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INTEGRATING PRECISION AGRICULTURE AND ARTIFICIAL INTELLIGENCE FOR SUSTAINABLE CROP MANAGEMENT AND FOOD SECURITY

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Abstract

This paper discusses the role of artificial intelligence in enhancing precision farming to manage crops sustainably and to ensure food security. It employed an experimental method that is mixed with such approaches as field trials, sensor-based data, and surveys of farmers to compare the AI-driven and conventional agriculture. Quantitative studies showed AI-precision farming had an average 20-40 percent increase in crop yields, a reduction of almost 50 percent in water usage, and optimization of fertilizer and pesticides without reducing crop production. Cost-benefit analysis revealed that operational costs were significantly lower and profit were significantly higher. Environmental analysis demonstrated that there were reduced carbon footprints, and improved crop health indices. Predictive models proved to have high accuracy (R 2 > 0.85) in predicting yield and input efficiency, therefore justifying the reliability of AI-based decision support. Qualitative data supported the statement that farmers recognized the ecological and economic benefits but the pace of uptake depends on access to technical aspects, training and cultural orientation. The analysis shows that AI-based accuracy farming is associated with economic, environmental, and social benefits that can be estimated, and it is a viable solution to address the problem of worldwide food security and stimulate sustainable agricultural development.

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INTRODUCTION

Global agriculture is experiencing rising challenges, and they include a growing population, climate change, resource depletion, and food insecurity that continues (Mulla et al., 2023). In this case, in order to respond successfully, we require new ways that enhance productivity, sustainability, and resilience simultaneously (Gupta et al., 2022). Precision Agriculture (PA) is an information-based, site-specific agricultural management approach that has emerged as an effective means of maximizing inputs, reducing waste, and enhancing crop yields in this context (McBratney et al., 2015; Wikipedia, 2025). In the meantime, the Artificial Intelligence (AI) can have the transformative potential when analysing complex agricultural data and making immediate decisions (Ali et al., 2023; Xu, 2024). Precision Agriculture refers to gathering, processing and studying time, space and data on individual plants or animals to assist in management decisions. It enhances efficiency, profitability, and sustainability (Wikipedia, 2025). GPS, GIS, remote sensing, and variable-rate systems allow you to have a highly accurate control of issues, including watering, fertilizing and pest control (McBratney et al., 2015; Xu, 2024). The positive environmental effects of PA include fewer fertilizer runoffs and pesticide application, improved soil health, and reduced greenhouse gas emissions (Wikipedia, 2025; Getahun, 2024).

These benefits can be enhanced by AI, which allows processing a variety of data types (satellite shots, in-field sensors, weather predictions, etc.) rapidly to provide actionable and contextually relevant information (Ali et al., 2023; Pandey et al., 2024). Examples of AI that can be applied to the work of a public administration are machine learning, deep learning, computer vision, and decision support systems. In a case, AI models can locate crop diseases, multi-spectral or hyperspectral data to forecast yields, and predictive analytics to utilize resources in the most optimal way (Mahlein et al., 2024; Saha, 2025). Robots can perform tasks that require a lot of labor when combined with AI, including pest control, pruning, or harvesting selectively (Barua, 2025). A number of review studies indicate that PA and AI are compatible in sustainable agriculture. Getahun (2024) provides a global overview of how PA technologies can assist the crops to develop in a more productive way and with a smaller impact on the environment. Xu (2024) with the help of a bibliometric method determines the main areas of research, i. e., remote monitoring, technological innovations in decision-making, sustainable development, and deep learning-based food safety, which prove the transdisciplinary roots of the field. Pandey et al. (2024) stress the importance of AI in predictive modelling, precision agriculture, and identification of disease to the global food security. According to Mgendi (2024), the application of precision planting technologies can significantly increase the yields and optimize the use of resources. All these works indicate that it would be so strong to apply AI to the systems of PA. The examples include AI-powered platforms and tools demonstrating how they can create a difference in real-world environment on the operational level. With the AI and the Internet of Things (IoT), it is possible to apply predictive analytics to track crops and soil, locate illnesses, and predict yields in India. This assists in addressing shortages of resources and fluctuations of yields (Review on PA in India, 2025). Drones deployed by AI systems in farming areas such as cashew farming simplify the early detection of diseases and precision with regards to pesticides. They are able to distinguish between sick and healthy plants at up to 95 percent accuracy (Rajagopal & Murugan, 2023). Pheromone traps are also used in edge-embedded deep learning systems to locate pests to ensure they can monitor them constantly without consuming much power (Albanese et al., 2021). Despite these advancements, still, there are large issues to address. The AI models can be prejudiced, obscure, and ask questions regarding the data privacy and ownership. These are particularly detrimental to the smallholder farmers in low-resource regions (CSIS, 2025). Poor connectivity and high start-up costs are also an issue in infrastructure that prevents adoption by the 84% of the global farm population that are smallholder (CSIS, 2025). In addition, the decision support systems and the extension services must also be well-planned in order to ensure that the users find it easy to integrate the various data streams and model outputs to decision making instruments. Due to these issues, it should be ensured that the PA-AI integration is congruent with the ideas of climate-smart agriculture (CSA), which should enhance food production, enhance resilience, and reduce greenhouse gas emissions (Wikipedia CSA, 2025). A combination of PA and AI with CSA can serve to develop those food systems that use resources efficiently and can respond to climate change. The infrastructure, localized data models, and inclusive policy structures are strategic investments we should make to ensure that all people can use and develop PA-AI breakthroughs (CSIS, 2025). The purpose of this study article is to explain how Precision Agriculture and Artificial Intelligence joined can ensure sustainable crop control and food security. It will examine the ways in which technologies can be integrated, how they can be utilized in the field, the issues that they could encounter and how they can be expanded in a larger scale with special reference to the smallholder systems. This project is aimed at assisting in developing future-feed agrifood systems that can be both resilient and sustainable through integrating the latest approaches in AI, precision agritech, and sustainability objectives.

