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**Integrating Digital Agriculture and Smart Farming Technologies for Climate-Smart
 Crop Management: A Field-Based Evaluation of AI, IoT, and Precision Systems**

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Abstract: We conducted a field-based evaluation of digital agriculture and smart farming technologies across 20 research farms in diverse agroecological regions, employing 360 plots in a randomized complete block design over three cropping seasons. The study integrated IoT-based soil moisture monitoring, AI-driven crop health assessment, drone surveillance, GPS-guided precision farming, remote sensing, automated irrigation, a cloud-based farm management platform, and a climate forecasting decision support system. A hybrid deep learning framework combining Long Short-Term Memory and Convolutional Neural Network models was developed for crop growth prediction, disease identification, and irrigation scheduling, achieving a prediction accuracy of 97.1%, precision of 96.5%, recall of 96.0%, and an F1-score of 96.2% with a root mean square error of 0.16. The implementation of these technologies resulted in a 32.8% increase in crop yield, a 30.6% improvement in water-use efficiency, a 26.9% reduction in fertilizer consumption, and a 23.8% decrease in crop disease incidence compared to conventional farming. Multiple linear regression revealed that AI-based decision support was the strongest predictor of climate-smart crop management ($\beta = 0.48, p < 0.001$), followed by IoT soil moisture monitoring ($\beta = 0.43, p < 0.001$), with the model explaining 80.1% of variance in crop productivity. Principal component analysis extracted three components accounting for 85.8% of total variance, representing AI-driven crop management, IoT-based water optimization, and climate resilience. The Smart Farming Index showed a strong positive correlation with crop productivity ($r = 0.88, p < 0.001$). These findings demonstrate that integrating AI, IoT, remote sensing, and precision systems provides a robust pathway toward sustainable agricultural intensification under climate variability, significantly improving resource-use efficiency and environmental outcomes.

Keywords: Digital Agriculture, Smart Farming Technologies, Climate-Smart Agriculture, Precision Agriculture, Artificial Intelligence (AI) and

Introduction

Climate variability and unprecedented increase in population and reduction of environmental damages are the unprecedented challenges of the agricultural system of the world. Traditional farming has been productive, but in recent years it has proven inefficient in its use of resources and is also extremely straining when affected by climatic shocks, which may endanger food security in the medium- and long-term (Khan et al., 2024). The idea of climate-smart agriculture (CSA) has responded with an approach that aims at being more resilient, sustainable and efficient in boosting productivity and reducing greenhouse gas emissions (Leippert et al., 2020). However, technologic innovations that can provide on-line data driven-practice are needed if CSA is to be made viable on a large scale.

Digital agriculture technologies and smart farming technologies including Internet of Things (IoT) sensors, Artificial Intelligence (AI), remote sensing, UAV (unmanned aerial vehicles), cloud-based decision support systems are promising to be useful for operationalizing CSA (Gemtou et al., 2025). For soil moisture monitoring, for instance, the Internet of Things (IoT) can control the schedules of irrigation machines and, with AI image analyzes of drone scans, signs of stress in crops can be detected (Ahmed et al., 2022). These tools may have potential in theory, but there is a great need to have these tools assessed under real field conditions across multiple seasons to measure their impact on productivity and resource use efficiency and sustainability impacts across agroecological landscapes (Mollel et al., 2025).

The primary research hypothesis was that when implementing digital agriculture and the smart farming technologies, crop yields and agricultural resource utilization efficiency, as well as adaptability to the climate variations would be significantly improved compared to traditional agriculture. The main goal was to properly assess innovations designed for smart farming at 20 matching agricultural research farms in various agroecological zones using a randomized complete block design with 360 experimental plots across three successive seasons of production. In the current study, a hybrid deep learning model made up of two different architectures: Long Short-Term Memory (LSTM) network and Convolutional Neural Network (CNN), was designed and tested for the prediction of crop growth, identification of diseases, and irrigation scheduling. We also wanted to quantify how the different specific technologies compare from the perspectives of their effects on the indicator measures for total climate-smart crop management.

The outcome of this research has important contributions. First, there's plenty of empirical evidence that achieving a 32.8 per cent greater yield, a utilised water use efficiency of 30.6 per cent and a reduction in fertilizer use of 26.9 per cent can be possible for a large-scale, multi-site field experiment, incorporating the use of AI, IoT, remote sensing and precision systems in farming. By using AI, IoT, remote sensing and precision systems, the field experiment of a multi-site, large-scale experiment provides adequate empirical evidence that yields can be improved by 32.8% while water use and fertilisers can be lowered by 30.6% and 26.9% respectively, as compared to conventional farming. The second is that the hybrid AI achieved the prediction accuracy of 97.1% for agricultural field related applications, demonstrating its high accuracy prediction. Third, multiple linear regression analysis revealed that the system of AI based decision support is the one that most closely reflected the situation of crop productivity ($\beta = 0.48$, $p < 0.001$), followed by IoT soil moisture monitoring ($\beta = 0.43$, $p < 0.001$), and the overall model is able to explain 80.1% of the variance in crop productivity ($p < 0.001$). The results serve as a data policy-driven guide to policy makers, agronomists, and farmers looking to find a way towards sustainable intensification that can be scaled to technology empowerment of agricultural adaptations to more uncertain climate conditions in the future.

For this paper, literature search has been conducted regarding work done on digital agriculture, smart farming and climate smart crop management in the second part. Experimental design, data collection and analysis methods used in this study are described in Section 3. The key results are packaged up into Section 4: Summary of Model performance and Summary of outcomes - comparative outcomes and statistical analysis. The implications of these results on sustainable agriculture, as well as restrictions and future studies are presented in section 5. The paper ends with the main contributions and recommendations in Sections 6.

Literature Review

However, there is a considerable body of literature produced, as well as agricultural research and science, that speaks to the impact of data technologies on increasing productivity and sustainability. Much information exists about how data technology can be used to address challenges to productivity gains and environmental sustainability in agriculture. Early research on precision agriculture paved the way for the basic concept of site specific management with the advent of variable rate technologies and georeferenced farming equipment where precise management, which involves patternization of input variability over fields, was enabled (Thangamani et al., 2025). While the first steps proved somewhat successful in improving input-use efficiency, a lack of capability in many aspects prevented their integration, especially with respect to high costs of equipment and the absence of an embedded (separate) decision-support framework.

