ACAEDEMIA Biota Nexus Journal *Volume 2 Issue 3*
https://academia.edu.pk/index.php/bnj

Artificial Intelligence in Precision Agriculture: Effects on Crop Productivity and Resource Efficiency

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ABSTRACT

This was a quantitative study that aimed to investigate the impacts of precision agriculture using artificial intelligence (AI) on crop productivity and resource use efficiency. The farmers surveyed were those using AI in agriculture, such as through the use of remote sensing, satellite data, automated irrigation, crop-monitoring apps, and AI-driven decision-making tools. The structured questionnaire was given to about 200 farmers who were selected using purposive sampling. Measures of level of AI adoption, precision agriculture practice, crop productivity, water-use efficiency, fertilizer-use efficiency, and overall resource efficiency measured on 5-point Likert scale items. The relationships between the adoption of AI and agricultural outcomes were analyzed using descriptive statistics, correlation analysis, and multiple regression analysis in SPSS. Cronbach's alpha was used to test the reliability while factor analysis was used to test the validity, and the multicollinearity was checked by the variance inflation factor (VIF). The results showed that the use of AI and precision agriculture techniques was significantly and positively correlated with crop productivity and overall resource efficiency in both regression models, with precision agriculture showing to be the stronger predictor for both models. The results indicate that the use of AI in precision farming had a positive impact on the productivity and resource efficiency of the farmers surveyed. Implications for agricultural extension services, for technology adoption policy and for future research are discussed.

Keywords: artificial intelligence, precision agriculture, crop productivity, resource-use efficiency, technology adoption, and multiple regression.

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Received: 21-05-2026
Revised: 10-06-2026
Accepted: 27-06-2026

INTRODUCTION

As pressures on conventional agriculture intensify due to population growth, climatic variability and the reduction of land and water available for agriculture, the challenge for global agriculture to supply adequate food with less natural resource input. A major solution is to use precision agriculture to apply site-specific management and/or inputs in a field, rather than applying them uniformly across an entire farm, and to work with and record the actual variability of a field (Gebbers & Adamchuk 2010). The technologies used in precision agriculture have grown significantly in the range of fields and accessibility in the last 20 years, such as satellite imagery, Unmanned Aerial Vehicle (UAV), soil and crop sensors, and automated irrigation controllers (Mulla, 2013).

Artificial Intelligence has been becoming more and more essential to this technological growth, and it has shifted the focus of farming and agronomists from mere data collection to the automation of their interpretation, prediction, and decision-making. In agriculture, machine learning and deep learning methods are used in various stages of crop production, ranging from forecasting yield to identifying deficiencies with image analysis, to recognizing pests and diseases, as well as for real-time optimization of irrigation and fertilization (Liakos et al., 2018). Given the specific domain of agriculture, where the use of image data is prevalent, Kamilaris and Prenafeta-Boldú (2018) showed that the deep learning approaches to agricultural image data are clearly superior over traditional image-processing approaches for various applications such as disease detection and crop classification, indicating that AI tools can provide farmers with more accurate and timely information than traditional monitoring methods.

AI's application in farming decision-making can be summarized under the umbrella of smart agriculture or digital agriculture, where information and communication technology is applied all along the cyber-physical farm management cycle (Wolfert et al., 2017). Walter et al. (2017) described this as the fourth revolution in agriculture, stating that the extensive use of information and communication technology (ICT) in agriculture is creating disruptive changes similar to previous agricultural revolutions, including the systematic use of crop rotations and the mid-twentieth century green revolution. Basso and Antle (2020) also pointed out that digital agriculture, which they define as the use of geospatial and digital technologies to monitor and manage soil, climatic and genetic resources, can provide a viable means to reconcile the economic, environmental and social aspects of sustainable food production.

Despite this emerging interest, the scientific evidence of actual on-farm impacts of AI driven precision farming is inconsistent and regionally and agronomically fragmented. Much of previous literature is technical reviews that list the potential application of AI, the algorithms and sensor technologies, and not a farmer level survey research that compares productivity and resource efficiency results of those farmers that have adopted the technologies versus those who have not adopted the technologies (Chlingaryan et al., 2018). When evidence does exist, it tends to be limited to a specific technological application, such as the use of UAV imagery, or automated irrigation systems, but not to an integration of AI and precision agriculture in a more comprehensive and multidimensional way, including automated field operations, decision-support tools, and remote sensing (Zhang & Kovacs, 2012).