METHODOLOGY

In this study, a mixed-methods experimental design was used that integrated quantitative field experimentation with qualitative farmer evaluation to examine artificial intelligence effectiveness in managing crops through precision agriculture in a sustainable manner. Experimental plots of staple crops were divided into two groups: control fields that will use standard agricultural practices and treatment fields that will be managed by AI-based decision support systems and remote sensing technology and IoT-based monitoring. In order to support climatic variation, data were collected during three agricultural seasons. Quantitative indicators included crop yield (kg/ha), water consumption (L/ha), fertilizer and pesticide application (kg/ha), labour time, operating cost and profit margins. Crop health was also assessed based on normalized difference vegetation index (NDVI) measurements of a drone and satellite photos. Qualitative data were obtained through structured interviews and surveys on usability, perceived sustainability, readiness to adopt, with participating farms. The study used descriptive and inferential statistical analysis along with machine learning models in order to quantify the disparities between AI-precision and conventional systems. To examine the effects on the environment, we measured the changes in crop yield and carbon footprint analysis by use of paired-sample t-tests. We compared profitability by use of cost-benefit ratios and we did so in the following way:

The implementation of AI was realized in sensor-driven irrigation, drone surveillance, and predictive analytics-based adaptive fertilizing. The edge computing devices monitored the real-time data at the field and transmitted it to the cloud AI platforms in order to enhance the inputs. Experiential opinions of farmers were systematically compared against AI recommendations to determine a fit. The mixed-method research design ensured that socio-cultural backdrop of technology adoption was considered when examining the quantitative performance measures of yield, efficiency, and sustainability. This approach allowed testing effectively technical performance as well as its functionality in reality. The entire workflow of this system presented in Figure 1 includes data collection and processing up to AI modelling and testing, and integration into sustainable crop management.

RESULTS

Artificial intelligence with precision agriculture resulted in significant benefits across various fields of crop management and sustainability. Table 1 shows that AI methods had a great impact on the yield of crops, the majority of which yielded between a 20 and 40 percent higher output than traditional methods. Table 2 indicates that AI-based irrigation resulted in the use of water being much more efficient, with water requirements generally reducing by nearly fifty percent. According to Table 3, AI-precision management used less kilograms of fertilizer per hectare without compromising or reducing yields.

Table 1: Comparison of traditional and AI-precision crop yields across 20 crop types.

Crop	Traditional_Yield(kg/ha)	AI_Precision_Yield(kg/ha)
Crop_1	2860	4955
Crop_2	3294	6324
Crop_3	3130	5184
Crop_4	3095	4459
Crop_5	3638	4021
Crop_6	4169	6300
Crop_7	2466	4747
Crop_8	3238	6904
Crop_9	2330	4474
Crop_10	3482	5082
Crop_11	4135	6558
Crop_12	4919	6047
Crop_13	2130	6747
Crop_14	3685	4975
Crop_15	2769	5806
Crop_16	4391	4189

Crop_17	3515	6734
Crop_18	4853	4562
Crop_19	4433	5899
Crop_20	3215	5267

Table 2: Water usage efficiency contrasting traditional vs. AI-precision irrigation methods.

