Journal of Holistic and Scientific Studies

Article journey
Received
12/06/2026
Revised
13/07/2026
Accepted
20/07/2026
Published
27/07/2026

Smart Agriculture and Farmer Well-Being: Examining the Combined Effects of Precision Technology, Environmental Sustainability and Livelihood Security

Ronnie Concepcion
Center for Natural Sciences and Environmental Research, De La Salle University, Manila 1004, Philippines

Abstract— **Smart agriculture has emerged as a promising approach for improving agricultural productivity while supporting sustainable resource management. This study examined the relationships between precision technology, environmental sustainability, and agricultural performance using a secondary dataset of 500 farms from multiple agricultural regions. Because the dataset did not include direct indicators of farmer well-being or livelihood security, crop yield was used as a proxy for livelihood-related agricultural performance. A quantitative, cross-sectional research design was employed, and the data were analyzed using Python. The analytical framework included descriptive statistics, Pearson correlation analysis, multiple linear regression, and Random Forest-based feature importance analysis. The descriptive results indicated modest differences in crop yield across irrigation methods, fertilizer types, and disease-status categories. However, regression analysis showed that neither the Precision Technology Index nor the Environmental Sustainability Index had a statistically significant influence on crop yield. Correlation analysis also revealed generally weak relationships among the principal study variables, while the machine learning model demonstrated limited predictive accuracy, with environmental factors contributing more strongly than the constructed technology index. These findings suggest that agricultural productivity is shaped by multiple interacting environmental and management factors and that crop yield alone is insufficient to represent farmer well-being. Future research should integrate socioeconomic, livelihood, and well-being indicators with agronomic data to provide a more comprehensive understanding of the contribution of smart agriculture to sustainable rural development.**

Keywords: Smart agriculture, Precision technology, Environmental sustainability, Crop yield, Farmer well-being

1. INTRODUCTION

The agricultural sector is facing a major revolution as digital technologies revolutionize the traditional approach to farming and enable more efficient, productive and sustainable agriculture. With the rising demand for food, climate variability, degradation of natural resources, and the continued socioeconomic issues of farm communities, smart agriculture has gained increased pace in the world. Smart agriculture is the combination of modern digital technologies with traditional agricultural methods to enhance decisions making, resource efficiency and boost agricultural production while minimizing the environmental impact. When it comes to farming, artificial intelligence, the Internet of Things (IoT), remote sensing, drones, geographic information systems, and sensor-based monitoring have given farmers the ability to make decisions based on data, which has been their biggest advantage.In the fields of agriculture, AI, IoT, remote sensing, drones, geographic information systems, and sensor-based monitoring have proven to be the greatest assets for farmers when it comes to making decisions for irrigation, fertilization, pest management, and crop monitoring. All these innovations help in enhancing the production efficiency and also support the sustainable agriculture development (Duncan et al., 2021; Karunathilake et al., 2023; Garg et al., 2024). One of the main pillars of smart farming, precision agriculture has become a topic of interest given its ability to optimize the productivity of agriculture by using site-specific management and effective allocation of agricultural inputs. Precision farming techniques have recently been shown to enhance operational efficiency by leveraging real-time data on the environment and applying predictive analytics to facilitate timely and accurate management decisions in various farming systems (Mgendi, 2024; Padhiary et al., 2025; Mohyuddin et al., 2024).

Smart agriculture has become a vital approach towards environmental sustainability, not just in the context of boosting productivity. There is more and more pressure on modern farming systems to reduce the over-consumption of water, fertilizers, and pesticides, and other farming inputs, whilst maximizing crop production. Precision irrigation, ensuring that only the correct amount of nutrients are applied to the soil by the right time, and applying only the required amounts of fertilizer through data logging and monitoring, can help producers optimize resource use, lower production costs, and limit environmental degradation. Water and fertilizer management plays a crucial role in both soil and water resources conservation, as well as in crop growth and development, which are essential for the sustainable agricultural system (Xing & Wang, 2024; Srivastav et al., 2024). Likewise, good agricultural management can also boost water-use efficiency and improve productivity without increasing the environmental load, thus facilitating climate-resilient agriculture (Zhang et al., 2023). The soil health is also a key aspect in sustainable agriculture, where soil biodiversity directly contributes to nutrient cycling, crop yields, and ecosystem resilience. The safeguarding of the biodiversity of soil therefore becomes an integral part of the sustainable production of food which requires environmentally responsible agricultural practices (Guerra et al., 2021). Recent findings also show that precision agriculture (PA) technologies combined with sustainable resource management practices can lead to substantial improvements in environmental performance and minimize the use of unnecessary chemicals and the conservation of natural ecosystems (Getahun et al., 2024).