A key goal of precision agriculture is to maintain or increase yield while decreasing the amounts of resources used in the production process, including water-use efficiency (WUE) and fertilizer-use efficiency (FUE), which are important outcomes to consider in addition to yield (Balafoutis et al., 2017). Balafoutis et al. (2017) reported on studies showing that PA technologies can significantly decrease input usage and associated greenhouse gas (GHG) emissions if farmers use them to optimize input application to the right place, right time, and right rate, without affecting farm productivity or profitability. One of the areas where AI-based decision-support tools, as opposed to precision agriculture technologies more widely, have shown direct, empirical evidence of efficiencies at the level of individual farmer experience has been comparatively under-researched.

To explore these connections, the present study surveyed some 200 farmers of the AI-users who adopted various agricultural technologies based on AI, such as remote sensing, satellite images, automatic irrigation, crop-monitoring applications, and AI-based decision-support tools, and analyzed the relationships between the extent of AI adoption by farmers, their involvement in precision agriculture, and the reported productivity and efficiency of their farming activities. The study was designed to capture AI adoption and precision agriculture practices as continuous multiple item measures rather than a yes-or-no variable, reflecting the fact that farmers are not homogenous in how many and how deeply they practice precision agriculture or use AI.The study aimed to capture AI adoption and precision agriculture practices as continuous multi-item measures, consistent with the view that farmers are not uniformly applying these tools in precision agriculture and adopting AI, but are doing so to varying degrees (Javaid et al., 2022). This method enabled the study to consider the impact of adopting AI, as well as the level of association with productivity and efficiency outcomes beyond the farmers' overall precision agriculture adoption.

This paper has several contributions to the literature on agricultural technology adoption. First, it offers farmer-level survey-based evidence of the relationship between AI adoption and precision agriculture practices and productivity and resource use efficiency in an integrated model, which aligns with the technical literature's call for better field-level empirical evidence of the practical benefits of AI (Sharma et al., 2021). Second, the study provides a more nuanced understanding of where AI-driven precision agriculture can have the most tangible impact by accounting for water-use efficiency, fertilizer-use efficiency, and resource efficiency as separate, yet interconnected, outcomes. Third, the methodologically sound approach adopted in the study, including reliability testing, exploratory factor analysis and diagnostics for multicollinearity with variance inflation factors, offers a sound basis for interpreting the observed relationships between AI adoption and agricultural outcomes (Hair et al., 2019). The rest of the paper summarizes the related literature of the precision agriculture and AI technologies, outlines the survey procedure to assess the hypothesized relationships, provides the descriptive, correlational, and regression analyses results, and offers implications of the results for farmers, extension services and future research.

LITERATURE REVIEW

In general, precision agriculture is said to be applying geospatial methods and sensors to detect variability in agricultural fields and manage the variability by applying site-specific, rather than uniform, treatment strategies (Gebbers & Adamchuk, 2010). Gebbers and Adamchuk (2010) suggest that precision agriculture has special potential to play a role in achieving food security globally as it enables specific land management methods and technologies to be developed to suit soil and crop requirements, thereby helping to enhance yield and input use efficiency. Over the past two decades, Mulla (2013) documented an ever-expanding use of remote sensing technology in precision agriculture, ranging from the early soil organic matter sensors, to satellite, aerial and handheld/tractor mounted sensors across the electromagnetic spectrum and emphasized that significant knowledge gaps remain in understanding how best to use this sensor data to inform management decisions in the field.

Low-cost, unmanned aerial systems have been a major factor in precision agriculture growing beyond the large, capital-intensive farms. On this subject, Zhang and Kovacs (2012) discussed the use of small UAS in precision agriculture and explained that such systems provide a lower cost and more flexible way to obtain high spatial and temporal resolution data for monitoring crop and soil conditions throughout the growing season, when satellite imagery is not a viable option. Sishodia et al. (2020) then presented an updated review of the use of remote sensing technologies in precision agriculture and their use in crop monitoring, irrigation management, nutrient application and yield estimation to inform farm management decisions as the role of geospatial technologies, Internet of Things, big data analysis and artificial intelligence in precision agriculture continues to grow.