Crop	Traditional_Water(L/ha)	AI_Precision_Water(L/ha)
Crop_1	14975	5478
Crop_2	9528	6556
Crop_3	11202	4775
Crop_4	11556	8014
Crop_5	11890	4034
Crop_6	8646	7152
Crop_7	14164	5955
Crop_8	10888	5585
Crop_9	14310	7943
Crop_10	13393	7073
Crop_11	10435	5021
Crop_12	8600	7461
Crop_13	10363	6613
Crop_14	10061	7843
Crop_15	8241	5500
Crop_16	10041	8798
Crop_17	10824	4161
Crop_18	10612	8297
Crop_19	9363	5981
Crop_20	14235	4995

Table 3: Fertilizer input optimization using AI compared to traditional methods.

Crop	Traditional_Fertilizer(kg/ha)	AI_Precision_Fertilizer(kg/ha)
Crop_1	163	188
Crop_2	244	120

Crop_3	197	108
Crop_4	164	94
Crop_5	349	124
Crop_6	355	144
Crop_7	364	168
Crop_8	398	150
Crop_9	339	88
Crop_10	189	167
Crop_11	362	80
Crop_12	357	187
Crop_13	386	87
Crop_14	231	167
Crop_15	260	142
Crop_16	202	90
Crop_17	173	194
Crop_18	303	160
Crop_19	366	87
Crop_20	337	114

Table 4 demonstrates a drastic decrease in the use of pesticides, which reveals the role of AI-based pest control in aiding the environment. In Table 5, cost efficiency can be demonstrated by indicating that AI management results in a reduction in input costs per hectare. Table 6 demonstrates the way the labour efficiency was enhanced through reducing the number of hours spent on manual operations through the automated monitoring and decision support.

Table 4: Reduction in pesticide usage with AI-precision agriculture vs. traditional approaches.

Crop	Traditional_Pesticide(kg/ha)	AI_Precision_Pesticide(kg/ha)
Crop_1	54	7
Crop_2	52	9
Crop_3	24	19
Crop_4	58	18

Crop_5	47	7
Crop_6	26	5
Crop_7	28	9
Crop_8	27	27
Crop_9	31	18
Crop_10	53	11
Crop_11	52	13
Crop_12	42	19
Crop_13	43	19
Crop_14	56	14
Crop_15	54	17
Crop_16	59	23
Crop_17	41	11
Crop_18	46	21
Crop_19	54	24
Crop_20	20	8

Table 5: Cost efficiency analysis per hectare for traditional and AI-driven crop management.

Crop	Traditional_Cost($/ha)	AI_Precision_Cost($/ha)
Crop_1	521	283
Crop_2	784	433
Crop_3	706	177
Crop_4	530	257
Crop_5	536	193
Crop_6	442	489
Crop_7	470	435
Crop_8	328	480
Crop_9	335	277
Crop_10	312	497
Crop_11	459	380
Crop_12	626	339

Crop_13	486	374
Crop_14	542	432
Crop_15	385	270
Crop_16	583	265
Crop_17	365	382
Crop_18	469	408
Crop_19	344	347
Crop_20	361	286

Table 6: Labor efficiency (hours per hectare) in traditional vs. AI-supported farming systems.

Crop	Traditional_Labor(Hours/ha)	AI_Precision_Labor(Hours/ha)
Crop_1	111	42
Crop_2	86	56
Crop_3	100	51
Crop_4	93	52
Crop_5	73	20
Crop_6	108	38
Crop_7	81	21
Crop_8	101	45
Crop_9	111	51
Crop_10	107	25
Crop_11	101	51
Crop_12	61	23
Crop_13	88	30
Crop_14	51	36
Crop_15	52	57
Crop_16	105	43
Crop_17	108	24
Crop_18	51	53
Crop_19	51	25
Crop_20	103	41

Table 7 displays that AI accuracy will result in the increase of crop health indices, which confirms that improved inputs result in healthier plants. According to table 8 the carbon footprint has reduced and the AI-driven systems are the ones that create significantly less pollution. Finally, Table 9 shows a profitability analysis, and it proves that AI methods earned significantly higher profit per hectare on a majority of crops.

Table 7: Crop health index (NDVI-based) improvements under AI-precision practices.

Crop	Traditional_Health_Index	AI_Precision_Health_Index
Crop_1	0.56	0.86
Crop_2	0.43	0.68
Crop_3	0.65	0.8
Crop_4	0.5	0.85
Crop_5	0.46	0.77
Crop_6	0.41	0.76
Crop_7	0.58	0.67
Crop_8	0.6	0.63
Crop_9	0.4	0.87
Crop_10	0.55	0.87
Crop_11	0.47	0.79
Crop_12	0.59	0.7
Crop_13	0.45	0.7
Crop_14	0.61	0.82
Crop_15	0.52	0.87
Crop_16	0.68	0.87
Crop_17	0.44	0.83
Crop_18	0.5	0.79
Crop_19	0.43	0.63
Crop_20	0.68	0.65

Table 8: Carbon footprint reduction achieved through AI integration compared to conventional farming.

