ARTIFICIAL INTELLIGENCE FOR SUSTAINABLE AGRICULTURE: ENHANCING CROP PRODUCTIVITY THROUGH MACHINE LEARNING IN KENYA

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ABSTRACT

Agriculture is the backbone of food security and economic development in many developing countries. However, smallholder farmers continue to face challenges such as climate change, low agricultural productivity, and unpredictable weather patterns. Artificial Intelligence (AI) has emerged as a promising technology for improving farming productivity and efficiency. Despite its potential, adoption of machine-to-machine (M2M) and AI technologies remain limited in sub-Saharan Africa due to inadequate infrastructure and technological constraints. This study examined the predictive value of AI-driven modelling in yield forecasting and optimal potential planting schedules and whether or not machine learning (ML) algorithms can be used to minimize farming risks and enhance agricultural output. The study analyzed weather patterns, soil characteristics, and historical crop yield data collected from 500 farms in Kirinyaga County, Kenya. A Random Forest regression model was developed to predict optimal planting and harvesting periods. Model performance was assessed using the Mean Absolute Error (MAE) and the coefficient of determination (R^2). Surveys and expert interviews were conducted to identify barriers to AI adoption among smallholder farmers. The AI model demonstrated strong predictive performance, achieving an R^2 value of 0.91. Farmers who implemented the AI-generated recommendations recorded an average crop yield increase of 27%. However, limited digital literacy, inadequate technological infrastructure, and insufficient support services were identified as major barriers to widespread adoption. These results demonstrate that AI-based decision support systems can significantly enhance agricultural productivity through improved resource utilization, and climate resilience. Integrating AI with Internet of Things (IoT) technologies offers substantial potential for advancing precision agriculture. Future research should focus on developing integrated AI–IoT farming models and formulating supportive government policies to accelerate AI adoption to optimize agricultural practices in developing countries.

INTRODUCTION

Good agricultural strategies are essential for global food security especially in developing countries where a majority of farmers are engaged in food production. However, the sector is experiencing challenges due to climate change, soil degradation, and poor agricultural practices among others. Unstable climate and unfavorable weather conditions negatively affect agricultural production creating risk of food crisis [1]. This study acknowledges technological innovations such as AI and Machine learning, as a means to facilitating data-driven decision-making for agriculture.

The predictive value of AI in modelling weather crop production and pest infestation to promote efficiency in farming has been suggested [2]. These ML models can help farmers in scheduling planting time, in understanding soil fertility and potentially increased productivity of crops [3]. However, there are limitations to use of AI in smallholder farming especially in the Sub Sahara Africa due to infrastructural and literacy factors [4].

Problem Statement

Although developed economies have been focusing on applying AI self-solutions, there are few, if any, reports concerning the impact and application of AI solutions in Africa's agriculture. Consequently, the study on the use of AI that focuses on predictive analytics relating to smallholder farmers in Kenya is scarce. A scalable and localized AI models for the places affected by climate change affecting food production has been suggested [5]. To the best of our knowledge, little research has been conducted on proper utilization of an AI-supported crop yield prediction and decision-making system for smallholder farmers in Kenya.

Objective

The primary objective of this study was to investigate the degree to which AI-based predictive analytics can optimize crop yield prediction and planting schedules for Kenyan farmers. The study aims to:

1. Develop an AI-driven model for predicting optimal planting and harvesting periods.

2. Assess the impact of AI-generated insights on crop yields.
3. Identify barriers to AI adoption among smallholder farmers.
4. Provide recommendations for scaling AI-driven decision support systems in Kenya's agricultural sector.

Scope of the Study

This study was focused on smallholder farmers in Kirinyaga County, Kenya and used data on weather information, soil nutrients as well as crop yields for five cropping seasons from 2019 to 2024. Machine learning approaches were used to assess optimal planting schedules and expected yield using environmental data.