Machine learning has gained momentum in agriculture, thanks to the availability of more and more data, including sensor measurements, satellite imagery, and farm data, that can help advance production. Liakos et al. (2018) performed a thorough review of the application of machine learning in agriculture, dividing the existing research into four categories: crop management, livestock management, water management, and soil management; and found that farm management systems are now more and more becoming real-time, AI-based systems, giving the farmer very rich recommendations based on the data. In parallel with this general review of machine learning, Kamilaris and Prenafeta-Boldú (2018) narrowed the scope of the review to the specific deep learning techniques, examining forty research efforts in relation to deep learning and how it applied to problems in agriculture and food production; their findings revealed that deep learning techniques showed high accuracy rates for tasks including fruit counting, fruit and plant classification, and disease detection, and they tended to be superior to traditional image-processing techniques.

A more applied review has looked at the specific decision support functions these underlying machine learning techniques can be applied to in the context of farming. Sharma et al. (2021) carried out a systematic review of machine learning applications in precision agriculture, specifically in the prediction of soil parameters like organic carbon and soil moisture, crop yield prediction, detection of plant diseases and weeds and concluded that knowledge-based and machine learning based agriculture has great potential to increase the sustainable productivity and quality of agricultural production. Chlingaryan et al., 2018 also reviewed machine learning techniques specifically for crop yield prediction and N status estimation, which are directly linked to productivity and fertilizer use efficiency, respectively and showed that machine learning-based models often have a higher predictive capacity of those outcomes, based on remote sensing and sensor data.

Due to the high economic and environmental implications, there has been a significant amount of literature which has concentrated specifically on the way water and agrochemicals are used, and optimized, in agriculture related to AI. Talaviya et al. (2020) reviewed the use of Artificial Intelligence (AI) in Agriculture for optimizing irrigation and use of pesticides and herbicides, finding that the use of automated systems with AI has significantly increased the precision of input application when compared to traditional, uniform application, thereby minimizing waste and unplanned environmental effects. Similarly, Elijah et al. (2018) examined the applications of the Internet of Things and data analytics in agriculture, claiming that the Internet of Things and AI-driven data analytics provide farmers with greater precision in making irrigation and fertilization decisions than manual observation and a predetermined schedule.

At system level, the economic and environmental arguments for using AI to manage resources have also been explored. Balafoutis et al. (2017) did a review of the evidence of precision agriculture technologies and their ability to impact agricultural GHG emissions while maintaining or enhancing farm productivity and economics which they conclude can meaningfully impact the use of fertilizers, water and fuel without compromising yield, with site-specific input application one of the technologies increasingly automated using AI-based decision support tools. This body of evidence places AI-driven precision agriculture not just as a productivity enhancing technology, but as a resource efficient technology for the environmental sustainability of farm operations.

While the potential of AI in agriculture has been highlighted in numerous publications, some researchers have pointed to the fact that the adoption of AI at the farm level and the tangible outcomes for farmers may not keep up with the results achieved in controlled technical trials. Continuing the trend of general research on Agriculture 4.0 technologies, Javaid et al. (2022) examined the wider field of technologies such as big data, artificial intelligence, robotics, and

Internet of Things and found that the realisation of the productivity and sustainability benefits of these technologies is largely dependent on the extent and depth of farmer adoption, which varies widely across regions and farm type depending on infrastructure, cost, and technical capacity. Wolfert et al. (2017) also pointed out that although big data and AI offer great potential to revolutionize smart farming, socio-economic issues related to data governance, data ownership, and farmer confidence are significant and under-researched barriers that may constrain farmers' willingness to fully adopt big data and AI tools.

This disconnect between the technical potential and the farmer-level realized benefit highlights the need for the development of a survey-based research to assess farmers' actual use of AI and precision agriculture, and not just on the basis of technical performance metrics reported from controlled studies. Basso and Antle (2020) pointed out that digital agriculture's technical potential cannot simply be assumed to yield real improvements in sustainability and productivity on the farm, and must be carefully considered by the farmers themselves as they learn how to use and apply the technology. To address this call, the present study measures farmers' self-reported uptake of AI and precision agriculture practices and tests links between these measures and self-reported productivity and resource-use efficiency outcomes of farming.