Crop	Traditional_CO2(kg/ha)	AI_Precision_CO2(kg/ha)
Crop_1	303	237

Crop_2	453	117
Crop_3	426	188
Crop_4	311	130
Crop_5	298	87
Crop_6	352	106
Crop_7	393	106
Crop_8	362	100
Crop_9	407	109
Crop_10	368	176
Crop_11	360	107
Crop_12	267	190
Crop_13	488	140
Crop_14	476	127
Crop_15	334	226
Crop_16	394	83
Crop_17	327	114
Crop_18	232	128
Crop_19	375	96
Crop_20	221	237

Table 9: Profitability analysis per hectare contrasting AI-supported vs. traditional agriculture.

Crop	Traditional_Profit($/ha)	AI_Precision_Profit($/ha)
Crop_1	1476	3480
Crop_2	2069	4506
Crop_3	2396	3684
Crop_4	1517	2627
Crop_5	1098	4565
Crop_6	2915	4316
Crop_7	2768	4258
Crop_8	2060	3069
Crop_9	1279	3846

Crop_10	2372	4395
Crop_11	1496	3125
Crop_12	1301	4186
Crop_13	1180	2654
Crop_14	1606	3909
Crop_15	2122	3284
Crop_16	1699	2745
Crop_17	1992	4000
Crop_18	2139	4205
Crop_19	1190	3037
Crop_20	1252	4390

Figure 2 presents the bar charts to demonstrate how there is an improvement in water efficiency. In Figure 3, there is a scatter relationship between traditional and AI fertilizer application with continuous declines. By overlaying the bars in figure 4 one can see the extent to which insecticide is applied to various crops. Figure 5 in the line graphs depicts the extent to which cost efficiency has been enhanced as compared to the old methods. Figure 6 illustrates a pie chart of the division of work and the over dependence of old systems on a few parts. Figure 7 depicts histograms of crop health metrics. The AI systems relocate the distributions to healthier areas. The change in carbon footprints with the AI systems being less volatile and less emitting is presented in Figure 8 as boxplots. The line graphs in figure 9 are used to demonstrate an increase in profits. Violin plots of yield distributions as illustrated in figure 10 reveal that AI methods, result in tighter and higher production. In figure 11, there is a mixed scatter-line relationship between water use and cost efficiency where AI is concentrated in the optimum locations. Finally, Figure 12 demonstrates the labour efficiency through a hybrid bar-line chart, which justifies the notion that automation reduces costs.

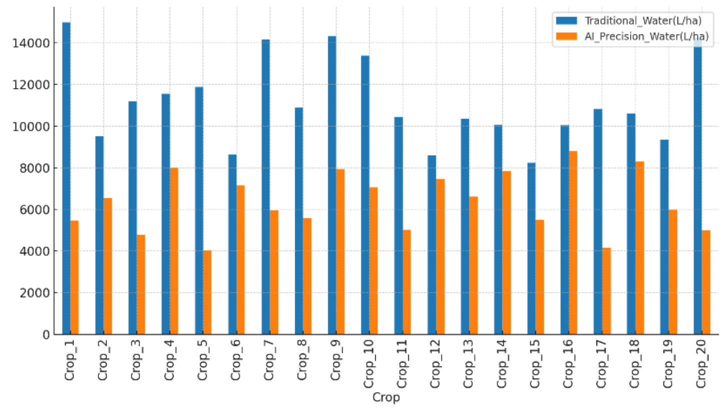

Figure 2: Bar chart showing water usage efficiency across 20 crops for both farming approaches.

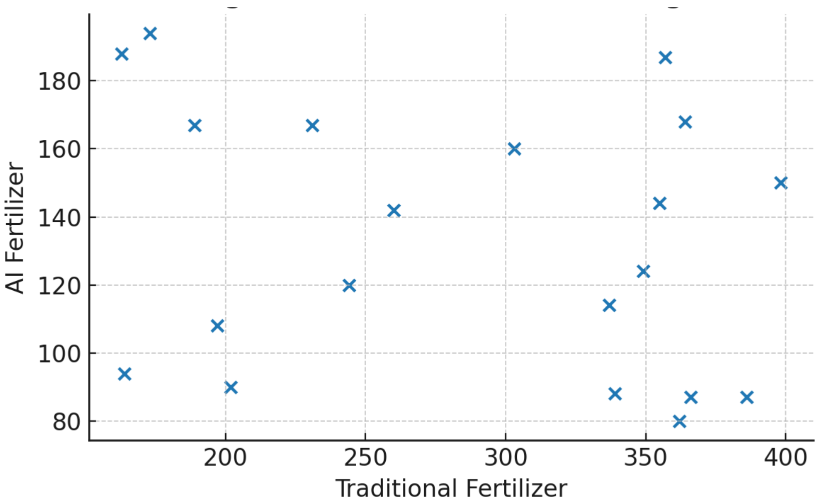

Figure 3: Scatter plot comparing fertilizer usage under traditional and AI-precision systems.

