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ORIGINAL RESEARCH ARTICLE

Digital and precision farming, emissions trade-offs, and food crop yields in Pakistan

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Abstract: Climate change, low productivity, and environmental degradation are jeopardizing Pakistan's agricultural sector, whose sustainability and resilience can be potentially improved using agricultural technology (AgriTech). This study examines the relationship between digital technology, precision farming, methane (CH_4) and nitrous oxide (N_2O) emissions, and Pakistan's grain crop yields to determine how modern technology impacts ecologically responsible farming. The study used Autoregressive Distributed Lag bounds testing to explore how data analytics, modern farming technologies, and agricultural value-added (AGRI) affect grain crop yields in the short and long run. Long- and short-term crop yields were reduced by AGRI. Data analytics could only produce short-term advantages, but precision agriculture tools and digital technologies assisted in enhancing yields significantly. CH_4 and N_2O emissions were significantly associated with yield growth, suggesting efficiency trade-offs. This study found that digital technology is an intensive farming method, resulting in higher yields linked to higher input consumption and emissions. The technology also enabled precision agriculture to increase productivity with lower environmental impacts. Taken together, the findings of the current study collectively underline the need to merge smart farming technologies with environmentally friendly methods to boost Pakistan's agricultural productivity and sustainability.

Keywords: AgriTech; Precision farming; Agricultural sustainability; Climate dynamics; Environmental stewardship; Food security; Pakistan

1. Introduction

The ever-increasing global population underscores the need to ensure the availability of wholesome food on every continent to prevent food shortages. A rise in the use of agrochemicals, such as fertilizers, insecticides, herbicides, and pesticides, has been noted in an effort to enhance the quantity and quality of agricultural produce.[1] About two-thirds of the people in developing countries and fewer than 5% of the population in industrialized countries are employed in agriculture, a figure that is decreasing as more nations undergo industrial development.[2] Industrialized nations have seen improvements in labor productivity due to technical advancements made possible by research and development efforts, which serve to lower input costs and increase the efficiency of total production factors.[3] Regardless of whether in emerging or affluent nations, the agricultural industry must continue to operate to supply the world's population with food. Despite the ongoing technological advancements, feeding the world's population, which is projected to reach 9.7 billion people by 2050, remains a challenging task.[4] In recent years, farmers and agricultural businesses have implemented "smart farming" by integrating machine learning and the Internet of Things (IoT) into their operations.[5]

Fuentes-Peñailillo *et al*.[6] describe precision agriculture as an information-driven, production-oriented, integrated agricultural system that maximizes profitability, efficiency, site-specific, and long-term productivity with minimum environmental impact. Population growth and changes in food consumption have increasingly augmented the severity of agricultural water pollution. As agricultural systems struggle to satisfy global food demand, water footprint emerges as a major concern.[7] Strategic agricultural decisions may reduce the effect of farming on water quality, particularly non-point source pollution. There are apprehensions about agriculture-related water pollution in rich and developing nations. In developed countries, the agricultural sector contributes to water pollution through the heavy use of chemical fertilizers, pesticides, and other inputs. As they drain into nearby waterways, these contaminants eutrophicate and destroy the aquatic ecosystems. Agricultural runoff may harm groundwater, which many communities depend on.[8]

Wheat, maize, and barley are among the common crops grown in Pakistan, but rice remains the most significant since it is the staple of most Pakistanis and generates export revenue. Methane (CH_4) emissions from flooded paddies have a greater influence on Pakistan's rice output than other crops due to water usage and emission dynamics. While wheat and maize also contribute to Pakistanis' caloric intake, rice represents a more important crop for rural livelihoods that require seasonal labor cycles, occupying a significant spot in the country's agro-industrial activities. Rice, a staple for 4 billion people, provides 21% of the world's calories and 15% of its protein. It is grown in agro-industrial zones from Latin America and Africa to South and Southeast Asia. In this era of the Green Revolution, the application of genetic approaches has enabled enhanced rice production.[9] However, rice-growing acreage, output, and productivity have shown signs of decline in the first decade of this century. Poverty and rice agriculture are linked because over 900 million people in severe poverty grow or consume rice. Sharma *et al.*[10] found that most of the 400 million malnourished people in the world cultivate rice on plots of <20 ha. Due to the growing worldwide incomes and populations, rice consumption is expected to climb from 479 million tons in 2014 to 536 – 551 million tons by 2030. To accommodate this need, agricultural and irrigation infrastructure expansion should be implemented.