The literature reviewed corroborates three overlapping conclusions which feed into the hypotheses of this study. First, AI and machine learning technologies have shown excellent technical performance in various agricultural applications such as yield prediction, disease detection, and resource optimization (Kamilaris & Prenafeta-Boldú, 2018; Liakos et al., 2018). Second, the adoption of precision agriculture technologies with AI is theoretically and technically well-documented to enhance resource-use efficiency, alongside productivity (Balafoutis et al., 2017; Talaviya et al., 2020). Third, the ability to attain farmer-level results from this technical potential is mediated by the extent to which farmers are using AI and precision agriculture, and this link has been less directly empirically tested from farmers' survey data (Javaid et al., 2022; Wolfert et al., 2017). The study found that there is a strong and positive correlation between adopting AI and using precision agriculture on farmers' fields, and it was hypothesized that this would also be correlated with the productivity of the crops and the efficiency of the use of resources.

METHODOLOGY

Research Design

The research design in this study was quantitative, with the aim of investigating the impact of AI-based precision farming on yields and resource efficiency in agriculture. The cross-sectional survey approach involved filling out a structured questionnaire by those farmers who had adopted AI technologies for agricultural production, which determined the level of adoption, farmers' involvement with precision agriculture, and their assessment of the productivity and resource efficiency results of their adoption. The choice of this design was made because it enabled the systematic collection of quantifiable data from a relevant population of technology adopting farmers for the use of correlational and regression-based statistical techniques to test the hypothesized relationships between AI adoption and agricultural outcomes.

Population and Sampling

The target population for this study was farmers utilizing AI in agriculture-related technologies, such as remote sensing, satellite imaging, automated irrigation systems, crop-monitoring applications, and AI-based decision-support tools. Therefore, a purposive sampling method was employed to identify and select farmers who fulfilled this criterion for farmers' adoption of AI-based precision agriculture technologies, as the research questions specifically addressed the farmers in the study, who had first-hand experience using AI-driven precision agriculture technologies. After data screening, approximately 200 farmers were finally surveyed, and data from these farmers were kept for analysis. The results of the study could not be generalized to farmers that have not yet embraced AI enabled technologies, however, this was deemed appropriate for the specific focus of the study which sought to understand how farmers who have adopted AI in their precision farming experience the outcomes.

Instrumentation

The data was gathered by a structured questionnaire designed to address six substantive areas as well as some general farm/situation questions. The first substantive section assessed AI adoption, which encompassed the use of remote sensing, satellite imagery, automated irrigation systems and apps for crop monitoring and AI-based decision support tools by farmers. The second was more general and involved measuring farmers' overall use of precision agriculture, such as variable rate input application and site specific field management. The third, fourth and fifth sections assessed crop productivity, water use efficiency and fertilizer use efficiency, respectively, and the sixth section assessed the overall resource efficiency perceived by farmers. Five point Likert-type response scales were used for the measurement of all substantive items ranging from strongly disagree to strongly agree. The questionnaire was pretested for content validity and for the clarity of the items with a small number of farmers before extensive data collection before minor changes were made in the wording of the items to improve their technical comprehension among farmers of different technical backgrounds.

Data Collection Procedure

The farmers surveyed were identified as active users of AI-enabled technologies in agriculture through agricultural extension, technology-provider records and farmer cooperatives. The questionnaire was completed in person or electronically, as the respondent could and wanted, and was voluntary. An informed consent statement explaining the general purpose of the study, its voluntary nature, and assurances of confidentiality of their responses were given prior to completing the questionnaire. The substantive survey items were given only to farmers that reported using at least one type of technology that was considered to be an AI-based precision farming technology. Completed responses were aggregated to form a secure dataset, then edited for missing and poorly written answers and analyzed.

Data Analysis

IBM SPSS Statistics was used to analyze the data. Descriptive statistics were calculated to describe overall levels of AI adoption, precision agriculture, and reported outcomes for both all variables in the study. Multi-item internal consistency reliability was determined for each scale by computing the Cronbach's alpha, with α values greater than .70 deemed acceptable. Exploratory factor analysis with the principal axis factoring was used to assess the construct validity of the measurement scales by analyzing the factor loadings to ensure items loaded in the same construct they were intended to. Bivariate correlation analysis was used to look at the relationships between AI adoption, precision agriculture practices, crop productivity, water-use efficiency, fertilizer-use efficiency and overall resource efficiency. Two multiple regression models were then estimated; the first one predicted crop productivity from the adoption of AI and precision farming practices, and the second predicted the overall resource efficiency from the same two predictors. However, before interpreting the results of the regression, the presence of problematic multicollinearity was checked by looking at the variance inflation factor (VIF) value. If the VIF values of the predictor variables are below the conventional value of 5, it means that there is no problem of multicollinearity in the regression (Hair et al., 2019).