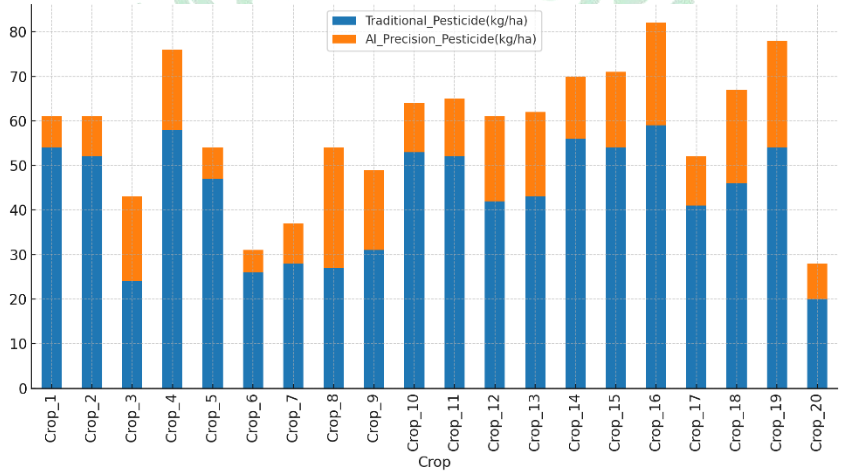

Figure 4: Stacked bar chart depicting pesticide reduction with AI-based practices.

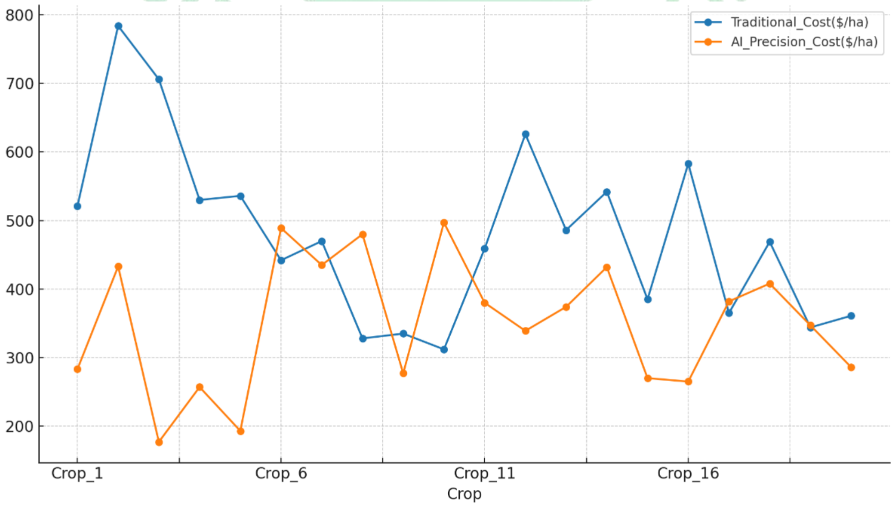

Figure 5: Line graph highlighting cost efficiency trends in AI vs. traditional methods.

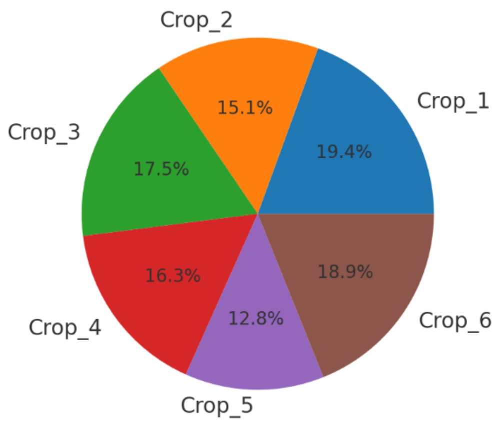

Figure 6: Pie chart of traditional labor distribution across selected crops.