The use of IoT sensors was one of the significant advancements in the field of real-time monitoring of agricultural systems. Cloud-based technologies have been harnessed to retrieve this soil data in real-time and upload it to cloud system for analytics and visualisation via wireless sensor networks (WWSNs) (Hassan et al., 2024). With a substantial decrease in irrigation water saved (20%–40% over the traditional scheduling methods), it has previously been evaluated that implementing Irrigation Water Treatment (IWT) using IoT-based soil moisture monitoring would benefit farmers, since they are able to irrigate crops while receiving only the required required water, which is less than what was being applied with conventional measurement methods. As previously evaluated, the benefits of implementing the Irrigation Water Treatment (IWT) with the application of the IoT-based soil moisture monitoring for water will benefit farmers, since they will be able to irrigate their crops while at the same time not applying excess water that is not useful for the crop. However, these investigations were limited to technology focused on a single-technology intervention and provided limited information on the synergistic impacts of multiple digital tools in regard to integration.

crop disease detection, yield prediction and resource optimization popular zone are among areas where AI plays a role in problem solving in agriculture. In agricultural applications, AI is increasingly being integrated into a multitude of problem-solving scenarios, including crop disease detection, yield prediction, and optimizing resource usage as popular zone. In agriculture, AI is increasingly being used in a variety of problem-solving scenarios, such as optimizing resource usage, crop disease detection, and yield prediction, which is the popular zone. CNNs have been found to be accurate in plant disease classification based on leaf images, and on benchmark data, even exceeding 95% accuracy (Fuentes et al., 2021). Similarly, crop yield predictions based on previous meteorological data, soil properties and crop cultivation technologies (Klompenburg et al., 2020) have been conducted with the help of recurrent neural networks and LSTM, among others. While these AI-driven approaches hold potential to enable sensors to provide significant information and insights, data spread across years and agroecoci is still limited.

A new source of information for assessing crops over different spatial and temporal extents comes from remote sensing technologies such as satellite imagery and unmanned aerial vehicle (UAV) sensors. The

Normalized Difference Vegetation index (NDVI) has been extensively applied for monitoring the crop status and its growth environment such as the nitrogen input and/or biomass product (Bekhoucha et al., 2002; Jr et al., 2003) and has proven to be correlated with final grain yield. Additionally, UAV multispectral imaging could be able to ensure a higher spatial resolution than other satellite platforms and allow to detect intra field variability, which would not be identified with these other platforms (Manfreda et al., 2018). The integration of remote sensing data into the multi-site field trial decision supporting system has, however, not been fully explored in multi-site field trials, nor has the use of ground based IoT data and AI based intelligence analysis.

Both, conceptual framing and policies regarding climate-smart agriculture have gained high visibility for discussions on how to include practices as part of a climate-smart agriculture approach that have a potential triple win — productivity, resilience and emissions reductions (Branca et al., 2011). CSA has been considered as an enabler for technology, and as a data infrastructure that will facilitate adaptive management with the help of climate variability (Ikram & Moni, 2026). The evidence base linking particular digital interventions to specific measurable CSA outcomes — such as water-use efficiency — as well as disease incidence and fertilizer use — is, however, disjointed. Many current studies focus on the individual technologies examined separately and/or on the use of simulation models and not field experiments.

In recent years, the number of smart farming systems has grown, and several review papers have been published to recommend reference architectures or conceptual frameworks for integrating smart farming technologies such as the IoT, AI, and precision technologies (Kakamoukas et al., 2021). All of these types of contributions are useful to establish the theoretical basis but they may not include empirical study or support obtained from extensive, multi-season field experiments. Furthermore, fewer studies have been conducted to address the economic and operation part of these integrated systems under various agroecological situations.

The contribution of our study for these gaps is holistic field-based evaluation of 20 research farms in three successive cropping seasons (2016, 2017 and 2018) based on randomized complete block design with 360 research plots across different agroecological regions. We used a combination of technologies, including IoT sensors, AI analysis, remote sensing, unmanned aerial vehicles (UAVs), GPS-guidance and precision approaches and cloud-based decision support in our research, which has been different from the previous one and dealt with only a single technology or the use of short-term trials. Our hybrid model (LSTM-CNN) made a 97.1% prediction accuracy which is higher than the reported prediction accuracy of individual models. Moreover, the results of our multiple linear regression model indicated that the AI-based decision support has proved to be the best individual technology component to predict the climate-smart outcomes, revealing the importance of this technology in its contribution to the study field. This empirical knowledge is a solid base for the understanding of how digital agriculture technologies can be optimally applied and combined to increase sustainable and productive agriculture under climate variability.

Materials and Methods

Study Design and Experimental Setup

Experimental research design was a field experiment aiming to evaluate the effectiveness of a digital agriculture and smart farming for climate-smart management approach. The study was conducted on the 20 smart-agricultural research farms placed in the various agroecological zones differing in climatic conditions, soil fertility and farming systems for crops. In order to remove year to year difference of the experimental plots and give more confidence to the results, the plots were laid out by Randomized

Complete Block Design (RCBD) with a total number of three seasons of cultivation during which 360 plots were replicated with 12 treatments per replication and 3 replications per season. The plots were each numbered and numbered 10 m × 10 m and had a 2 m buffer zone between each plot to reduce the edge effects, and treatment interference.

Ten digital agriculture technologies were applied in different combinations and applied to various plots as the experimental treatments. These ranged from a farm management platform that collects and displays data in the cloud, an app for delivering real-time farming advice to farmers and their managers, and a system for integrating 7 day weather forecasts with crop growth models to help set target nutrient levels, to variable-rate seeding and fertilizer application and smart irrigation systems, which activate solenoid valves according to moisture levels in the soil. These included a cloud-based farm management platform that collects and visualises data, as well as a mobile advisory app to enable real-time recommendations to farmers and their farming teams that integrates 7 day weather forecasts, crop growth models and sets specific targets to know the specific nutrients required, variable-rate nutrient application that works based on the most up-to-date data from a crop's nitrogen status, and automated, on-demand irrigation based on capacitance soil moisture sensors that are placed at 15, 30 and 45 centimetres below the surface.

Data Collection and Measurement Protocols

Multiple modalities of data collection were used to capture data from all aspects of the biophysical and management elements. The field observations were conducted by the trained agronomists on weekly basis, and the crop phenology and diseases incidence and pest pressure were evaluated visually. They collected the information every 15 minutes from the sensors deployed on IoT and transmitted them to the central database via the LoRaWAN network. The NDVI, together with other vegetation indicators, was derived from the images taken with the drone at 7 days intervals during the growing season at 50 m altitude with clear sky resulting in ground sampling distance of 2.5 cm. Satellite data was acquired from Copernicus Open Access Hub and converted to a variety of vegetation indices, such as NDVI. Samples were collected at planting and at harvest time and analysed in a laboratory for soil pH and macro-nutrient (N, P, K) and micro-nutrient level. Automated weather stations set in each research farm was used to continuously monitor the weather variables such as air temperature, relative humidity, wind speed, etc. and rainfall.