Technology development has largely been measured in terms of productivity, although there is a growing focus on the impacts of technology on the well-being and livelihood security of farmers. Sustainable agriculture is not only about growing food, but also about ensuring economic viability, food security, environmental resilience and a better life for farmers. The concept of livelihood security covers various aspects such as sustained income earning, effective resource use, minimizing production risks and sustainability of farm households. Resilient farming systems with diversified farming practices and resource-efficient technologies have been reported to substantially enhance livelihood security of the smallholder farmers and environmental resilience (Ravisankar et al., 2022). Likewise, evaluations of Sustainable Agricultural Livelihood Security have also shown that sustainable agricultural practices have a significant impact on addressing farmers' socioeconomic security, increasing their production efficiency, and reducing their exposure to external shocks and risks (Das et al., 2025). On the other hand, the transformation of land use and the deterioration of environmental quality pose a risk to food production systems, rural livelihoods and farmers' well-being, thereby underscoring the need for systemic solutions to address technological aspects, environmental conservation, and socioeconomic sustainability, all in one go (Li et al., 2024).

While past research has studied precision agriculture, environmental sustainability and livelihood security separately, the empirical research has been relatively limited in investigating how the interplay of these dimensions can affect the well-being of farmers when studied together under a single analytical framework. A lot of the available literature has focused on either technological uptake or environmental impacts without assessing them both in terms of agricultural productivity and livelihoods performance. In addition, there is limited empirical evidence that has combined traditional statistical modelling and machine learning approaches to detect the most influential factors and their impacts on farm results in smart farming systems (Mohyuddin et al., 2024). This is crucial to understand the contribution of technology enabled sustainable agriculture practices to agricultural systems that are resilient and livelihood outcomes.

Hence, the present work explores the synergies of precision technology and environmental sustainability on agricultural outcomes using farm level data and by using crop yield as a proxy measure of output related to livelihoods. The study combines descriptive analysis, correlation analysis, multiple regression modelling and feature importance analysis based on machine learning to give a holistic evaluation of the variables affecting smart agriculture and sustainable farming. The results are likely to help build the knowledge base on digital agriculture by providing evidence to facilitate resource efficient farming and knowledge-based decision making for sustainable agricultural development.

The following are objectives of the study:

1.To examine the influence of precision technology on agricultural performance as a proxy for farmer well-being.

2.To evaluate the effect of environmental sustainability on agricultural performance under smart farming systems.

3.To investigate the combined effects of precision technology and environmental sustainability on agricultural performance using statistical and machine learning approaches.

2. MATERIALS AND METHODS

2.1 Research Design

The method used in this study was quantitative with a cross-sectional design. This design was used to analyze the relationship among smart agriculture practices, environmental sustainability and agricultural performance as a proxy of farmer's well-being. A cross-sectional approach was deemed to be suitable as it allowed a range of agronomic, environmental and technological variables to be assessed at one point in time, on a variety of farms. The analytical framework was based on the assessment of precision technology and environmental sustainability with crop yield in the context of specific environmental conditions. Since there were no direct indicators of household income, livelihood security or psychological well-being in the available data, crop yield was used as a proxy measure of farm-level livelihood performance and the results were interpreted in this context.

2.2 Data Source and Study Sample

The research was based on secondary data which included 500 observations on the farm level from various agricultural zones (Soundankar, 2024). The data-set consisted of farms in Central USA, South USA, North India, South India, and East Africa growing five major types of crops. The variables available were crop yield, irrigation method, fertilizer type, disease condition, soil moisture, soil pH, rainfall, temperature, humidity, sunshine duration, pesticide application and Normalized Difference Vegetation Index (NDVI). The data set was screened in relation to data completeness, consistency and data quality before analysis. The available technological and environmental indicators were combined into composite indexes of Precision Technology and Environmental Sustainability to get closer to the study goals. As no direct indicators of farmer well-being and livelihood security existed, the investigation focused on agricultural productivity outcomes from the available data.

2.3 Measurement of Study Variables

The dependent variable was the crop yield (kg/ha), a measure of agricultural productivity as a proxy indicator of the livelihood related farm performance. Two composite independent variables were created for the analysis. The Precision Technology Index was created using technology-related indicators contained in the data, such as NDVI-based crop monitoring and precision farming attributes; the environmental sustainability index was built by combining the environmental sustainability indicators (after proper normalization), such as soil conditions, vegetation status, pesticide use, etc. Other agronomic factors, such as rainfall, temperature, growing duration, soil moisture, humidity, type of irrigation, type of fertiliser and disease were also kept as explanatory or contextual factors in order to make a comprehensive assessment of the farm management practices. Furthermore, before inferential analysis was carried out, descriptive statistics were generated for all the study variables for consistency with the proposed analytical framework.