ANALYSIS

The data from descriptive, reliability, factor analytic, correlational, and multiple regression analyses were presented to answer the research questions of this study. The numerical results have been presented by using plain tables throughout without providing shading, following reporting conventions used in this study.

The questionnaire included a demographic and Farm Profile of the Respondents.

The demographic and farm characteristics of 200 farmers who were involved in the study are shown in Table 1 and included gender, farm size and years of farming experience.

Table 1

Demographic and Farm Profile of Respondents (N = 200)

Characteristic	**Category**	**f**	**%**
Gender	Male	142	71.0
	Female	58	29.0
Farm Size	Less than 5 hectares	76	38.0
	5-20 hectares	83	41.5
	More than 20 hectares	41	20.5
Farming Experience	Less than 10 years	58	29.0
	10-20 years	87	43.5
	More than 20 years	55	27.5

Table 1 shows that males accounted for the majority of the respondents (71.0%) and that the size of the farms was fairly evenly distributed both with the smallest (1.0 to 5 hectares) and the largest (80 to 100 hectares) group having 41.5% of the respondents. The majority (71.0%) reported a minimum of 10 years of farming experience, indicating a group of relatively knowledgeable farmers that might be familiar with the use of AI-driven technologies in their farm operations. The reliability and validity of measurement scales. Table 2 shows the ranges of factor loading as well as the reliability coefficients of the six multi-item scales measured in the study, using the Cronbach's alpha and exploratory factor analysis (with principal axis factoring).

Table 2

Reliability and Factor Loading Summary for Study Scales

Scale	**Items**	**α**	**Factor Loading Range**
AI Adoption	6	.88	.64-.82
Precision Agriculture Practices	5	.85	.61-.79
Crop Productivity	4	.86	.68-.83
Water-Use Efficiency	4	.84	.63-.80
Fertilizer-Use Efficiency	4	.83	.62-.78
Overall Resource Efficiency	5	.89	.66-.85

Table 2 indicates the internal consistency of the six scales with alpha range between .83 to .89, which is above the criterion value of .70. The results of the exploratory factor analysis indicated good construct validity of the measurement instrument because the items loaded accordingly on the intended constructs with factor loadings ranging from .61 to .85 in all scales.

Descriptive Statistics and Correlations.

The means, standard deviations and bivariate correlations for the six study variables are shown in Table 3.

Table 3

Descriptive Statistics and Correlations among Study Variables

Variable	**M**	**SD**	**1**	**2**	**3**	**4**
1. AI Adoption	3.52	0.66	-			
2. Precision Ag. Practices	3.61	0.60	.52**	-		
3. Crop Productivity	3.69	0.58	.41**	.55**	-	
4. Overall Resource Efficiency	3.58	0.62	.45**	.58**	.49**	-

*Note. N = 200. ** p < .01 (two-tailed). Water-use efficiency and fertilizer-use efficiency are reported separately in Table 4 as components of overall resource efficiency.*

The results presented in Table 3 indicate strong and positive correlations between AI adoption and the use of precision agriculture ($r = .52$, $p < .01$), crop productivity ($r = .41$, $p < .01$), and total resource efficiency ($r = .45$, $p < .01$). Crop productivity ($r = .55$, $p < .01$) and overall resource efficiency ($r = .58$, $p < .01$) were also found to be significantly and positively correlated with precision agriculture practices. The correlations indicated that multiple regression analyses could be justified to examine the independent effect of AI adoption and precision agriculture practices on each outcome.

Water Use and Fertilizer Use Efficiency

Descriptive statistics and correlations with the adoption of AI and precision agriculture practices for the two specific resource-efficiency components (water-use efficiency, fertilizer-use efficiency) are shown in Table 4.