Soil moisture content (volumetric water content, %), soil temperature (°C), air temperature (°C), relative humidity (%), rainfall (mm), Nutrient Status (N, P, K concentrations in plant tissue, %), Crop disease incidence (percentage of plants with symptoms of disease), water consumption (total water volume during irrigation, m³ ha⁻¹), fertilizer consumption (total nitrogen inputs in fertilizers, kg ha⁻¹), crop yield (fresh weight, t ha⁻¹), water-use efficiency (yield per unit evapotranspiration, kg m⁻³), and energy consumption (Field operations and irrigation pumping, kWh ha⁻¹) were the measured variables.

Data preprocessing/quality assurance

Various steps were performed sequentially in data preprocessing to guarantee both data quality and consistency. Observed variables along with data that were more than 20% missing were dropped (incomplete observations). The data for time series variables was linearly interpolated for missing values and for cross sectional data, the missing values were filled with kNN imputation. Using a range of $1.5 \times \text{IQR}$ (below the first quartile and $1.5 \times \text{IQR}$ above the third quartile), values outside the range were noted as those which require further investigations for possible sensor failures carried out by replacing the values with either the next coming larger value or the next coming smaller value depending on the adjacent valid data points. All became continuous variables were then min-max scaled so that all

variables can be compared in different measurement units and measurement scale. Validation of the calibration and verification of the offsets and gains of IoT sensors were carried out at the start of each cropping season, by comparing IoT sensor readings with gravimetric moisture measurements, and tuning them as needed. These pre-processing remotely sensed images in this process were performed on drones and satellite images through a radiometric calibration, geometric correction, and atmospheric correction using a dark object subtraction (DOS) algorithm. The features like image texture features obtained from gray-level co-occurrence matrix and vegetation indexes derived from image (NDVI, NDRE, NDGI) were known in the image segmentation. A cross check of sensor data with manual data, GPS data with known reference points, inter-laboratory comparisons of soil and plant tissue analyses were performed for quality assurance and validation.

Hybrid Deep Learning Framework

Three essential applications have been modeled and implemented using the hybrid deep learning system – the combination of Long Short-Term Memory (LSTM) model and Convolutional Neural Network (CNN) model: crop growth prediction, disease diagnosis, and irrigation scheduling. The LSTM was built to capture temporal variation in the time series data such as soil moisture, temperature and vegetation indices across the growing season. To get spatial features from the multi-spectral image CNN was utilized which captured variations in crop health and nutrient uptake on the presence of disease symptoms. The output was further configured as an output to a concatenation layer followed by fully connected layers which would provide an output of regression for the prediction of yield, a classification of multiple classes for the identification of disease (healthy section of the crop/healthy section of the crop but with bacterial blight/fungal leaf spot/viral mosaic) and a bin classification for irrigation scheduling (two outputs: irrigate/do not irrigate).

On classification problems the data was split into a training (70%), validation (15%) and testing (15%) sets and stratifies were achieved to have balanced data sets for training, validation and testing. Five-fold cross validation was performed for training on all models to ensure generalisation and early stopping, based on the validation loss, was used to avoid overfitting by training for a maximum of 10 epochs, whenever the validation loss did not increase over these epochs. Hyperparameter optimization was conducted using a grid search over learning rates (0.001, 0.0001, 0.00001), batch sizes (16, 32, 64), number of LSTM units (64, 128, 256), number of CNN filters (32, 64, 128), and dropout rates (0.2, 0.3, 0.5). The best setting was: Learning rate = 0.0001, batch size = 32, LSTM unit size = 128, CNN filter size = 64 and drop out = 0.3. The model evaluation metrics comprised accuracy, precision, recall, F1 score and Root Mean Square Error (RMSE), evaluated on the held-out test set.

Statistical Analysis and Index Computation

The statistical analysis was done using a descriptive and inferential method. To analyse the data for treatment comparison, descriptive statistics were used, such as finding mean, standard deviation and range values of all measured parameters separately for each treatment. To see if there were significant differences among the treatment combinations multiple comparison tests (Tukey HSD tests) were subsequently compared for the outcome variables: crop yield, water-use efficiency and others by using a one-way and two-way Analysis of Variance (ANOVA). The data of the Smart Farming Index were correlated with Productivity of the Agricultural crops and Water-use efficiency (WUE), respectively, with single technologies on the farm by Pearson correlation. The multiple linear regression was conducted for detecting those independent variables which have significant impacts on dependent variable Climate-Smart Agriculture Index, and independent variables were the scores of technologies adopted by the farmers. All the measured variables were used as variables in Principal component

analysis (PCA), for dimensionality reduction and identification of latent factors that explained the observed variance, eigenvalues greater than 1 and the scree plot criterion were used.

A number of composite indexes were calculated, which summarized the overall system performance. The steps taken for assessing the Smart Farming Index involved calculating average scores for technology adoption intensity, data integration level and automation degree and summarizing these scores into a weighted index by normalizing the scores. Agricultural productivity, resilience and emissions reduction parts of CSA were given a balanced weight to create a Climate-Smart Agriculture Index. Yield data, as well as biomass and harvest index data were used to calculate index Crop Productivity Index. The Water-Use Efficiency Index (WUE); Yield/ET (normalized 0–100). The following efficiencies were also taken into account: Water Use Efficiency Index (WUE), Fertilizer Use Efficiency Index (Fe), and Energy Use Efficiency Index (Eu). Three sustainability indicators – the environmental, economic, and social were picked up by the Sustainability Performance Index (SPI). To perform all statistical analysis, Python 3.12 scripts using TensorFlow, Scikit-learn, Pandas and NumPy libraries were used, R version 4.3, SPSS 29 software, as well as ArcGIS Pro, QGIS and Microsoft Excel.

Results

The findings of this field-based assessment are broken down into six subsections, starting with an overview of the experimental characteristics and the performance of the hybrid deep learning model, followed with the performance of climate-smart farming, agricultural sustainability performance and results from regression analysis and the principal component analysis, and ending with comparative results for digital and conventional farming systems.

Experimental Characteristics and Performance Metrics

The final number of experimental plots suitable for final analysis was 360 distributed in 20 smart agriculture research farms after a comprehensive quality checking and data pre-processing. In this evaluation these plots were monitored in the following three cropping seasons to provide a strong temporal dimension to the evaluation. The technologies employed in the experiment ranged from the Internet of Things based moisture monitoring system to artificial intelligence based plant health and efficiency assessment, from drone based crop monitoring and GPS based precision farming, to climate forecasting and decision support systems, from mobile crop advice app and automation of the smart irrigation system to remote sensing crop vegetation monitoring and precision nutrient management. This large-scale combination of technologies was tested on the different plots, allowing an in-depth analysis of the individual and synergic effect on the outcomes of climate-smart crop management.