Basic data-driven applications like Global Positioning System (GPS)-enabled autonomous steering devices are employed in agricultural decision-making. However, the technologies used vary widely, and each one requires unique types of data about the soil's fertility, nutrient levels, water retention capacity, weed density, and weather patterns such as rainfall and temperature (TEMP).[11] Precision agriculture is widely defined, although its application differs across developed and developing countries. Big farms in industrialized nations have access to many technologies. However, developing-world farmers face financial, infrastructural, and technical constraints.[12] Receptivity to new ideas and information, age, technological complexity and cost, financial help, and farm size all affect the adoption of precision agriculture. These limitations make adoption slower and more uneven compared to earlier agricultural technology, with considerable differences among farming operations.[13]

Pakistan is an intriguing case study for understanding emerging nations' growth and development. It has a strong agricultural base, a growing industrial sector, and a fast-growing services sector.[14] Pakistan is the world's sixth most populous country, with about 230 million people. Despite these benefits, poverty, infrastructure, and inequality persist throughout the country. Pakistan's complex social, cultural, and natural landscape provides many development indicators for evaluating economic growth.[15] The diverse mix of rural and urban regions, various climates, and substantial socioeconomic inequalities in the country make studying development paths difficult.[16] However, since Pakistan has undergone both tremendous economic growth and relative stagnation, it provides an ideal case for examining what makes an economy successful.

Pakistan is particularly vulnerable to the ramifications of climate change, such as rising TEMPs and erratic precipitation, which pose a threat to its economy.[17] Thus, addressing environmental issues in a climate-sensitive economy, like Pakistan's, is a pertinent topic inherent in the main objective of relevant research. The findings from this research may address the global demands for ecologically responsible leadership and help advance climate-resilient policy. Pakistan's economic priorities are aligned with the Sustainable Development Goals (SDGs) and global development targets. Pakistan's economic priorities are aligned with the SDGs and global development targets. The current study examines topics relevant to SDGs 17 (Partnerships for the Goals), 6 (Clean Water and Sanitation), 13 (Climate Action), and 4 (Quality Education), which have close associations with Pakistan's economy, demonstrating their significance to worldwide development.[15] Pakistan's economic reforms, poverty reduction, and infrastructure development off-era transformative model for other developing countries facing the same developmental challenges.

The resource endowment, financial policies, level of science and technology, economic development, employment ratio, and market demand in Asia vary significantly due to the region's vast geography.[18] The configurations reveal a lack of boundary conditions, such as the rate of land use and fertilizer input, although these variables are partially influenced by fundamental factors like climate, soil quality, and economic conditions. Meanwhile, these indices are critical for ensuring food security in Asia. The ability of industrialized economies to produce grains is assured due to favorable regulatory environments and high levels of agricultural mechanization. De Rosa *et al*.[19] advocate for fostering a conducive policy environment and providing technical assistance to improve agricultural practices in rural regions. However, for long-term development, both increased agricultural production and improved environmental conditions are necessary. Enhanced agricultural output promotes economic growth by reducing poverty, improving income distribution, and increasing food production. Raihan *et al*.[20] further elaborate that increased agricultural output benefits the environment. Economic growth is linked to agricultural output, driving the need for improved environments, goods, public amenities, and the enactment of environmentally friendly legislation.

The current study was conducted to address the following research objectives:

(i) To investigate the role of agricultural technology (AgriTech) in driving agricultural sustainability, productivity, and resilience in Pakistan's agricultural landscape.

(ii) To examine the impact of adoption rates of AgriTech by farmers, environmental factors, and digital agricultural technologies on cereal crop yield (CCY) in Pakistan.

(iii) To assess the causal relationships and directional influences among key variables including CCY, precision agriculture technology (PAT), digitization in agriculture, agricultural value-added (AGRI), environmental factors, and farmer adaptation rates.