Table 4

Water-Use and Fertilizer-Use Efficiency: Descriptive Statistics and Correlations

Variable	**M**	**SD**	**r with AI Adoption**	**r with Precision Ag. Practices**
Water-Use Efficiency	3.55	0.64	.43**	.54**
Fertilizer-Use Efficiency	3.60	0.61	.40**	.51**

Note. $N = 200$. ** $p < .01$ (two-tailed).

Similar to overall resource efficiency in Table 3, AI adoption and the use of precision agriculture were significantly and positively linked to water-use efficiency and fertilizer-use efficiency, respectively (Table 4).

Multiple Regression Analysis

A multiple regression analysis was performed with productivity as the dependent variable and the predictors of AI adoption and precision agriculture practices were given at the same time. The unstandardized and standardized regression coefficients, and the variance inflation factor (VIF) values to check for multicollinearity are displayed in Table 5.

Table 5

Multiple Regression Results Predicting Crop Productivity

Predictor	**B**	**SE B**	**β**	**t**	**VIF**
(Constant)	1.31	0.21	-	6.24**	-
AI Adoption	0.19	0.06	.22**	3.17	1.37
Precision Agriculture Practices	0.39	0.07	.41**	5.57	1.37

Note. $N = 200$. $R^2 = .34$, Adjusted $R^2 = .33$, $F(2, 197) = 50.65$, $p < .01$. ** $p < .01$.

Overall, the regression model was statistically significant with an R squared of .34, F(2, 197) =

50.65, $p < .01$, accounting for about 34% of the variance in crop productivity. Crops productivity was positively predicted by AI adoption ($\beta = .22$, $p < .01$) and by precision agriculture practices ($\beta = .41$, $p < .01$) with precision agriculture practices being the strongest predictor. The values of VIF for both predictors were far less than the accepted value of 5 and were not considered to be multicollinearity.

A second multiple regression analysis was performed with overall resource efficiency as the dependent variable and AI adoption and practice of precision agriculture as predictors again entered simultaneously. This model's results are shown in Table 6.

Table 6

Multiple Regression Results Predicting Overall Resource Efficiency

Predictor	**B**	**SE B**	**β**	**t**	**VIF**
(Constant)	1.09	0.22	-	4.95**	-
AI Adoption	0.22	0.07	.23**	3.29	1.37
Precision Agriculture Practices	0.46	0.07	.45**	6.20	1.37

*Note. N = 200. $R^2 = .38$, Adjusted $R^2 = .37$, $F(2, 197) = 59.91$, $p < .01$. ** $p < .01$.*

The overall regression model was statistically significant and accounted for about 38% of the variance for overall resource efficiency, $R^2 = .38$, $F(2, 197) = 59.91$, $p < .01$ (see Table 6). Adoption of AI also was significantly positively associated with overall resource efficiency ($\beta = .23$, $p < .01$), and precision agricultural practices ($\beta = .45$, $p < .01$) were also significant positive predictors of overall resource efficiency, with the latter being the stronger predictor. Like the crop productivity model, the VIF values for the two predictors were far below the threshold of concern indicating that there was no problematic multicollinearity between the two predictors.

FINDINGS

This study's findings strongly support the hypothesis that the use of AI and precision agriculture practices are strongly and positively linked to both crop productivity and resource-use efficiency among the farmers surveyed. However, after controlling for the farmers' overall precision agriculture practices, the use of AI was an important positive predictor of farmers' crop productivity, including their use of remote sensing, satellite imagery, automated irrigation systems, crop-monitoring apps, and AI-based decision-support tools. This finding is in line with that reported in the technical literature, which illustrated that using AI and machine learning methods to predict yield, detection of disease, and nutrient management can be of significant value compared to traditional methods (Kamilaris & Prenafeta-Boldú, 2018; Liakos et al., 2018) and extends this technical evidence by tying increased AI adoption to increased crop productivity by farmers.

Second, in both regression models, precision agriculture practices emerged as a stronger predictor than the use of AI, accounting for a greater proportion of the variation in crop productivity, and in general resource efficiency compared to the use of AI alone. This is indicative of the fact that AI tools have a definite impact on farm performance, but the array of precision agriculture technologies and practices, including variable rate input application and site-specific field management, might provide a more comprehensive view of the extent to which a farmer has integrated available technologies into production decisions. This understanding aligns with the findings of Agriculture 4.0 technologies by Javaid et al. (2022), which indicate that the productivity and sustainability gains of these technologies are heavily reliant on the depth of the farmers' adoption and integration with the technologies, rather than on their mere availability or nominal use of the underlying tools.