Held-out test set shows excellent predictive performance for the hybrid deep learning framework in which the connecting two important algorithms of the deep learning framework, namely Long Short-Term Memory (LSTM) model and Convolutional Neural Network (CNN) model, are hybridized together. Table 1 shows that predictions were with an accuracy of 97.1% from the model, which is almost perfect accuracy in predicting the crop growth, type of diseases, and timing of irrigation. This 96.5% accuracy rate translates to a fairly low rate of false positive indicators (96.5%), or a fairly high rate of true positive rates of indicator (96.0%) which is known as recall. The F1-score of 96.2% (shown as a harmonic mean precision and recall score) reaffirms a well-rounded performance in both precision and recall. At present, the RMSE measured by comparing the model to real data is 0.16 (normalized in this case) indicating a good accuracy for regression models as can be applied to predict yield. All the performance measures were near constant across the five-fold cross-validation with a maximum standard deviation for all of the measures of classification of under 1.5%, indicating good generalizability of the counts across the partitions.

Table 1. Performance metrics of the hybrid deep learning model on the test dataset.

Metric	Value
Prediction Accuracy	97.1%
Precision	96.5%
Recall	96.0%
F1-score	96.2%
RMSE	0.16

This high accuracy is caused by the correlation between the temporal information and spatial information of the images mentioned above: The temporal correlations between the sensor readings captured by the pairwise sensors can be captured by the hybrid model, while the spatial information in the multispectral image can be captured by the CNN model. This multi-modal technique was particularly helpful in the diagnosis of disease, since changes between the lower limit of the spectrum and the growth rate of a disease, the initial stages, were minimally characterized. The accuracy in the binary classification, 97.2%, and recall 96.8%, was also worth noting in the performance of this model in the irrigation scheduling, which led to lesser amount of over and under irrigation event recorded. The results of these provide a reliable baseline for further investigations into the performance and sustainability impacts of the farmers under different climate-smart farming scenarios across the various experimental farms, whilst the increased accuracy of the AI models has an appreciable influence on the impacts of the various decision support systems being instigated on each of the experimental farms.

Climate-Smart Farming Performance

Over 840 different technologies and solutions were deployed on the 20 research farms and more than significant improvements were achieved in critical climate-smart farming performance indicators. The technology system induced a 32.8% yield gain, a 30.6% improvement in water use efficiency, a 26.9% decrease in fertilizer use and a 21.7% decrease in energy use compared to the traditional farming systems. As a whole, all the above results demonstrate that Digital Technologies provide support in terms of productivity and limiting resource use, by following the fundamental principles of Climate-Smart Agriculture (Branca et al., 2011).

This is a significant yield increase of 32.8% observed, which might be attributed to the different mechanisms acting. Through the early detection made by AI crop health assessment, the discovery of nutrient deficiency and pest infestation before they affect crop production resulted in loss of harvests being avoided (Rani et al., 2026). IoT based real time information helped to manage the soil water stress and water logging condition which hampered crop production were avoided and optimum soil water content was maintained at critical growth stages (García et al., 2020). Furthermore, the nutrient application varied according to the spatial variability of soil fertility under precision nutrient management giving enhanced efficiency of nutrient uptake and nutrient use efficiency (Thangamani et al., 2025).

The water-use efficiency figures were increased by 30.6%, a performance truly outstanding given the significant water shortages issues that agri-food systems are facing today. This improvement was achieved with the synergistic use of soil moisture monitoring radar through the assistance of IoT, sharing irrigation scheduling for recommendations with the assistance of AI. The LSTM was trained to capture the temporal evolution of soil moisture depletion and evapotranspiration needs of a crop, and used to

make predictions which helped decide on a optimum time and amount of water to be applied in irrigation to avoid waste (Klompenburg et al., 2020). Multi-spectral data was used with the CNN component to test for signs of water-stress before field observations, thus enabling optimal application of water and timing. This led to a reduction in water usage along with the maintenance and/or enhancement of crop production, and hence a current increase in WUE.

This fertilisers savings of 26.9% also has a significant environmental impact, especially regarding the impact on other GHG emissions and water pollution from agriculture, including nitrogen fertilizers. This reduction was achieved through very precise nutrient management, which included using detection sensors on a drone to measure in-season crop nitrogen status and implementing variable-rate application of fertilizer (Manfreda et al., 2018). The other benefit of the AI crop health assessment was the ability to include recommendations for the reduction of fertilizer application where the plant vigour as assessed by the NDVI measurements was not consistent throughout the field (Spatial Variability of Crop Vigor) which were suggested to ensure field yields (Jr et al., 2003). These data were aggregated into a cloud-based farm management platform, and then site-specific fertilizer recommendations were made by fertilizer application rates, using GPS-assisted variable-rate fertilizer spreading.

An increase in energy use efficiency contained within the 21.7% water energy savings was a significant component of this. optimising irrigation pumping operation accounted for 17.9% of the water energy savings. With support from the AI-based(automatic) smart irrigation system and the radiating algorithm, this has reduced the amount of irrigation and even the amount of water pumped, thus, all the accumulated energy costs have been dedicated in distributing the water (Hassan et al., 2024). In addition the GPS-guided precision farming system optimised the way field was operated, cutting the overlap in passes used for seeding, fertilising and pesticide application, and leading to further energy savings. The climate forecasting and decision support system likewise was helpful as farmers could optimise activities on farms at the best weather time to avoid wasting energy on the farms if the weather was not right for them.

In all three cropping seasons and the diversity of cropping conditions and agroecologies that constitute the 20 research farms, the improvement in performance was similar. Both regions and seasons were tested for interaction effects for the four main performance indicators (crop yield, water-use efficiency, power and fertilizer inputs) but no significant interaction effects were found in each of the analyses, suggesting that the benefits of the digital agriculture technologies are viable in the face of inter-annual variation in the climate and possible differences in soil and weather. The uniformity bolsters the generalizability and applicability of the results and findings, particularly for a wider field scenario on agriculture.

Agricultural Sustainability Outcomes

The agricultural sustainability outcomes evaluation builds on the indicators of the operation of climate-smart farming, and it offers a more accurate picture of the sustainability of the agricultural outcomes of the integrated digital agriculture system. Several composite measures and direct indicators were employed to quantify sustainability outcomes, and indicated significant improvements in agricultural sustainability with respect to various aspects.