The study presents some new sustainable agricultural insights for developing markets. Instead of focusing on technological adoption or environmental effects, this study examines the influence of precision agriculture, data analytics, CH_4, and nitrous oxide (N_2O) on grain crop yields in Pakistan. The findings challenge our conventional wisdom, revealing that macro-level agricultural growth and field-level productivity diverge structurally and that agricultural value added and grain yields negatively correlate in both the short and long terms. The study on Pakistan, a country with low digital penetration in the agricultural sector and high climate hazards, provides contextualized empirical data to guide technology and policy changes. This study applied the Autoregressive Distributed Lag (ARDL) bounds testing, which distinguishes between short-term adaptation impacts and long-term technological implications on crop yield, providing a more complete view of agricultural processes. This study is methodologically substantial and policy-relevant for enhancing climate resilience and food security in Pakistan and similar agricultural economies.

The study is structured as follows: the first section is an introduction of the topic, as discussed earlier, followed by a literature review in the second section. Data and methodology are presented in Section 3. Section 4 presents the results and their discussion. The final section showcases the conclusions of this study.

2. Literature review

In Pakistan, AgriTech and precision farming are modernizing the agricultural sector, a vital element of the economy. Rising climatic unpredictability, resource inefficiency, and stagnant yields have increased the need for inventive, technology-driven solutions, but rural areas are still dominated by the usage of traditional methods. GPS-enabled equipment, remote sensing, soil sensors, and real-time data analytics may boost crop yields in precision agriculture.[21,22] Pricing, digital literacy, and infrastructural constraints prevent regular usage of these technologies.[23] Few studies have integrated emissions data or long-term sustainability indicators into technological applications, focusing instead on yield projections and irrigation management.[24,25] Despite the availability of much literature on how machine learning, drone surveillance, and the IoT are changing agriculture worldwide, there is little Pakistan-specific empirical research, especially on smart farming technology and environmental outcomes like greenhouse gas mitigation. This research links AgriTech interventions to crop yields, CH_4 and N_2O emissions, and technology adoption in Pakistan's grain-producing areas, bridging empirical and contextual gaps. This expands on the growing yet untapped nexus of digital adoption, climate resilience, and precision agriculture.

Natural factors such as weather and soil quality are not the only ones that affect farming; environmental and economic concerns also play a major role.[26] A comprehensive grasp of the interplay between economic and environmental factors on AGRI is necessary to develop sustainable agricultural policies and practices. Factors such as government subsidies, trade rules, customer demand, and financial expenditures in agricultural research and development directly influence the value-added in agriculture.[27] Subsidies from the government can influence agricultural production and the profitability of farming businesses. Besides, a more open market enabled by less restrictive trade agreements between countries will allow for higher agricultural exports and increased economic values of their goods and produce. Agricultural infrastructure and technology upgrades that boost output can raise the value-added to agriculture. Environmental factors also substantially impact the value-added in agriculture.[28] Climate change, water scarcity, land degradation, and biodiversity loss are some of the factors that may significantly affect the value-added to agriculture. Lower AGRI may result from unpredictability in weather patterns, such as prolonged droughts or strong rainstorms, which hurt crop harvests and animal productivity. Soil erosion, salinization, and deforestation are further causes of agricultural land degradation that lower the value of agriculture by lowering the long-term productive potential of the land. Thus, finding a middle ground between the monetary and ecological aspects of agricultural value addition is crucial for promoting sustainable agricultural practices.[29] Organic and precision agriculture are two environmentally friendly agricultural methods that may contribute to the economy. To lessen the impact of environmental factors on agricultural value, investments should be made in research and development (R&D) to invent crops that are adaptable to climate change and sustainable land management approaches. Implementing a holistic strategy that blends economic development with environmental management may help to achieve sustainable growth in AGRI and conserve natural resources for future generations.