2.4 Statistical Analysis

Data were analysed using Python. Data preprocessing consisted of the verification of the type of variables, treatment of missing values if necessary, normalization of selected variables and building of the indices of Precision Technology and Environmental Sustainability. To summarize the characteristics of the study variables, descriptive data such as means, standard deviations, minimum and maximum values were computed. Comparative analysis was performed to compare the differences in crop production among irrigation methods, among disease-free and affected plants and among fertilizer types. Pearson correlation analysis was then used to measure the linear association between the main variables and the correlation matrix was plotted as a heatmap. Several multiple linear regression models were estimated to explore the effects of the Precision Technology Index, Environmental Sustainability Index, rainfall, temperature, and cultivation times, separately and in combination, on crop yield. Finally, a Random Forest regression model was used to complement the conventional regression results and determine the importance of the predictor variables, which is a good indicator of their predictive influence on agricultural productivity.

2.5 Software and Analytical Environment

All the analytical pipeline was developed in python using open source scientific computing tools. Data management and preprocessing were done using Pandas and NumPy and descriptive statistics and correlation analysis were done using SciPy. Using the Statsmodels package, multiple linear regression modelling was done, which enabled the estimation of regression coefficients, robust standard errors and goodness-of-fit statistics of the model. The machine learning was done with the Scikit-learn library and a Random Forest regression algorithm was used to identify the importance of the predictors. Visualizing the data in graphical forms such as bar charts, correlation heatmaps, and feature importance plots was done using Matplotlib. This analytical environment allowed to have a reproducible and transparent framework to evaluate the smart agriculture variables and their association with agricultural productivity.

3. RESULTS

There were 500 observations at farm level that were uploaded, across five regions and five crop categories. It failed to however, contain direct measures of farmer well-being, household income, livelihood security, psychological health and attitudes towards technology-adoption. Therefore, crop yield was used as a partial indicator of agricultural performance for livelihoods, and precision technology and environment sustainability indices were developed using the available agronomic indicators. Therefore, the results should be taken as evidence on conditions in smart farming and productivity in farms, but not directly as evidence of the well being of farmers.

3.1 Descriptive Characteristics of the Farms

The data set included farms of Central USA, East Africa, North India, South USA and South India. The largest regional group was in Central USA with 109 farms followed by East Africa with 107 farms. Maize was the crop with the highest number of observations (111) while rice had the lowest number of observations (82 farms). The average yield of the different crops was 4,032.93 kg/ha as presented in Table 1, which shows a significant variation between farms. The precision technology index was, on average, 0.453 and the environmental sustainability index was, on average, 0.455. The mean soil moisture was 26.75%, while the mean NDVI value was 0.602 which was also considered moderate vegetation health in the samples. There was a large difference in pesticide use ranging from 5.05 to 49.94 ml.

Table 1. Descriptive Statistics of Smart-Farming and Agricultural Performance Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Precision Technology Index	0.453	0.263	0.000	1.000
Environmental Sustainability Index	0.455	0.171	0.076	0.897
Soil Moisture (%)	26.750	10.150	10.160	44.980
Soil pH	6.524	0.586	5.510	7.500
Pesticide Usage (ml)	26.587	13.202	5.050	49.940
NDVI Index	0.602	0.175	0.300	0.900
Yield (kg/ha)	4,032.927	1,174.433	2,023.560	5,998.290

3.2 Agricultural Performance Across Management Categories

The crop yield means under irrigation, fertilizer and crop-disease levels are given in table 2. The highest yield was found in sprinkler irrigated farms 4084,41 kg/ha, which was closely followed by manual irrigation with 4070,09 kg/ha. Unspecified/rainfed farms had the lowest mean yield of 3,972.13 kg/ha. However, the range of differences among irrigation groups was fairly small in comparison with the overall standard deviation. The highest mean yield of 4,087.12 kg/ha was obtained by the inorganic fertilizer users while mixed fertilizer users had the lowest mean of 3,972.41kg/ha. A slightly higher average yield was found for the farms reporting mild crop disease as compared with the other disease categories. These descriptive differences should not be viewed causally due to the fact that the data set accounted for neither crop specific nor regional management conditions.

Table 2. Mean Crop Yield by Irrigation, Fertilizer, and Disease Status

Management Category	Group	Number of Farms	Mean Yield (kg/ha)	Standard Deviation
Irrigation	Sprinkler	121	4,084.41	1,097.29
Irrigation	Manual	118	4,070.09	1,159.11
Irrigation	Drip	111	4,019.45	1,240.98
Irrigation	Unspecified/Rainfed	150	3,972.13	1,204.37
Fertilizer	Inorganic	167	4,087.12	1,196.55
Fertilizer	Organic	166	4,039.28	1,184.32
Fertilizer	Mixed	167	3,972.41	1,146.14
Disease status	Mild	125	4,089.87	1,216.38
Disease status	None/Unreported	130	4,082.65	1,129.67

Disease status	Severe	133	4,029.34	1,210.50
Disease status	Moderate	112	3,915.92	1,140.95