The resource-use efficiency index shows that implementation of Digital Agriculture technologies led to an increase of 28.4% in the efficiency of use of these resources. This composite index combined the water productivity, fertilizer productivity and energy productivity and hence enabled estimating the overall productivity in the farming system with respect to the inputs used in the production of its output. The biotic benefits of the different technologies used may be the reasons why the use of resources is

more efficient. The introduction of ASoMoD monitoring and the precise nutrient scheduling with AI reduced excess moisture losses and fertility loss, respectively. Precision farming incorporating GPS facilitated the best use of field operations thus minimizing use of fuel and equipment wear. The farm management platform in cloud gathered these and directly sought a concerned manager of all the farm managers to overcome inefficiencies in the field. These findings are consistent with other studies which have shown that integrated digital systems can have an important positive impact on resource-use efficiency in agriculture (Gemtoui et al., 2025).

Disease management improved by 23.8%, due to visually reduced crop disease incidence and an improvement in disease control measures. The AI based crop health evaluation was one of the critical steps in this improvement of the hybrid deep learning approach. Multispectral images are extracted from drone and satellite sensors and processed using the CNN to discover the beginning stages of disease infection, in some cases, even prior to symptoms appearing (Fuentes et al., 2021). Timely and timely fungicide applications or other disease control measures were applied due to this early detection, which resulted in a decrease in the disease pressure applied to the crop and a decrease in yield loss. The mobile advisory application also gave the on-site management treatment suggestions and notifications in real time for farms, with the timely actions to take. The high disease risk period prediction also supported by the climate forecasting and decision support system led to successful proactively addressing of high disease risk periods as opposed to do it reactively due to the weather conditions. The 23.8% improvement in disease management not only lowered crop losses, but also lowered the use of broad spectrum pesticides, which helped make this more environmentally friendly and reduced input costs.

The overall sustainability performance (assessed in terms of the Sustainable Performance Index) was 29.2% better than the conventional farming systems. This approach of merging all the indicators of environmental, economic and social sustainability into a single indicator was constructed to provide a general sense of the long-term sustainability of the farming system. The environmental part comprised of GHG emissions, water pollution and biodiversity loss. The economic relationship is that of profitability increase, due to the increase of yield, reduction of the cost of inputs and better use of the resources. Social concerns were considered including aspects such as labour conditions, food safety and community involvement. All the above improvements relate to the general improvement of the digital agriculture system from a sustainable point of view, which emphasizes the fact that not only are improvements achieved in productivity, but also in the overall improvement of the digital agriculture system from a sustainability perspective, including in the field of climate-smart agriculture (Branca et al., 2011).

The sustainability results were also corroborated through the results of the correlation analysis; it showed a very high positive correlation between the composite indicators and the individual technology components. The Smart Farming Index had a positive strong correlation with Sustainability Performance Index ($r = 0.85$, $p < 0.001$), suggesting that the farms that were more technologically advanced (more integrated with technology and better technology adoption) had better sustainability results. Similarly, the Resource-Use Efficiency Index ($r = 0.82$, $p < 0.001$) indicating the strong linkage between climate-smart and efficient-use of resources, was very well related with the CSA Index. Whether the correlation is the theoretical relationship between the agricultural sustainability and digital agriculture technologies is empirical (Ikram & Moni, 2026)?

Results for sustainability are replicated over the three cropping seasons and 20 research farms bringing evidence for robustness of results. Two-way ANOVA tests did not find any significant interactions between season and region in any of the sustainability indexes, which means that the positive impacts of digital agriculture technologies on sustainability are transferable to various agroecological settings.

The sustainability impacts of these technologies is seen as a positive feature in the possibility of scaling; it may become an additional benefit in a wide range of farming production systems. Furthermore, as demonstrated within evidence-based, the overall sustainability performance with an increase of resource use efficiency by 28.4%, disease management by 23.8% and overall sustainability by 29.2% indicates that the integrated digital agriculture system holds potential to scale up sustainable agricultural intensification in climate variability.

Regression Analysis and Predictors

The contribution of each of the individual technologies in digital agriculture to the Climate-Smart Agriculture Index was determined by using a multiple linear regression analysis. In this study, we focused 10 distinct technologies, which represent the conditions under which certain technologies are going to alter responses which are variables not controlled by the researcher. This was the same for both technologies and score for adoption. For technologies evaluated and scores for adoption, the variables were the same. The regression model was statistically significant ($f(10, 349) = 140.2, p < 0.001$), and explained a large percentage of variability in the crop productivity from climate-smart practices ($R^2 = 0.801$), which implies that the selected technology predictors can explain a high proportion of the variances observed for the crop productivity from climate-smart practices.

In total, there are 10 technology components indicated in Table 2, four of which are statistically significant in predicting climate-smart crop management. The standardized β for AI-based decision support was the highest (0.48, $p < 0.001$), suggesting that this technology component could have the biggest impact when it comes to relative importance for improving climate-smart outcomes. The result shows an accuracy in predicting results similar to that of the hybrid deep learning model outlined in 4.1, which was employed in the AI-driven decision-making and optimization of irrigation scheduling, disease, and nutrient management decisions. The capability for accurate predictions is a testament to the transformative potential of AI in managing vast amounts of sensor data and imagery in the construction environment, and in translating those insights into actionable management advice that ultimately improves productivity and resource use.

Table 2. Multiple linear regression results identifying significant predictors of climate-smart crop management.

Predictor Variable	Standardized β	p-value
AI-Based Decision Support	0.48	< 0.001
IoT Soil Moisture Monitoring	0.43	< 0.001
Precision Nutrient Management	0.36	< 0.001
Remote Sensing-Based Crop Monitoring	0.31	0.002

IoT for the soil moisture monitoring was the second best predictor ($\beta = 0.43, p < 0.001$) and demonstrates that the real-time soil moisture monitoring status information is critical towards maximising the irrigation management efficiency system. The AI-based irrigation scheduling algorithm optimized the soil moisture levels over time with this real-time data stream provided by the IoT sensors, which resulted in intelligent irrigation decisions. Based on the algorithm, the smart irrigation decision was realized, making an improvement in irrigation scheduling during the entire growing season with real-time data acquired from IoT sensors. This is in line with past studies which showed that water-use efficiency and agricultural crop yields may be greatly improved using IoT monitoring systems within these agricultural systems (García et al., 2020).

Precision nutrient management also had strong predictive power ($B = 0.36$, $p < 0.001$) which validates the application to enhance productivity and reduce the wastage of fertilisers. With the help of the nutrient-monitoring drone sensors and the analysis by AI, the customized nutrient application provided with an improved use of the soil by crops was better. It falls under the concept of precision agriculture which focusses on site specific management for making the maximum utilisation of the input (Thangamani et al. 2025).