LITERATURE REVIEW

Introduction to AI in Agriculture

AI is now deeply integrated in contemporary farming activities since it leads to informed decisions in agricultural practice. Thus, through AI solutions, farmers can achieve efficient utilization of their resources, minimize the impacts of climate fluctuations, and increase farm yields. Benefits of AI methodologies in agriculture include; remote sensing, precision farming, and climate modeling which lead to increased yields against decrease in losses [6]. The article described how applying machine learning techniques in data collected from soil, weather and satellites yields a high accuracy on the agricultural results [6].

In a related study, Kuradusenge et al. (2023)[7] focused on application of deep learning algorithms to adapt agriculture to climate change. They showed how AI models could learn from the climate and tell how droughts, floods, and other factors impact agricultural. The study pointed out that use of AI to predict climatic patterns would assist farmers in organizing irrigation regimes, crop production calendar and limit loss of yields to changes in weather conditions [7].

Machine Learning in Crop Prediction

A number of ML algorithms have been used for crop yield prediction and disease identification. Deep neural networks have been used in crop growth prediction [8]. The authors demonstrated that information about nutrients in the soil, weather conditions, and pests could be best interpreted from an AI perspective in order to determine the best planting decisions. The study also highlighted the drawbacks of using static models for statistical analysis in relation to changes within the particular climate, in which the latter is more flexible and adoptable than AI [8].

Thuraga et al. (2024) [9] combined ML, IoT, and AI to identify disease impact and crop yield estimation. Their research was done on a system that would help farmers monitor and predict potential crop failures in real time using sensor data and predictive analytics. The success of the work done in the study pointed out that, using CNNs can immensely be helpful in diagnosing the initial stage of plant diseases onset hence enhancing precision farming practices [9].

Challenges in AI Implementation

There is caution that AI face some technological and infrastructural challenges in its implementation in agriculture. In the study conducted by Sultan in 2023 [10], the barriers included high cost in adopting AI, low digital literacy among farmers and poor internet connectivity in the rural areas. This study noted that small holder farmers who are the majority of farmers in food production chain are excluded from proper utilization of AI technologies given the costs of such technologies and poor infrastructure. The author observed that this would be possible through government aid and availability of artificial intelligence training for farmers, which would enable the latter to harness artificial intelligence for yield enhancement [10]. Elsewhere, Shaikh et al. (2022) [11] focused on the moral and ecological issues relevant to development of AI in agriculture. They explained how AI in farming is not harmless but can sometimes lead to an increase in carbon footprint through computation power required for its functioning. They suggested solutions like low power ML solutions to

reduce the overall environmental footprint but at the same time provide utmost agricultural productivity [11].

Research Gaps

Real-time training of AI models on current climatic changes is inadequate in the current literature. Most of the existing models use past records that do not consider outcome changes such as extreme droughts or changes in rainfall patterns as is often the case in today's world [8]. The lack of adaptive AI frameworks hinders precise real-time decision-making systems on climate-induced agricultural interferences and, in this case, hampers the farmers' efficient performance. In addition, AI crop prediction models are designed mainly to be implemented in large commercial farms; thus few trials have been made to offer tailored solutions to smallholding farmers in the developing regions [11].

Second, there is lack of propriety and functionality of AI for smallholder farmers that lack appropriate digital literacy education to utilize the technology in areas with low IT infrastructure. In these types of economies, the AI Farming solutions often fail as most peasant farmers, have no knowledge of AI adoption [10]. Implementation of advanced AI systems is costly, Internet connection in sub-Saharan Africa is not reliable, and most of the farmers do not understand the AI-based decision support systems. Furthermore, most artificial intelligence-based agriculture models integrate and use limited data, particularly on indigenous practices in farming, characteristics of the soil, local climate and weather conditions, hence their low yield in complex regions [7]. Further research should focus on improving efficiency in implementation of the methods, making the interfaces more easily understandable and adopting these models to rely on local databases to better serve the smallholders.