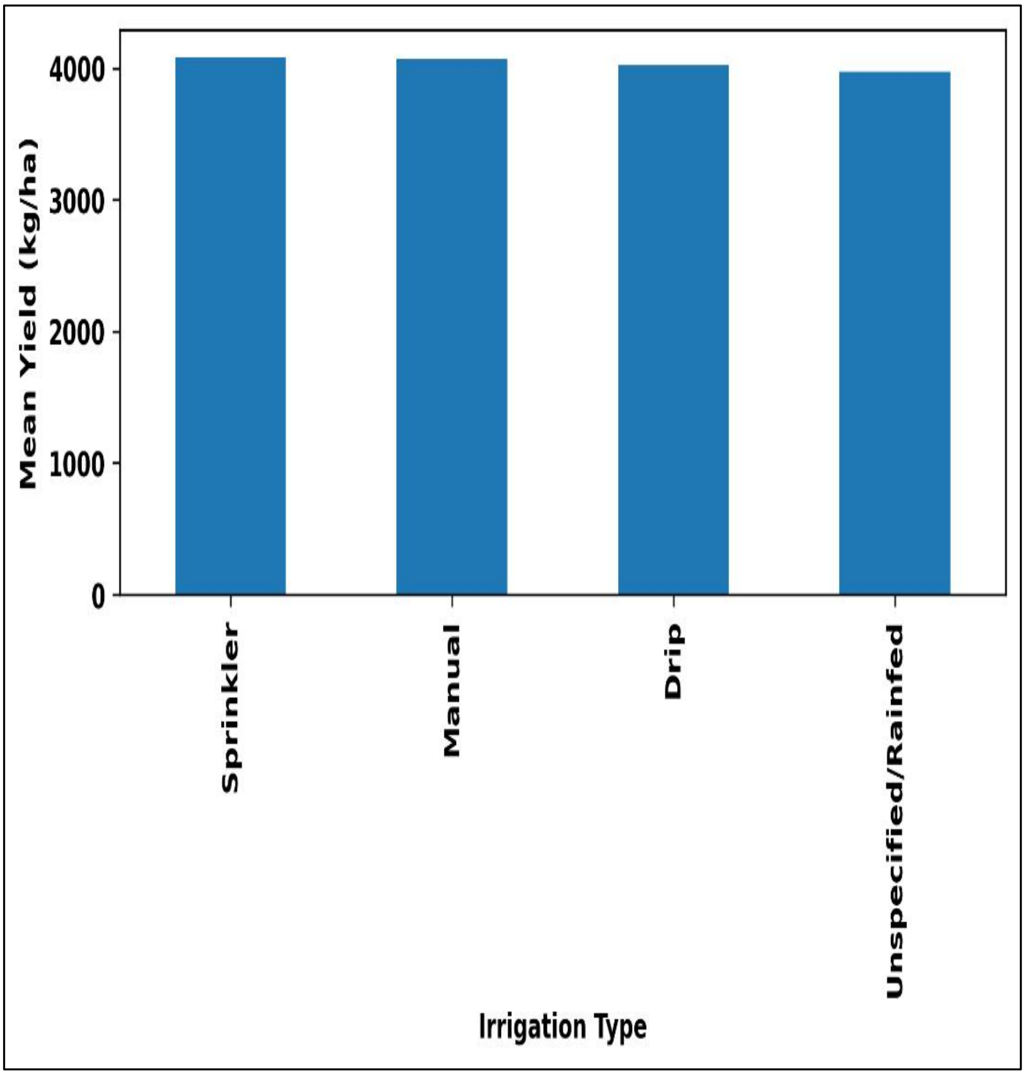

Figure 1. Mean Crop Yield Across Irrigation Categories

3.3 Correlation Analysis

Figure 2 shows the Pearson correlation matrix between the built indices and crop yield which reveals weak correlation, in general. There was a small positive correlation with precision technology and yield ($r = 0.031$) and a small negative correlation ($r = -0.053$) with environmental sustainability. There was a weak positive correlation between NDVI and yield ($r = 0.038$) and between pesticide applied and yield ($r = 0.041$). The highest correlation in the matrix was that between precision technology and NDVI ($r = 0.542$), which included information about monitoring of vegetation in the precision technology construct. Environmental sustainability was moderately and negatively related to pesticide usage ($r = -0.425$) as pesticide intensity was coded inversely in the sustainability index. The correlations as a whole revealed that all variables studied accounted for very little variation in crop yield.