Crop monitoring via remote sensing related to the use of satellite and drone imagery ($\beta = 0.31$, $p = 0.002$) was another significant predictor, highlighting the value of satellite and drone imagery for crop health, stress, management intervention. A number of vegetation indices derived from remote sensing were used together with other key vegetation indices to provide an early warning of the crop vigour/productivity factors that compromises the production, enabling appropriate management intervention in time. This result adds to the growing evidence of the use of remote sensing tools for crop monitoring and for agriculture decision making procedures (Jr et al., 2003).

Drone-based crop surveillance, GPS-guided precision farming, automated smart irrigation, cloud-based farm management platform, mobile application for advisors, and climate forecasting and decision support system were not significant ($p < 0.05$) predictor regression coefficients in the regression model and did not appear as significant independent variables. These technologies are not inconsequential but rather could be associated with the four key predictors, and may be strongly correlated with other predictors. For example, the climate forecasting and decision support system can provide weather data input into the AI-based decision support system, and the cloud-based farm management platform can be the platform for connecting data and visualization. These variables do not appear to be important in the regression model and their influence is therefore indirect or is explained by the influence of other, more important, variables.

Pearson correlation analysis was conducted in addition to regression analysis and looked at bivariate relationships between key indices and the components of technology. The Smart Farming Index ($r = 0.88$; $p < 0.001$) was significantly correlated to crop productivity, confirming that as more of these technologies are adopted/integrated on farms crop productivity improves significantly. The correlation demonstrates a broader set of evidences that the use of multiple digital technologies brings greater synergies when used together as the Smart Farming Index reflects end-to-end intensity and integration of technologic application/implementation, not any single technology/innovation as a standalone.

Some additional strong positive correlation with water-use efficiencies to certain technological components was found. As indicated in section 4.2, the best water-use efficiency reported by the AI-based irrigation scheduling had $r = 0.83$ and the lowest p value < 0.001 making optimized irrigation timing and amounts have played a significant part to the reported improvement of 30.6% in water-use efficiency. Water-use efficiency was also strongly correlated with nutrient management ($r = 0.80$, $p < 0.001$) highlighting that better nutrient management would likely have led to an improved ability of crops to recover water from the soil, and the efficiency of transpiration, which contributes to overall water productivity. The correlations are helpful to explain how interactions between individual technologies and how improvements towards the objectives for resource-use efficiency and sustainability occur.

The climate-smart outcomes predicted by this regression model also had a high R^2 value of 0.801, suggesting that the model explains a high proportion of the variance but there is still around 20% of climate-smart outcomes that is unexplainable by technology predictors used in this study. This unexplainable difference may arise from the farm manager's skill in making decisions, his experience, the types of soil, inherent differences in fertility, and other random factors including exposure to extreme

weather and pests etc. These other factors could further improve the predictive model and identify some complementary approaches to improving the management of farming systems to be climate-smart in future research.

Principal Component Analysis

Data set of the measured variables was then subjected to Principal Component Analysis (PCA) for understanding the underlying structure of the variables measured, and to find the underlying factors that have generated the observed variability in climate smart crop management. The results of the analysis yielded 3 main components, each of which has an eigenvalue value greater than 1, and explains 85.8% of the variance of the data. This indicates that the amounts of information contained within the three main components is very high in respect to the data.

The first principal component (PC1) had a strong association with those variables related to crop management and productivity using the AI techniques and accounted for 41.8% of the total variance with variable entries that loaded highly positive. The accuracy of prediction reached 0.89 for such as loaded crop yield, 0.87 for AI, 0.84 for NDVI, 0.81 for chlorophyll content and 0.78 for LAI etc. The variables related to the use of resources, such as fertilizer consumption (-0.72) and water consumption (-0.76), had strong negative loadings on PC1 which indicated that their association with higher PC1 scores was a negative one; producing more with less use on the farm. It can thus be concluded that this is a spectrum of low productivity/high input systems and high productivity/low input systems through the use of AI optimise technologies. In general, the results of the regression analysis are consistent with the results of the major components analysis and the highest predictor value is given by AI-based decision support ($\beta = 0.48$, $p < 0.001$ for the regression analysis; the maximum values of the major components of the regression analysis are: AI-based decision support, senior mobility, agricultural mechanization and rural life, respectively).

The variables related to optimization water resources and monitoring with IoT had high loading in the second principal component (PC2), which accounted for 28.0% of total variance. These were: soil moisture content, soil temperature, frequency of IoT sensor readings, and water-use efficiency. Significant positive loading for PC2 were obtained for irrigation frequency (loading = 0.76), and total volume of irrigation (loading = 0.73) for other irrigation variables. The component underscores the importance of effectively using water resources and current moisture monitoring in the field, thus underlining the critical role of soil moisture sensors made with IoT in irrigation scheduling and management. Its high positive loading on PC2 was coherent to the results from the correlation analysis showing that water-use efficiency has the closest correspondence ($r = 0.83$, $p < 0.001$) with the AI-based irrigation scheduling and reflected data loads from the sensors for irrigation scheduling provides information stream enabling the use of AI for optimisation.

Principal component 3 (PC3) explained 16.0% of the overall variance and had a high loading for all the variables associated with climate resilience and sustainable resource use. The latter comprised the three conditions of higher rainfall variability (loading = 0.83), air temperature range (loading = 0.79), relative humidity (loading = 0.75) Sustainability Performance Index (loading = 0.72). Crop disease incidence (-0.68) and number of times a farm was applying fungicide (-0.65) showed a negative loading on PC3; the higher a farm scored on this component, the lower the disease pressure and reliance on fungicide use was on the farms. This is one way of adaptive capacity to climate variability and integration of sustainable management that would enhance system adaptive capacity. PC3's emergence as a stand-alone component demonstrates that a climate-resilient dimension in itself should be taken into account along with the productivity and use efficiency of resources.

These three major components are the pillars of a comprehensive strategy for understanding and implementing the multifaceted notion of "climate smart crop management. Productivity gains and less input needed for technology through AI is understood by PC1, water use optimization using water monitoring systems on the IoT is understood by PC2 and the aspects of climate resilience and sustainability through integrated systems of decision support are understood by PC3. The solution results from the PCA analysis make it possible to obtain good separation of these components in the solution; this solution is well supported by the theoretical approach of Branca et al. (2011) which suggests that acting in order to reach multiple objectives of productivity, resilience and reinforcement of sustainability would be simultaneous. Besides, CVE (85.8%) shows that the three latent dimensions are good representations of the three items which gets measures, so it could be said that measurement scales are comprehensive and things measured are obtained using the method given in this study.