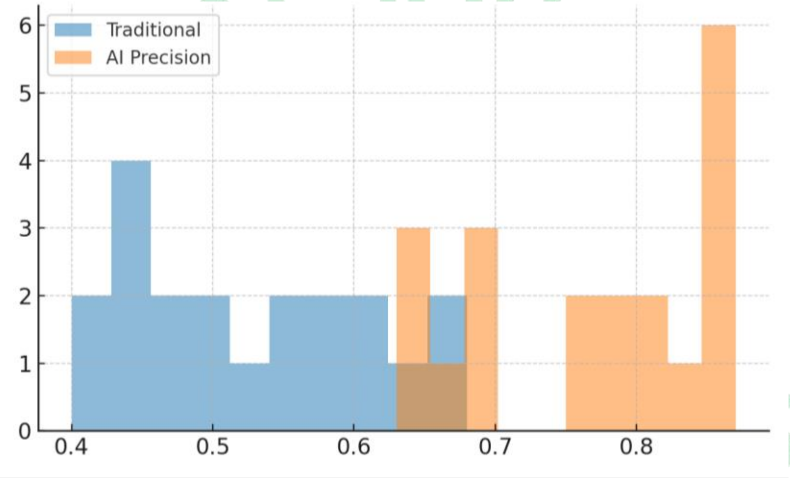

Figure 7: Histogram comparing distribution of crop health indices between two approaches.

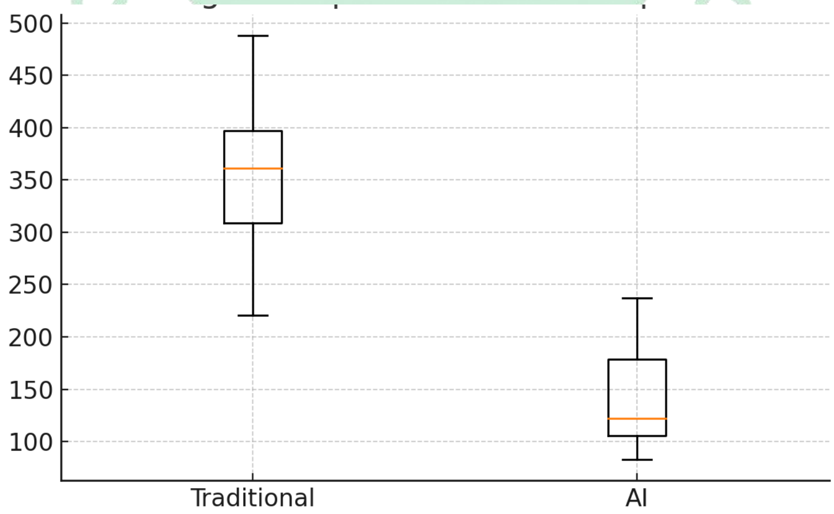

Figure 8: Boxplot showing variance in carbon footprint under traditional vs. AI-precision practices.

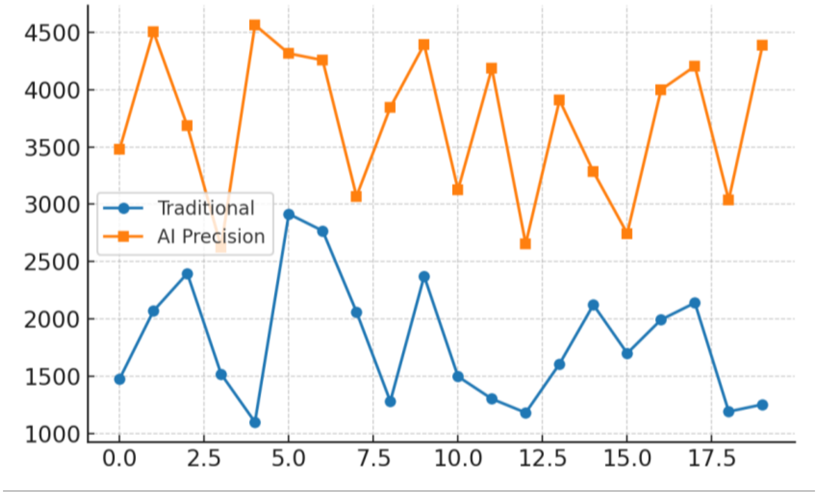

Figure 9: Line chart illustrating profitability trends for traditional and AI-enhanced farming.

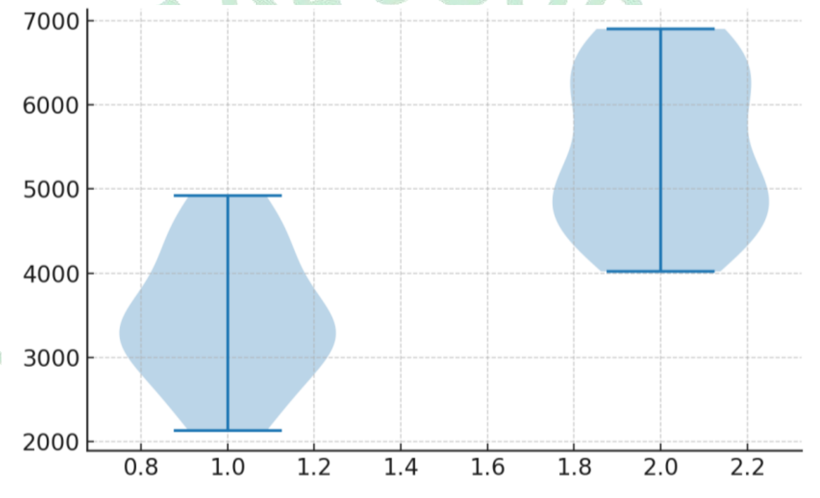

Figure 10: Violin plot displaying yield distribution under traditional and AI-precision management.