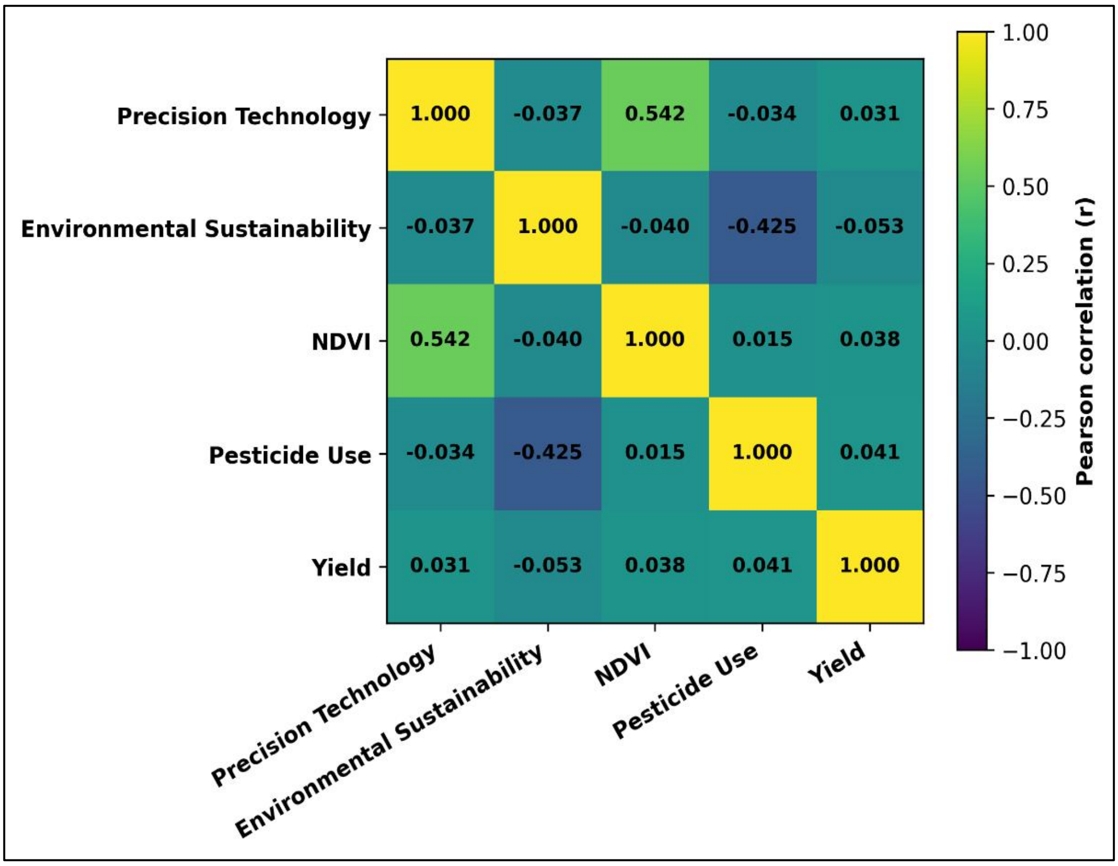

Figure 2. Pearson Correlation Heatmap of Smart-Farming Variables and Crop Yield

3.4 Regression Analysis

To quantify smart-farming conditions and crop yield, three regression models were estimated. Model 1 was not significantly predictive of yield ($\beta = 0.032$, $p = 0.480$) as shown in Table 3. The model accounted for only 0.1% of the variance of the observations. Results for model 2 also showed no statistically significant differences between environmental sustainability and yield ($\beta = -0.053$, $p = 0.241$). The precision technology, environmental sustainability, cultivation duration, rainfall and temperature were all modeled in Model 3. The combined model was not statistically significant and accounted for 1.1% of the variation in yield. Rainfall had the highest standardized coefficient in the model, but it was not conventionally significant and was negatively associated with the model ($\beta = -0.079$, $p = 0.078$).

Table 3. Regression Models Predicting Crop Yield

Model	Predictor	Standardized β	Robust SE	t-value	p-value	R^2	Adjusted R^2
Model 1	Precision Technology Index	0.032	0.045	0.706	0.480	0.001	−0.001
Model 2	Environmental Sustainability Index	−0.053	0.045	−1.173	0.241	0.003	0.001
Model 3	Precision Technology Index	0.039	0.046	0.850	0.395	0.011	0.001
	Environmental Sustainability Index	−0.046	0.045	−1.010	0.313		
	Total Cultivation Days	−0.010	0.046	−0.218	0.828		
	Rainfall	−0.079	0.045	−1.762	0.078		
	Temperature	0.030	0.044	0.686	0.493		

3.5 Machine Learning Feature Importance

The relative contribution of the agronomic and smart-farming variables to the prediction was evaluated by a Random Forest model. The model was found to have a negative test-set R^2 value of −0.073 with an out-of-sample M.A.E value of around 1,066 kg/ha, suggesting poor out-of-sample predictive performance. However, the relative importance of the predictors has been illustrated in Figure 3. Environmental sustainability was rated as the highest scoring parameter (0.112), followed by temperature, pesticide use, rainfall, soil moisture and humidity. The importance score for precision technology was less than these environmental variables at 0.077. These rankings need to be viewed with some degree of caution, given that the importance of features may be spread out across the predictors despite a poor performance of the predictive model as a whole.