The PCA also provides some information about the relationship between aspects of technology and sustainability measures. The similarity of the Sustainability Performance Index with high loading onto PC3 and crop disease incidence loading in the opposite direction suggests that overall climate resilience and sustainable resource management correlate strongly with the good management of disease. This outcome is attributable to wins in disease management, as reported in section 4.3, that occurred when they started implementing the digital agriculture system and shows the importance of also tackling climate-smart agriculture along with disease monitoring and control. In this respect, the PCA solution helps with the analysis and the results: indeed, it can be confirmed that when technologies are used together in an integrated manner, digital agriculture technologies have the potential to achieve improvement in productivity, in the use of resources and their efficiency, and in resilience to climatic variability.

Comparative Findings

It was demonstrated in a comparative analysis of the integrated digital agriculture system with traditional agriculture that better and durable results were recorded on all the measured performance indicators. Table 3 summarizes the difference (percentage) among some of the basic measures by the results of these comparisons.

Table 3. Comparative performance of digital agriculture versus conventional farming systems.

Performance Indicator	Improvement with Digital Agriculture
Crop Yield	32.8% higher
Water-Use Efficiency	30.6% greater
Sustainability Performance	29.2% better
Fertilizer Consumption	26.9% lower
Crop Disease Incidence	23.8% lower

An impressive increase of crop productivity in yield of up to 32.8% with respect to the DA system was observed on all the 20 research farms including the three crop seasons. This yield improvement is the result of synergies between the various technologies. Conventional fertigation systems (Rani et al., 2026) compared to the AI-based crop health monitoring system that enabled early detection and correction of nutrient deficiencies in the soil and pest problems prior to yield damage. The automated smart irrigation system that uses real time soil moisture data from the IoT system kept soil water content at optimal level but no soil water stress or soil water logging was recorded (García et al., 2020).

Precision nutrient management enabled to optimize the application of nutrients as per the spatial variations of the soils with respect to higher nutrient application rates compared to the requirement for maximum uptake efficiency and growth of crops (Thangamani et al., 2025). The combination of the above interventions resulted in a greater yield benefit than usually discussed for the use of individual innovations.

In particular, digital agriculture is 30.6% more water-use-efficient, and this factor is potentially significant, as the agriculture sector becomes increasingly water insecure in the world. So this improvement has been achieved by the seamless collaboration between soil moisture monitoring with IoT and water scheduling with AI. For the hybrid deep learning model, the LSTM learned the temporal dynamics of how much water is consumed by the soil and how much the crop wants to take up, which enabled management decisions to be made around irrigation only to release only the required amount of water in time and place (Klompenburg et al., 2020). Previously, signs of water shortage would only become visible in the field but by analysing the multi-spectral images the CNN could find signs earlier to enable them to water at an optimal time and quantity, even more accurately. This led to not only the reduction in total water used, but also the water use efficiency was either maintained or improved due to improved yields, as observed. This result corresponds with previous works which indicate that a reduction of 20% to 40% in water consumption can be accomplished with smart irrigation systems based on the Internet of Things (IoT) while maintaining the production of crops with the same quality (García et al., 2020).

Improvements in the sustainability performance across the three dimensions – social, environmental and economic – through the digital agriculture system are reflected in the 29.2% increase. The environmental aspect also restricted to lower use of fertilizers, which resulted in a reduction in greenhouse gas emission, as well as lower nutrient (fertiliser) pollution of the water and increased biodiversity due to reduced pesticide use. The economic component helped to achieve better profits thanks to increased yields, reduction of input costs, more efficient water, fertilizer and energy use and, consequently, more efficiency in the use of resources. The social aspects assessed various benefits of automation of repetitive activities in the farm, like better working conditions, lower use of chemicals in food production and greater involvement of the communities using the mobile advisory app. This extensive boost in sustainability performance demonstrates that better performance in subsequent dimensions of sustainability (reduction of global warming potential, mitigation of risk and adaptation to climate change) in vegetable crop production is obtained thanks to the this integrated digital agriculture system, that goes beyond productivity increase.

Improvements to the digital agriculture system did not only yield lower costs for farmers, but were also good for the environment, by reducing the amount of fertilizer used by 26.9 per cent compared to the conventional system. Most of the greenhouse gases and aquaculture pollution is generated by nitrogen fertilizers. The cost reduction was achieved by implementing precision nutrient management applications in which plant crop nitrogen status was measured and recorded in-season by a drone-mounted camera containing a sensor which guided the application of variable rates of nitrogen fertiliser (Manfreda et al., 2018). The machines also acquired information regarding the vigour of the crops as a function of the spatial variations present in the field, which was used to see the crops' health condition via one of the vegetation indices, NDVI, and help the farmer determine if there is any variation in the field that opt for the improvement of the crops without causing any damage to the harvest. A cloud-based farm management platform has come together now to integrate these data streams, and then to generate fertilizer recommendations, on a per-field basis, using GPS-guided variable rate fertilizer application devices. Results were consistent with earlier studies that reported a reduction of 20–30% of

fertilizer application, along with either maintaining or improving yields with the practice of precision nutrient management (Thangamani et al., 2025).

AI-driven disease detection and management are effective as shown by the 23.8% reduction in the incidence of crop diseases in the digital agriculture system. The CNN part of the hybrid deep learning model used multispectral images obtained from drones and satellite platforms to detect early indications of the infection from disease at times when symptoms were not visible (Fuentes et al., 2021). The early work enabled fungicides or other disease control to be applied at the time and at the control areas of the geographical field of the crop, thus minimising the disease stress and crop damage. Mobile and flexible advisory app delivered real time alerts and recommendations for treatments to farm managers, allowing timely action. Climate Forecast and Decision Support System (c-DSS) also contributed to the project through forecasts of high risk windows for diseases to allow for proactive rather than reactive disease management. Not only was the incidence of the disease reduced by 23.8%, thus reducing the impact of the disease on the crop, but the reduction in the need to use broad spectrum pesticides also helped to achieve the objective of living in a sustainable environment, and to reduce the cost of the input.

Such consistency of the comparative advantages across the three cropping seasons and 20 research farms lends strength to the results obtained. The results from the Two way ANOVA indicated no interaction between the seasons (autumn, summer and winter) and the regions (Bari, Pordenone and Macerata) for all indicators analyzed, thus demonstrating that the advantages of using digital agriculture techniques can be replicated also between different agroecological contexts and climate conditions for the different seasons. This uniformity will not only be crucial for the scaling-up of these technologies, but also indicates that the AR4W benefits of productivity, efficiency and sustainability will be present not only for certain climatic and soil situations but in a broad set of agriculture production systems. The comparative results thus confirmed that the use of combined digital agriculture and smart farming technologies represent a viable and effective way to implement climate-smart crop management and provide significant gains in terms of crop productivity and resource-use efficiency, as well as environmental sustainability when compared to conventional farming.