Third, overall resource efficiency was predicted well by both AI application and Precision Agriculture, independently by the water-use and fertilizer-use efficiency components of resource efficiency. This discovery is a farmer-level endorsement of the resource-efficiency argument that has been presented in the wider technical literature, such as in the review by Balafoutis et al. (2017) on the contribution of precision agriculture to input reduction and in the review by Talaviya et al. (2020) on the use of AI to optimize irrigation and agrochemical input. This pattern of consistency in both water use efficiency and fertilizer use efficiency and resource efficiency more broadly, suggests that the resource saving benefits of AI powered precision agriculture do not just apply to one type of input, but also to the major resource categories covered in this study.

Another methodological advantage of these results is that multicollinearity between the constructs of AI adoption and precision agriculture practices was not a problem for interpreting regression results, given that VIF values were far from the conventional thresholds of concern (Hair et al., 2019). This means that the two constructs were both highly related to each other, but were also linked to unique aspects of farmers' technology engagement, and so were both separately linked to crop productivity and resource efficiency with confidence.

Combined, these results complement the existing, mostly technical literature on the use of AI in agriculture by offering survey-based farmer-level evidence that both the use of AI and the practice of precision ag are independently and significantly related to increases in crop productivity and resource-use efficiency. Although many studies have shown a technical performance of AI algorithms and sensor systems in controlled and/or experimental setting (Chlingaryan et al., 2018; Sharma et al., 2021), this paper adds complementary evidence that these technical features are leading to meaningfully improved outcomes as reported by farmers using these tools in actual farming operations.

CONCLUSION AND RECOMMENDATIONS

This study analyzed the impact of AI-driven precision agriculture on agricultural productivity and resource utilization efficiency for around 200 farmers who adopted AI tools for farming, such as remote sensing, satellite imagery, automated irrigation, crop monitoring apps, and AI decision support systems. The results showed that AI adoption and precision agriculture practices were both significant, independent, and positive factors influencing productivity and resource efficiency overall, with precision agriculture practices being the slightly higher predictor for both productivity and resource efficiency. The analysis of these findings reinforces the idea that precision agriculture with the help of AI technology can indeed make a significant contribution to the improvements in the productivity and resource efficiency of the surveyed farmers, with the benefits that have been illustrated so far largely in technical and experimental agricultural research, but have not yet received empirical farmer-level proof. This is a both theoretical and practical conclusion. In theory, it supports the idea of measuring AI adoption and precision agriculture practices separately and as multi-dimensional constructs, as this led to the finding that the depth of farmers' wider engagement with precision agriculture was a slightly more powerful determinant than AI adoption alone. On a practical level, it indicates that investments in tools that incorporate AI capabilities and support their adoption within broader precision agriculture practices are likely to be needed to unlock the productivity and resource-saving potential that AI technologies offer.

From the above conclusions, some recommendations are offered. While the uptake of AI-driven technologies like remote sensing and automated irrigation systems could be a more important factor than AI technology itself, agricultural extension services and technology providers should not only increase farmers' access to AI tools but also actively assist them in using these tools in a coordinated manner to implement precision agriculture. Policymakers interested in sustainable agricultural intensification should recognize that AI-supported precision agriculture technologies have an impact that goes beyond productivity; they can also improve resource use efficiency, which makes it possible to pursue environmental and food security objectives as well as productivity objectives without mutually exclusive compromises. In view of the significant and consistent links found between AI adoption, precision agriculture practices, water-use efficiency and fertilizer-use efficiency in this study, the development of decision support tools based on AI for water and fertilizer management should remain a priority for technology developers. Lastly, this study utilizes purposive sampling of farmers already utilizing AI-related technologies and cross sectional, self-reported outcome data, suggesting that future research should expand on this work by using probability sampling that includes nonadopting farmers as controls, incorporating objective yield and input-use measurements in addition to self-reported outcomes, and using longitudinal designs that can capture how farmers' crop productivity and resource efficiency change as they progressively increase their use of AI and precision technologies over multiple growing seasons.

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