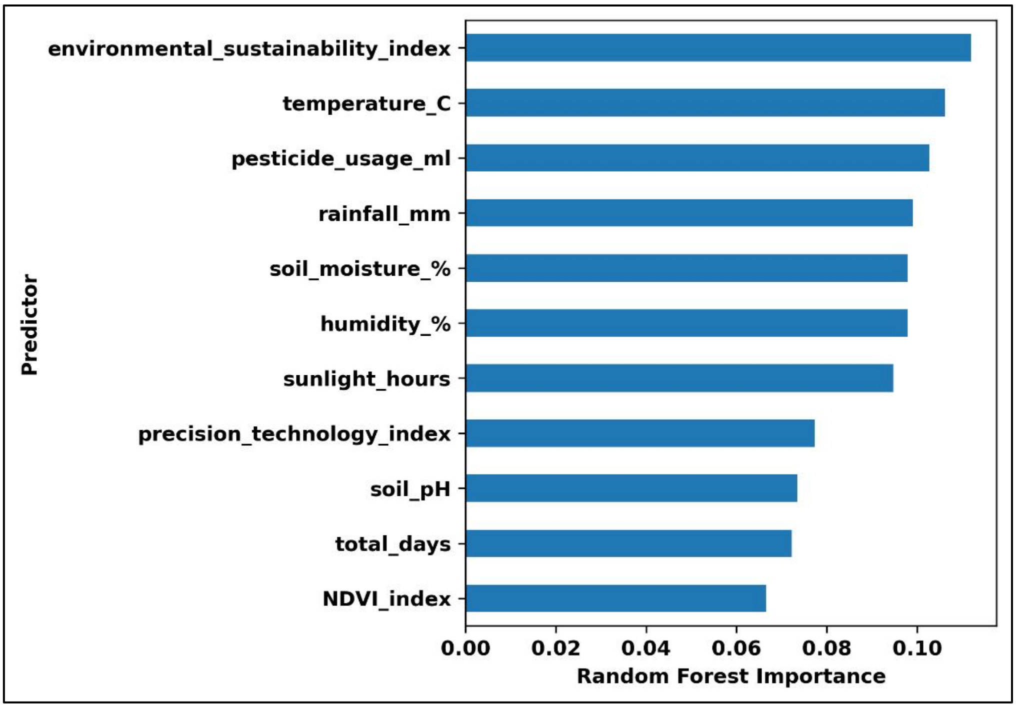

Figure 3. Random Forest Feature Importance for Predicting Crop Yield

4. DISCUSSION

The present study focused on correlation between precision technology, environment and agricultural performance as a representative indicator for the livelihoods related farm performance. Results show that while there were some descriptive differences among irrigation systems, fertilizer practices and disease categories, none of these variables were statistically significant in the regression models for crop yield for either Precision Technology Index or Environmental Sustainability Index. Also, the machine learning analysis reported low predictive power indicating that measured technological and environmental factors were not enough to explain a significant difference in agricultural productivity as per the available data. The results emphasize the complexity of agricultural systems, in which productivity depends on many environmental, socioeconomic, and management factors that interact: technology adoption is not the only one that will influence productivity.

The weak linkage between precision technology and crop production should not be mistaken to mean that Smart Agriculture is not practice oriented. Rather it's an expression of the restrictions in the variables and the complexity of agricultural production. Even though previous studies have always demonstrated that when precision agriculture technologies are properly used and technical knowledge is adequate, the results provide better decision making, better use of resources and better efficiency of the processes. Improvements from technology adoption are often step by step as farmers need to be given time to incorporate digital technology into their current production practices and adjust their management (Abdul-Majid et al., 2024). Similarly, empirical evidence from precision agriculture shows that the benefits to farmer well-being go beyond yield improvements to decrease the need for labour, increase management confidence, create more stable production and improve long-term resilience (McFadden et al., 2026). Thus, the lack of significant yield impacts in the current analysis may be due to missing out on the overall benefits of smart agriculture.

There was also a weak and statistically insignificant correlation between the environmental sustainability index and the crop yield. Sustainable agriculture is mostly aimed at maintaining soil quality, protecting the environment, conserving water and keeping ecosystem healthy for long-term periods instead of short-term improvements in productivity. The studies in precision livestock farming and sustainable production systems also show that technologies often do not bring about significant short-term yield increases, but they still have a positive impact on the environment, animal welfare, and productivity (Schillings et al., 2021). Furthermore, the benefits from sustainable agriculture are not necessarily immediate, as they can lead to better economic security through enhanced food security, risk reduction, and resilience to climatic uncertainty, which may take time to be achieved (Woudneh, 2025).