Discussion

This evaluation in the field has implications for both practical and theoretical development of CA, and for this reason, is important. Theoretically, the regression results prove the importance of digital technologies as key drivers of sustainable agricultural intensification (Branca et al., 2011), since, the AI decision support tools, soil moisture monitoring using IoT, precision nutrient management, and remote sensing based crop monitoring can predict the results of their experiments with a relatively high degree of accuracy. The extraction of three main components in “AI-enabled productivity”, “IoT-enabled water efficiency”, and “Climate resiliency”, further refined this framework by showing that those components are independent, but not mutually exclusive components of the overall system, which each represented in its own particular way, and hence each contributes to whole system performance. The multi-dimensions of the structure mean that in the future, models of agriculture under climate change need to explicitly model interactions, which are interdependent but not independent, between different types of technologies within a multi-purpose system. The findings of these elements showing the high level of agreement with system performance (85.8%) does fall in line with the thought that these variables measured the major aspects of system performance by their degree of agreement and the result thus was supportive of the idea that these variables did capture the major aspects of system performance, and also offer a validated analytical framework for future research design and assessment of systems technology.

The results will have implications for farmers, agricultural advisors and agricultural technology developers and policy makers. The positive performance of 32.8% crop productivity gains and 30.6% Water use efficiency achieved by the farmers and farm managers are good opportunities for the economy gained from the adoption of Integrated Digital Agriculture system. The additional value added on these levels of fertilizer reduction (26.9%) and reduced crop disease (23.8%) is further advantage. The findings can guide agricultural extension and technology service providers in designing actionable strategies for rolling out climate-smart technologies, focusing on the most promising ones, such as those using AI for decision support and IoT for soil moisture monitoring, that were best associated with improved climate-smart outcomes. The 29.2% overall improvement on sustainability as evidence shows that Digital Agriculture can contribute to several dimensions of policy objectives such as food security; water resources conservation; climate change mitigation as well as protection of the environment. It suggests a policy focus on integrated approach in addition to on individual technologies, such as subsidies, tax relief and technical aid programmes. The outcomes will also identify the suitability of the DAs gamification technologies in different agroecological regions, therefore national/regional digital agriculture scaling up application strategies should share a similar approach.

The strengths of the findings are reinforced, but there are certain methodological limitations reported, which should be considered when interpreting the findings. The research is based on 20 research farms which were spread across different agroecological zones but may not comprehensively cover all the variety of farmers' systems and socio-economic contexts in which digital technologies could be used in agriculture. The farms were selected because they wished to participate and could adopt all technologies (may be bias towards higher/better tech level and resources). The results can be limited to their generalizability to the smallholder farmers in developing countries who encounter high initial cost investing in technology, low level of technical skill, and poor infrastructure (Gemtou et al., 2025). Use of the three-season seasonal time spans provided the temporal replication, but might not be representative of full inter-annual climate variability, and may not be adequate to evaluate long-term sustaining of the observed benefits. Furthermore, the use of experimental plots instead of commercial scale plants might have affected the size of the effects measured since research farms usually have more intensive management than might occur in a commercial-scale situation. Data-preprocessing methods (such as missing value imputation and outlier detection by the IQR) might have introduced some level of data smoothing that could impact the precision of the reported effect size. Thirdly, no systematic cost benefit analysis was used that would normally be required for a properly comprehensive evaluation of the economic potential of the integrated technology system with respect to various size and type of farms.

The differences indicated suggest a few potential future research avenues. Sustainability and productivity impacts observed in the short term (5–10 years) should be confirmed with long-term studies and impacts on resilience of digital agriculture system to issues such as drought, flood and heatwaves should also be determined with a long-term study. Moving technologies to the smallholder farming system also needs investigation, as the farm size and capital may limit the technology requirements and it may need other forms of technology delivery like services or cooperatives to accommodate other constraints such as technical capacities. Low computational and/or data intensity Artificial Intelligence models and low cost and simple sensor networks would be particularly helpful to boost access to digital farming opportunities in resource-constrained settings. Some of the social and behavioral issues related to acceptance of AI recommendations, applications and sustainability are still under-researched as are social networks as enablers of technology diffusion and impacts of digital agriculture on socio-economics and rural livelihoods. Future studies needs to focus on these in either mixed method approaches, incorporating quantitative performance measures with qualitative

information from farmers and other stakeholders. In addition, there is a demand for comparative analyses to evaluate the effectiveness of architectures for AI and sensor systems for different kinds of crops and agroecological conditions, and make choices of the best technology combinations for them, based on cost. Other climate smart technologies such as conservation agriculture, agroforestry and integrated pest management are technologies to be included and analyzed for potential synergies and trade-offs with the Digital Agriculture technologies. Finally, a detailed economic appraisal of the adoption, such as an NPV calculation and ROI analysis, should be included in further studies with varying prices and climate for use by farmers and policy makers to help with adoption decisions.

Conclusion

This assessment is carried out in-field, providing empirical evidence for the role AI, Internet of Things (IoT) connections (sensors), remote sensing, unmanned aerial vehicles (UAVs), GPS specific crop guidance and systems with digital decision support can contribute to the production of a more climate-smart crop within different agroecological environments in an economical and time-efficient way. The hybrid deep learning framework showed exceptional predictive capabilities and implementation of this framework resulted in increased yield production by 32.8%, 30.6% water use efficiency, decreased fertilizer consumption by 26.9% and crop diseases by 23.8% compared with conventional farming techniques. AI-based decision support and IoT soil moisture monitoring were found to be the most effective predictions for the climate-smart outcomes through the regression analysis, especially in the context of the decision support for farmers. In the interim, the Principal component analysis revealed three distinct but complementary dimensions of system performance: AI-driven productivity, IoT-based water optimisation and Climate resilience. Findings echo the other studies and offer another confirmation that digital agriculture is a viable path towards agricultural intensification while aligning productivity, resources efficiency and environmental stewardship goals amid climate variability.

The results presented here could be expanded by conducting long-term studies (over 5–10 years) to assess the sustainability of results (long-term benefits) and the resilience of the system to extreme climate events. Adjustments in technology configurations and other technology delivery models need to be explored to ensure that technologies are appropriate in smallholder farming environments that have a high incidence of both capital and technical constraints. Also, some social and behavioral backdrops of the adoption of farm technology like farmer confidence around the recommendations made by AI systems and the social consequences of the adoption of farm technology in the rural setup of the study area need to be investigated using the mixed method approach. Farmers' and policy makers' decisions on whether to adopt would be further informed by comprehensive economic analyses taking into account future price and climate scenarios, incorporating net present value and return on investment.

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