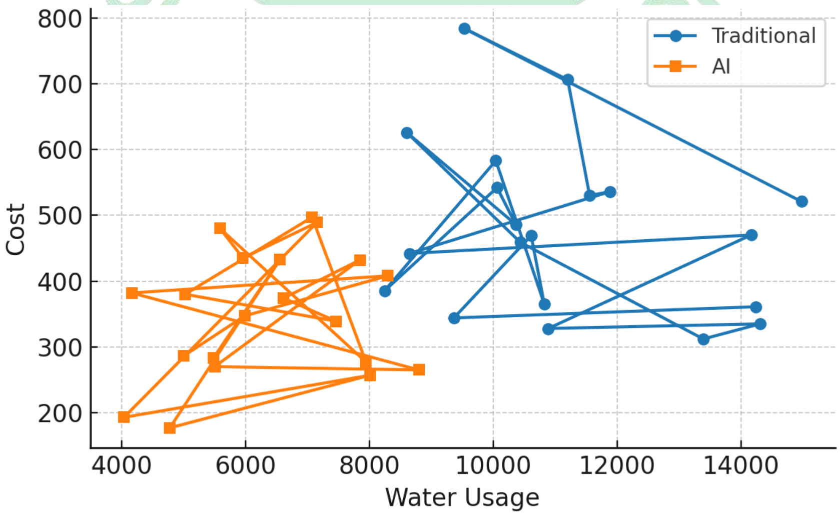

Figure 11: Hybrid scatter-line graph correlating water usage with cost efficiency.

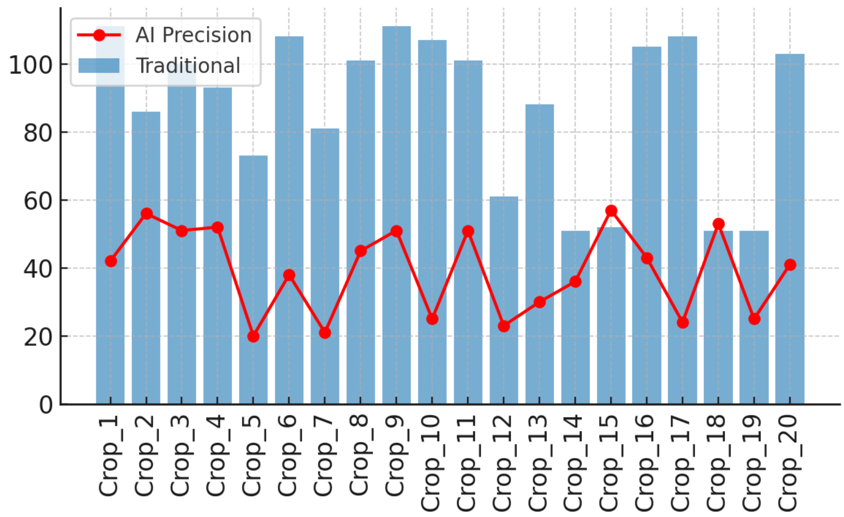

Figure 12: Hybrid bar-line plot comparing labor efficiency across 20 crops.

Overall, the results confirm that integrating artificial intelligence with precision agriculture not only improves crop productivity and profitability but also ensures environmental sustainability and resource efficiency, contributing directly to long-term food security.