An important implication of the present findings is that of the measurement of farmers' well-being. The research title highlights farmer well-being and farmer livelihood security, but the data set available did not include any direct socioeconomic indicators (e.g. household income, financial security, quality of life, psychological well-being and food security). Therefore, crop yield was used as an indicator of livelihood related performance, which is just one aspect of overall well-being. The current studies show that sustainable livelihoods are determined not only by agricultural production, but also by economic resources, social capital, financial literacy and institutional support and market accessibility. Financial literacy and better market access have been demonstrated to have a positive impact on the correlation between sustainable livelihoods and socioeconomic development, boosting farmers' ability to translate their agricultural productivity into sustainable income and improved livelihoods (Tulika & Ram, 2025). In the same way, the secure ownership of resources and institutional support contribute to household income and rural welfare indirectly, beyond agricultural production (Luo et al., 2024). All these observations indicate that future empirical studies, and the current study to some extent, should involve multidimensional measures of well-being, and not only productivity measures.

The machine learning analysis also showed that the environmental factors (temperature, rainfall, pesticide usage, and soil moisture) were more important than the developed Precision Technology Index for their predictive performance. The results of the Random Forest model showed low global prediction accuracies, but the importance of these predictors indicates environmental attributes still play a large role in agricultural outcomes. This is in line with recent findings that digital technologies should be used to complement good agronomic practices. Precision farming systems are best combined with decision support systems, environmental monitoring and adaptive management for farms that respond to changing production conditions, in relation to climate change (Priya et al., 2025). Similarly, the effective use of digital agriculture technologies is also greatly reliant on the digital literacy and technical skills of farmers, as well as their capacity to analyze the information provided by technologies. Digitally-empowered farmers are more likely to leverage advanced technologies and adopt sustainable farming methods that help achieve food security and sustainable agriculture (Mokhtar et al., 2022).

The results also highlight the need to take a wider perspective of the institutional and policy context of smart agriculture. The effectiveness of agricultural technologies is significantly affected by climate variability, quality of governance, infrastructure, extension services and regional policy frameworks. Institutional support, climate adaptation measures and reliable advisory services are important, as even the most sophisticated precision farming techniques can yield only a small gain otherwise. Comparative evaluations of climate adaptation governance have highlighted that coordinated agricultural policies, institutional collaboration and regional cooperation enhance farmers' adaptive capacity and boost effectiveness of technology-led interventions in agriculture (Hossain & Mumu, 2026). This means that integrated policy approaches are needed for the successful implementation of smart agriculture, which will simultaneously encourage technological innovation, environmental sustainability, farmer education and institutional capacity building.

In conclusion, the current research adds to the literature on smart agriculture as it shows that the evaluation of technology adoption and environmental sustainability needs to be done more broadly than focusing on crop productivity. Results showed that there were not any statistically significant relationship in the available data; however, results demonstrated the need for a multidimensional approach, integrating agronomic, socio-economic, environmental and technological indicators. Future research should use a set of data that includes direct measures of farmer well-being, livelihood security, household income, food security, and intensity of technology uptake to better understand the role of smart agriculture in contributing to sustainable rural development.

5. CONCLUSION

The potential of smart agriculture is high, and it can help to achieve sustainable agriculture through the use of precision technology and environmentally responsible practices. The descriptive analysis showed only small variations in the crop yield between the irrigation, fertilizer and disease-management categories; and neither the Precision Technology Index nor the Environmental Sustainability Index showed a statistically significant influence on the crop yield in the regression models. The machine learning analysis also yielded poor predictive ability indicating that productivity in agriculture is the result of a complex set of environmental, managerial, and contextual factors, not just the factors included in the dataset. Since there were no direct measure of farmer well-being or the security of their livelihood in the dataset, a proxy for agricultural performance related to livelihoods – crop yield – was used, and this means that conclusions about the broader socioeconomic outcomes implied by the study title were limited. But the results highlight the need to combine digital technologies and sustainable resource management, and not just the adoption of technologies to gain better results in agriculture. Future research needs should be conducted to include multidimensional measures of farmer well-being, household income, food security, resilience, and technology adoption to offer more empirical evidence on the role of smart agriculture in promoting sustainable livelihoods and long-term rural development.

