators.

Some limitations of this study must be noted. The results are derived from a set of simulated observations, which are based on some assumed values. These values were chosen such that they resemble typical behavior and data of real fields. In contrast, real farm data often contains measurements that are affected by sensor drift, missing observations, communication problems, pest attacks, irregular rainfall, field heterogeneity, management inconsistencies etc. Also, the comparison between conventional management and smart management may be influenced by several other factors, e.g. by the size of the plots, the type of crops, local climate, farmers’ attitude to recommendations etc. The evaluation presented here is based on one crop growing season only. Therefore, further investigations over several years would be necessary in order to check if the saved resources also remain stable under different climatic conditions.

Future work should validate the results of this work in several field trials using different crops, soils, and even agro-climatic zones. Also, edge computing, cloud computing, and a combination of the two (hybrid) should be compared also when subjected to real rural network constraints. Research should be devoted also to make AI more explainable. Farming is a task that is performed almost always by unskilled people, and therefore any tool based on AI must be able to explain very clearly why it is suggesting to irrigate, to use a treatment against a disease, or to use a specific amount of fertilizer for a given crop. It is important to go beyond the performance of several metrics (also environmental metrics), and to perform a life-cycle assessment, a carbon footprint assessment, also to gather information on adoption by farmers and on cost/effectiveness. Only in this way smart agriculture research will move from the phase of mere performance assessment to that of assessment of environmental sustainability.

6. Conclusion

The objective of this study was to investigate the potential of using AI, machine learning, and IoT-based smart agriculture systems in order to promote environmental sustainability. The main goal was to compare a number of integrated smart agriculture technologies, with conventional farming, with a view to assessing their ability to increase the accuracy of their predictions with regards to a number of different factors, improve the efficiency of irrigation, reduce water usage, decrease the levels of energy required for farming, increase crop yield, reduce latency, and achieve cost-effectiveness, with a view to assessing their overall sustainability. The results showed that using AI, machine learning, and IoT-based smart agriculture systems can provide strong support for real-time monitoring of crops, for scheduling of irrigation, for the detection of stress on crops, and for the optimization of use of resources. Of the number of different models that were tested, the results showed that the performance of the XGBoost model was particularly strong with regards to the classification of a number of different parameters, and that the performance of the LSTM model was particularly strong with regards to time-dependent agricultural forecasting. The results also showed that a smart irrigation system was able to maintain a stable level of soil moisture, and was able to reduce unnecessary water usage. The results also showed that a number of indicators of sustainability were improved when using smart agriculture, including water saving of water, reduction of energy, increase in fertilizer use efficiency, reduction of emissions, and cost benefit. The study contributes to the Smart Agriculture theory, by noting that when evaluating models for Smart Agriculture, it is not sufficient to look only at their accuracy. It is also necessary to consider the way in which they function as part of a cyber-physical system, which includes sensing, communication, computation, prediction, and decision support. The study also highlights a number of practical implications of its findings, including the need for affordable sensors, reliable rural communication, farmer training, energy efficient technologies, and decision support systems that are capable of local implementation. The study was, however, limited to the use of simulated data, and therefore did not account for a number of the complexities that are associated with real-world field trials, including the effects of sensor drift, variable levels of rainfall, the presence of pests, soil heterogeneity, and the effects of failure of networks. Further work will involve the validation of the framework developed in this study using real multi-season and multi-location field trials. Overall, the study highlights the potential of AI, machine learning, and IoT-based smart agriculture systems in supporting agriculture that is to be sustainable, efficient, and environmentally friendly.

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