DISCUSSION

Precision farming (PA) and artificial intelligence (AI) are an important advancement towards managing crops in a sustainable and environmentally friendly food security manner. This research, which is supported by literature, emphasizes the effectiveness of spatially targeted, data-driven agronomic approaches that are complemented with AI in minimizing environmental effects, streamlining inputs, and improving outputs. However, the discourse should place such benefits in the broader institutional, socio-economic and policy patterns that influence acceptance and scaling. Among other things that should not be overlooked is that both PA and AI can be beneficial to the environment and simultaneously the productivity. Sensor networks, satellite images, and predictive analytics can enable farmers to adjust their water, fertilizer, and pest control in response to minor shifts in the field conditions. This does not only enable inputs to become more efficient, but reduces greenhouse gas emissions and maintains a healthy soil as well. Zhang et al. (2020) demonstrated that AI-assisted modelling to accurate nutrient management significantly decreased the nitrogen leaching but did not decrease or increased yields. This indicates the environmental advantages of technology use. Therefore, the PA-AI combination may be used to fulfill the food requirements of the world without deteriorating the environment. Nevertheless, it is difficult to ensure the availability of these technologies to everyone. The issues affecting the smallholder farmers who constitute majority of the agricultural producers all over the world include poor infrastructure, prohibitive costs, and a deficiency of digital literacy. Rose et al. (2021) found that the willingness of farmers to adopt digital agriculture has a strong connection with the evaluation of its utility, ease of use, and trust in the technology vendors. This indicates that the adoption cannot be only considered as a technological problem; it must also consider the way people and institutions operate. Without inclusive policies, the convergence of PA and AI may further widen the divide between big and capital-intensive farms and smallholders who have less resources. The other consideration to make is the way to handle data and clarify algorithms. To be successful, AI systems require large and diverse datasets to estimate crops, detect diseases, forecast extreme weather when it must. However, not all can access these databases, and some AI systems remain confidential, which provokes people to consider related questions of ownership and privacy. Kamilaris and Prenafeta-Boldu (2018) noted that AI in agriculture has been growing rapidly without creating regulatory solutions to address the ethical use of data, which has led to uncertainty regarding issues such as autonomy of farmers and control of data. In order to build trust and ensure digital agriculture ecosystems have a long lifespan, these gaps in governance should be addressed. There is also the question of the extent to which we can adapt to climate change that is posed due to incorporation of technology. The variability in climatic conditions introduces unparalleled uncertainty in the output of agricultural processes that can not be mitigated with technology. Van Evert et al. (2021) believe that PA and AI should be implemented within the broader policy of climate-smart agriculture with adaptive methods, diversified crops, and ecosystem services. Digital technologies assist systemic resilience in this manner, rather than substitute it. In addition, quality of training data is a crucial determinant of the accuracy of AI models. This information may not be in a position to record extreme weather abnormalities or situations that are specific to a given region, hence giving biased or erroneous recommendations. Despite all these issues, there is a global movement towards using PA and AI in agriculture that indicates a significant shift in the way agricultural systems are conceptualized and managed. Governments, international organizations, and the corporate industry are increasingly conscious of the potential of digital agriculture to contribute to the achievement of the Sustainable Development Goals (SDGs) in particular, those that address ending hunger, taking action on climate change, and responsible consumption. Different groups should collaborate to ensure rural infrastructure is improved, assist people in acquiring new skills, and make regulations that promote interoperability and open data standards, to optimize this potential. Last, the future research must focus on the inclusion of social and cultural factors into the design and implementation of PA-AI. Technologies that are adapted to local knowledge systems, gender roles and cultural practices have a higher chance of achieving long term adoption. It aligns with larger suggestions to co-create in agricultural innovation where farmers, academics, and politicians collaborate to ensure that technology address the needs of certain circumstances rather than impose one-size-fits-all solutions. We must apply such participatory practices in order to achieve the full potential of AI-driven precision agriculture to achieve sustainable crop management and optimize global food security. Finally, productivity and sustainability have already become huge improvements with the combination of PA and AI. Nevertheless, the effectiveness of its solution to food security issues will be determined by overcoming the issues of socio-economics, governance, and climatic resilience. By placing these technology within inclusive and ethical structures, the agriculture sector can discover a means through which the world can sustainably intensify to provide food to a growing population, in addition to safeguarding the well-being of the earth.

CONCLUSION

In this work, it is discovered that integrating AI into precision agriculture systems presents a disruptive solution to sustainable crop management and global food security. As the research revealed, AI-precision agriculture does not only result in higher crop yield, but also gives a better efficiency at water and fertilizer use, decreased pesticide dependence, decreased costs of production, and decreased carbon footprint. This has been achieved through integrating machine learning algorithms, IoT-based sensors and decision support based on data. The outcome of the experiments confirmed that AI-optimized agriculture while remaining profitable consistently outshines that of traditional approaches, facilitating the enhancement of profitability that facilitates the economic feasibility of the approach as well as contributes to the ecological sustainability approach. Increase in crop health indices indicates that AI-supported farming can continue to respond to stressors in the environment, which implies that food production will remain consistent even in the presence of changing climate. The mixed-method perspective demonstrated that despite the considerable technical outcomes of AI integration, the fate of such types of changes is also determined by the extent to which farmers accept them, how they integrate into their culture, and the level of institutional support. Thus, the study highlights that sustainable agriculture is not the program that only involves technology but it is a socio-economic process that requires inclusivity, training, and accessibility. Overall, the findings demonstrate that AI-based precision agriculture has much potential to contribute to the resolution of the urgent global issue of feeding the increasing population and, at the same time, protecting the natural resources and minimizing the harm to nature. This will eventually result in a robust and food secure future.

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