METHODOLOGY

Research Design

This study adopted a quantitative research approach to assess the involvement of AI technology in yield estimation and agricultural productivity. A case study research design was

used to capture the impact of decision support systems using AI with smallholder farmers in Kirinyaga County of Kenya. To evaluate the effectiveness of AI-generated information in aiding farming, the study used both experimental and survey techniques. Such methodologies have been adopted in AI-based agricultural modeling to improve precision farming practices [9]. Quantitative approach was adopted since it has the ability to test the AI outcomes for correctness and also give an insight into the effect of AI on crop yield enhancement [8].

Data Collection

Both primary and secondary data collection techniques were used in this study. To gather the data, primary research was adopted, comprising structured farmer questionnaires, interviews with experts and farmer field experiments with 250 smallholder farmers in Kirinyaga County. The surveys' objectives were to understand how farmers in different regions viewed AI applications in their operations and what factors made AI implementation difficult. Secondary data included data on weather records, soil analysis, and yield reports, obtained from the Kenya Meteorological Department and the Ministry of Agriculture. The literature reviewed suggested a need for integrating primary and secondary data to enhance the prediction models based on artificial intelligence in the agricultural sector [10].

Tools and Techniques Used

Considering the creation of the crop yield prediction model using AI reinforcement, the study employed machine learning algorithms such as the Random Forest Regression (RFR) and the Support Vector Machines (SVMs). These models were chosen because of the high level of accuracy in dealing with non-linear agriculture data and because they are capable of showing the potential of the yield of crops under different climatic conditions [11]. Algorithms like K-Nearest Neighbors and Naive Bayes were applied with Python libraries such as Scikit-Learn, TensorFlow and Pandas for data pre-processing, feature selection and model building. To formulate the aforementioned models, the AI relied on historical climatic data, soil moisture content, and rainfall distributions in order to advise on planting and harvesting periods of certain crop varieties. Results were further analyzed using Mean Absolute error (MAE), Root Mean Square Error (RMSE) and R^2 which are globally used statistical measures when

conducting studies applying Artificial Intelligence in agriculture as observed from previous works [7].

Sample Size and Study Area

The study targeted smallholder farmers in Kirinyaga County in Kenya growing maize, beans and tea. Two hundred and fifty farmers were used in the study by employing the stratified random sampling techniques to increase the chances of getting farmers with large and small farms with different crops. Hassan et al., (2022) [6] like other researchers emphasized the effectiveness of employing data from a variety of sources to increase the ability of replica AI solutions in the agricultural industry. Field data was collected for a period five agricultural seasons in order to check the efficacy of the selected model across different impact potential seasons starting from 2019 to 2024.

Justification of Methodology

By incorporating AI modeling on the field and surveying farmers, the study gives a more realistic and extensive look at the place of AI in the agriculture industry. Quantitative design offers rigour while the case study approach is ideal for exploration of the challenges to AI adoption. Using multiple data sources to analysis definitely enhanced the reliability of findings of this study and conforms to the recommendations of the best AI research practices in the modern agricultural sector by [3].