REFERENCES

1. Duncan, E., Abdulai, A. R., & Fraser, E. D. (2021). Modernizing agriculture through digital technologies: Prospects and challenges. Handbook on the human impact of agriculture, 138-161.
2. Karunathilake, E. M. B. M., Le, A. T., Heo, S., Chung, Y. S., & Mansoor, S. (2023). The path to smart farming: Innovations and opportunities in precision agriculture. Agriculture, 13(8), 1593.
3. Mgendi, G. (2024). Unlocking the potential of precision agriculture for sustainable farming. Discover Agriculture, 2(1), 87.
4. Das, S., Sharma, K. K., Majumder, S., & Chowdhury, I. R. (2025). Evaluating sustainable agricultural livelihood security in West Bengal, India: a principal component analysis approach. Environment, Development and Sustainability, 27(2), 4769-4816.
5. Mohyuddin, G., Khan, M. A., Haseeb, A., Mahpara, S., Waseem, M., & Saleh, A. M. (2024). Evaluation of machine learning approaches for precision farming in smart agriculture system: a comprehensive review. IEEE access, 12, 60155-60184.
6. Garg, S., Rumjit, N. P., & Roy, S. (2024). Smart agriculture and nanotechnology: Technology, challenges, and new perspective. Advanced Agrochem, 3(2), 115-125.
7. Padhiary, M., Hoque, A., Prasad, G., Kumar, K., & Sahu, B. (2025). Precision agriculture and AI-driven resource optimization for sustainable land and resource management. In Smart water technology for sustainable management in modern cities (pp. 197-232). IGI Global Scientific Publishing.
8. Xing, Y., & Wang, X. (2024). Precise application of water and fertilizer to crops: challenges and opportunities. Frontiers in Plant Science, 15, 1444560.
9. Zhang, G., Zhang, Y., Zhao, D., Liu, S., Wen, X., Han, J., & Liao, Y. (2023). Quantifying the impacts of agricultural management practices on the water use efficiency for sustainable production in the Loess Plateau region: A meta-analysis. Field Crops Research, 291, 108787.
10. Srivastav, A. L., Patel, N., Rani, L., Kumar, P., Dutt, I., Maddodi, B. S., & Chaudhary, V. K. (2024). Sustainable options for fertilizer management in agriculture to prevent water contamination: a review. Environment, Development and Sustainability, 26(4), 8303-8327.
11. Guerra, C. A., Bardgett, R. D., Caon, L., Crowther, T. W., Delgado-Baquerizo, M., Montanarella, L., ... & Eisenhauer, N. (2021). Tracking, targeting, and conserving soil biodiversity. Science, 371(6526), 239-241.
12. Getahun, S., Kefale, H., & Gelaye, Y. (2024). Application of precision agriculture technologies for sustainable crop production and environmental sustainability: A systematic review. The Scientific World Journal, 2024(1), 2126734.
13. Ravisankar, N., Ansari, M. A., Shamim, M., Prusty, A. K., Singh, R., Panwar, A. S., ... & Bal, S. K. (2022). Sustainable livelihood security of small farmers improved through a resilient farming system in the semiarid region of India. Land Degradation & Development, 33(15), 2830-2842.
14. Li, M., Li, J., Haq, S. U., & Nadeem, M. (2024). Agriculture land use transformation: A threat to sustainable food production systems, rural food security, and farmer well-being?. PLoS One, 19(1), e0296332.
15. Abdul-Majid, M., Zahari, S. A., Othman, N., & Nadzri, S. (2024). Influence of technology adoption on farmers' well-being: Systematic literature review and bibliometric analysis. Heliyon, 10(2).
16. McFadden, J., Rosburg, A., Lim, K., & Arbuckle, J. G. (2026). Precision Agriculture and Multidimensional Attributes of Farmer Wellbeing: Evidence from Iowa.
17. Schillings, J., Bennett, R., & Rose, D. C. (2021). Exploring the potential of precision livestock farming technologies to help address farm animal welfare. Frontiers in Animal Science, 2, 639678.
18. Woudneh, A. F. (2025). Causal pathways from sustainable practices to economic stability through food security: An SEM approach.
19. Woudneh, A. F. (2025). Causal pathways from sustainable practices to economic stability through food security: An SEM approach.
20. Tulika, & Ram, P. (2025). Linking social capital and sustainable livelihood: the mediating effect of financial literacy and moderating role of market access. International Journal of Sociology and Social Policy, 1-19.
21. Luo, X., Li, L., Zhang, L., Ning, C., & Liu, X. (2024). The Impact of Forestland Tenure Security on Rural Household Income: Analysis of Mediating Effects Based on Labor Migration. Forests, 15(8), 1336.
22. Priya, N. K., Patil, S. S., Vishwakarma, S. K., Saikanth, D., Mishra, I., Tripathi, S., ... & Shastri, S. (2025). Digital innovations in extension education: A review of emerging technologies and their impact on agricultural

knowledge dissemination. Journal of Experimental Agriculture International, 47(5), 408-423.

23. Mokhtar, W. N. H. W., Izhar, T. A. T., Zaini, M. K., & Hussin, N. (2022). The importance of digital literacy skills among farmers for sustainable food security. International Journal of Academic Research in Business and Social Sciences, 12(1), 235-246.
24. Hossain, M. N., & Mumu, U. H. (2026). Evaluating Climate Adaptation Governance in South Asia: A Comparative Assessment of Policies, Institutions, and Regional Cooperation. Environmental Management, 76(5), 152.
25. Soundankar, A. (2024). Smart Farming Sensor Data for Yield Prediction [Data set]. Kaggle. https://www.kaggle.com/datasets/atharvasoundankar/smart-farming-sensor-data-for-yield-prediction