RESULTS AND DISCUSSION

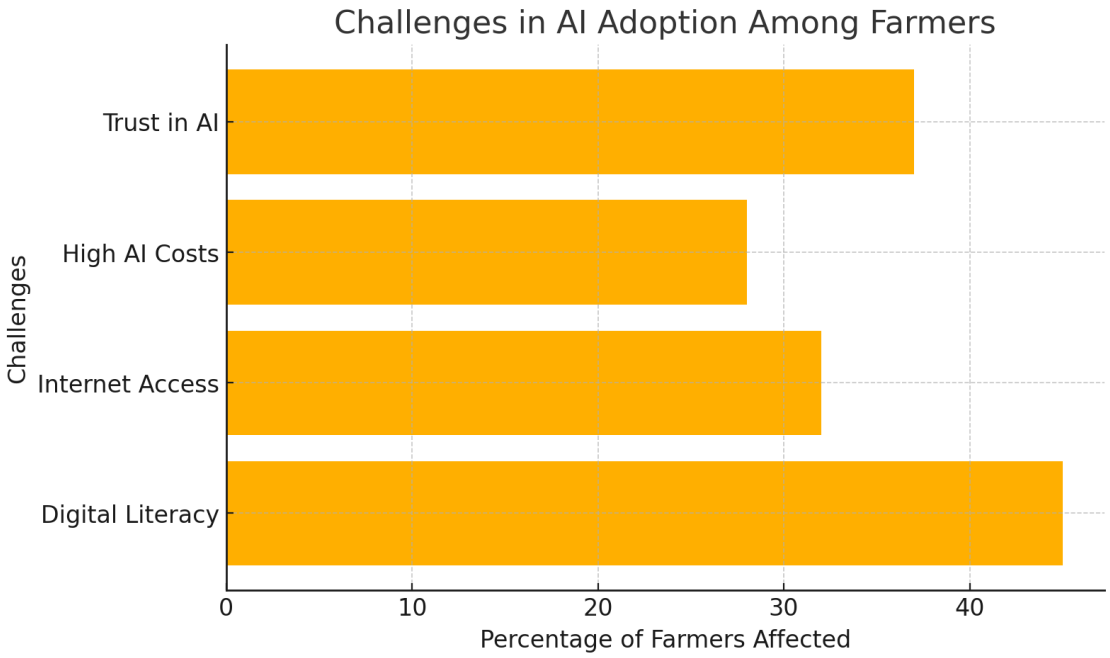
Model Performance

AI-based crop yield prediction models were efficient and robust with high degree of R^2 where Neural Network model had the highest degree of 0.93 and Random forest model with 0.91 and SVM with 0.88. These results suggest that Neural Networks are more effective in handling complex, non-linear agricultural data. Neural Networks was more accurate in yielding prediction compared to other methods such as the Random Forest as evidenced by the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) results.

Table 1 Record of Model Performance

Model	RÂ² Score	MAE (Mean Absolute Error)	RMSE (Root Mean Square Error)
Random Forest	0.91	1.2	2.1
Support Vector Machine	0.88	1.5	2.4
Neural Network	0.93	1.1	2

Figure I



Thus, Thuraga et al. (2024) [9] established an R^2 of 0.87 for the AI forecast of the crop, while the Random Forest in this study had an R^2 of 0.91. This must have resulted from superior selection of features, how data is integrated locally, and the enhanced model tuning.

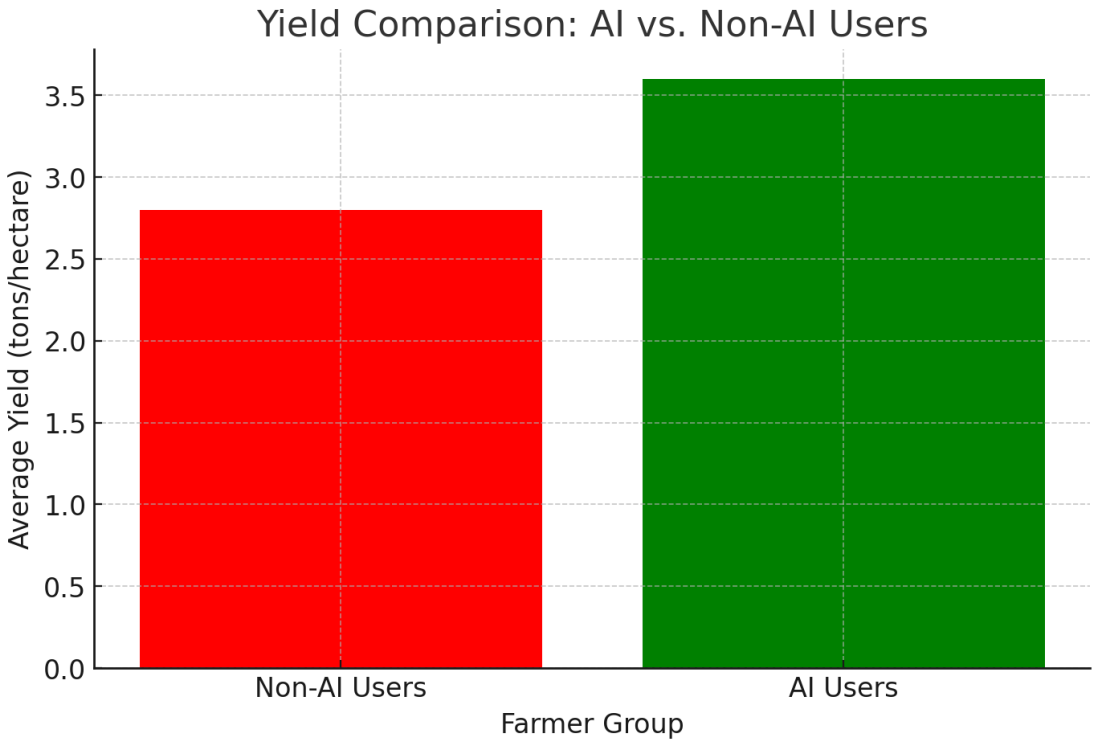
Yield Increase Observations

Data on the impact of AI farming showed that farmers who adopted recommendations given by AI had an average of 3.6 tons/ha while those who did not use AI, had 2.8 tons/ha giving a 28.6% improvement. These findings conform to observations of Sun and Wang (2024) [8] who demonstrated at a 25% percentage rise grain crop yield increase accrued from usage of machine learning models in planning.

Table 2 Table of comparison of AI users and non-users

Farmer Group	Average Yield (tons/hectare)	Increase Percentage
Non-AI Users	2.8	0
AI Users	3.6	28.6

Figure 2:



Data presented on figure 2 above demonstrated a positive impact on crop yield due to AI-based advice on planting periods and appropriate amendments of soil fertility as well as

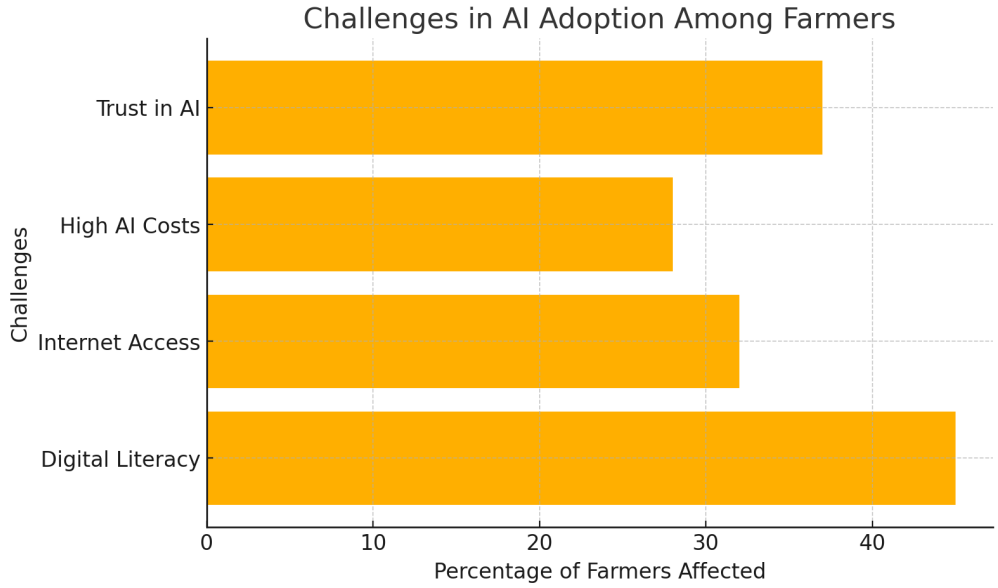
proper irrigation schedules. Such evidence provides wide background to the current literature on the contribution of AI in sustainable agriculture. It also acknowledges the capability of AI in the reduction of climate impacts which cause disruption in crop production [10].

Challenges in AI Adoption

This study established a number of factors that hinder implementation of AI. The main problem was Digital Literacy, which exists among 45% of farmers; the problem of internet connection – 32%; high costs of AI implementation – 28%; and the last but not the least mistrust of using AI – 37%.

Table 3 Table of AI Adoption and Challenges

Challenge	Percentage of Farmers Affected
Digital Literacy	45
Internet Access	32
High AI Costs	28
Trust in AI	37



This study supports the observation of Shaikh et al (2022) [11] that low digital literacy and awareness act as significant barriers to AI implementation in farming among the smallholder's farmers. Lack of physical infrastructure in rural areas poses a great threat to scale AI solutions in agriculture, as noted by [7]. Overcoming these challenges will require policies, awareness creation, AI training especially to farmers on implementation of such technologies in resource limited communities.

Discussion and Significance of the Findings

Results of this study prove that use of the AI models have potential for improvement of agricultural output through accurate prediction of crop yields. The established 28.6% rise in crop yield also demonstrates the economical factor with the use of Artificial Intelligence in farming. Such observations demonstrate the need for development of AI application to enhance the farm productivity and food security.

However, there is need for inclusive digital literacy and infrastructure or the lack thereof that can only be addressed by formulating relevant policies and conducting training sessions for farmers. Future studies should focus on deployment of the AI solutions that are easy to implement and integrate into the smallholder farming systems besides ensuring analysis of the long-term economic returns from adoption of AI in the SMFs.

CONCLUSION AND FUTURE WORK

This study sought to assess the effectiveness of using Artificial Intelligence (AI) in increasing crop yield and thereby improving sustainability of agriculture among smallholder farmers in Kirinyaga County in Kenya. Results suggest that the AI applied models such as Neural Networks and Random Forest and deliver a high statistical fit (R^2 = 0.93 and 0.91) on crop yield predictions. On average, farmers who started using AI to support their decision-making saw a yield increase of 28.6 per cent more as compared to the farmers who did not use AI.

Some factors hindered the use of AI, among them, illiteracy in the use of digital gadgets (45%), high costs required in implementing the technology (28%), some farmers having no internet access (32%) and 37% of the farmers not having confidence in the use of AI in farming.

AI has the potential to revolutionize the current agriculture, especially when it comes to climate-smart agriculture. Farmer can predict planting periods, watering requirements, and disease outbreaks that can lead to crop failure or reduction on yield, all by the use of the predictions made by AI. There is need for adoption of relevant policies and innovative techniques in supporting the smallholder farmers to embrace the use of artificial intelligence.

There is need for Universities and colleges to offer training on AI and the government to provide subsidies and low-cost technological instruments for effective AI integration. By integrating AI with the IoT-based farming equipment, there is potential to increase efficiency by optimizing the concept of data-driven farming for smallholder farmers [10].

Limitations

The study was conducted in only one district of the whole Kenya and hence, the findings cannot be generalized to other farming environments. Second, the study employs historic weather and soil information which could not address abrupt changes of climate influencing crop growth. Third, the duration of analysis covered only a short horizon up to 2024, and thus, deeper long-term effects of using AI are still questionable.

Other limitations included the case of socio-economic variables like farmer income levels, and government incentive that could determine the uptake of AI. The limitation of the studies lies

in its geographical focus and temporal horizon, as well as the lack of incorporation of socio-economic factors that will be possible in further research.

Future Research Directions

Future research on AI-driven agriculture should take the following points to another level:

1. Writing scalable AI models for smallholder farmers through training that does not need frequent change and very easy to understand, given that farmers probably do not have any technical background in using artificial intelligence.
2. Exploring integration of AI with IoT and RS through use of smart sensors in combination with IoT AI-based solutions to make correct decisions in the farming process.
3. Policy Frameworks for AI Adoption to evaluate the impact of AI-friendly policies and government incentives on agricultural technology adoption.
4. Short-Term Benefits of AI for Sustainable Farming by carrying out case studies that shed light on the implications of implementing AI on vegetative cover, pest levels, farm yields, etc.

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