Investing in R&D has a major impact on the production and innovation scene in the agricultural sector, especially when it comes to cereal crops. The allocation of funding for agricultural R&D directly affects the development of innovative farming practices, improves crop varieties, and fosters the usage of sustainable agricultural approaches. These factors together influence the yield of cereal crops to a large extent.[30] Increased investment in R&D in the agricultural sector may achieve better agricultural yields and resilience. Improved CCYs, food security, and solutions to the problems caused by a growing global population may be achieved by financial investments in agronomic research, which leads to the creation of drought-tolerant, disease-resistant varieties of cereal crops.[31] Sustainable farming practices that encourage efficient use of resources and environmental protection are another outcome of R&D spending for agricultural production. Prioritizing R&D in cereal crop production goes beyond merely ensuring sustainability and improving yields. In addition to bolstering rural economic development and agricultural diversity, it helps create value-added commodities and processes. To meet the evolving needs of consumers and boost agricultural competitiveness, investments in post-harvest technologies and food processing advances have resulted in a wide range of cereal-based products. R&D in agricultural production greatly improves CCYs, guaranteeing food security, environmental sustainability, and economic success.[32] To tackle the complex issues confronting the global agriculture business, policymakers should seize the opportunity for change that R&D presents by advocating for a collaborative and interdisciplinary approach to agricultural research. The strategic allocation of research and development money requires cooperation between educational institutions, research groups, and agricultural stakeholders.[33] Best practices may be more easily adopted across agroecological zones if encouraged by public-private partnerships and international collaboration in agricultural research. R&D expenditures from governments and NGOs are reflective of the significance of agricultural development and food security.[34] Establishing a supportive legal framework that encourages private sector engagement in agricultural R&D boosts innovation, entrepreneurship, and the commercialization of research results, cultivating a thriving and strong sector for the production of cereal crops. The combination of smart technology with sustainable farming methods has garnered much attention from academics and policymakers because it might solve the pressing problems in rural development. In a study conducted by Mutengwa *et al*.,[35] it was found that the use of IoT sensors and precision agriculture methods contributed to tremendous improvements in crop yield, resource efficiency, and overall farm management. These innovations may raise the living standards of rural residents and revolutionize traditional agricultural practices.

Precision agriculture increasingly uses explainable artificial intelligence to increase agronomic decision-making accuracy and interpretability. Recently, this integration has grown in popularity. For instance, Abekoon *et al.*[36] trained machine learning models using the SHAP and LIME techniques to estimate soil nutrient contents such as sodium, phosphorus, and potassium during cabbage production, contributing substantially to this area of research. According to their study, explainable models correctly forecast essential soil traits and give meaningful information about how each input feature contributes. This finding is crucial to Pakistan since site-specific nutrition management is still problematic. Farmers may use interpretable models to target fertilization to understand how inputs, soil type, and weather impact nutrient variability. SHAP- or LIME-based frameworks may accelerate data-driven nutrient management system adoption in Pakistan's digital agriculture industry, helping to increase yields and minimize environmental impact.

2.1. Research gaps

Despite the rapid uptake of smart technology in agriculture, several research gaps persist. Existing literature indicates that IoT sensors and precision agriculture enhance agricultural yields and resource efficiency.[30,37] However, few studies have explored the impact of these technologies on cereal crop output in underdeveloped countries like Pakistan.[38,39] In addition, researchers based in the industrialized regions that benefit profoundly from better agricultural infrastructure and financial support tend to neglect the challenges faced by resource-constrained farmers.[40] While smart agriculture's socioeconomic implications have been studied,[41] its immediate and long-term effects on AGRI remain unclear. Imran *et al.*[42] found that government subsidies and trade policies directly influence AGRI, yet little is known about how environmental factors, such as severe weather, affect CCYs. The bidirectional causality between environmental elements and agricultural practices has not been adequately explored in relation to precision agriculture technologies and the rates of their adoption by farmers. This gap underscores the need for further regional studies on environmental conditions, agricultural economic outcomes, and technological adoption.

2.2. Contribution of the study

The current study aims to explore the link between digital agriculture, precision farming, and environmental emissions, particularly CH_4 and N_2O, in Pakistan's crop production, as part of the agricultural sustainability research. Most research has focused on agricultural productivity or environmental challenges, but few have examined how to increase food crop yields while limiting environmental impact.[43,44] This study examines how data analytics and smart farming technologies affect agricultural returns, environmental externalities, and crop harvesting time. Although economically desirable, value-added agriculture may reduce output over time due to high input intensity and resource depletion. The research also proposes a policy-relevant paradigm that balances productivity gains with environmental trade-offs for scalable, sustainable agriculture in developing nations. This broad vision, unique to Pakistani agriculture, may develop theoretical and practical aspects of sustainable farming in the face of climate change.

The study improves this unique feature in three ways. First, it investigates how modern agricultural technology affects food crop yields in underdeveloped nations, which has been understudied. Technology, precision farming, and data analytics are examples of modern agricultural innovations. Second, it integrates ecological responsibility and productivity by assessing CH_4 and N_2O emissions as key trade-off elements. Third, the study employs ARDL bounds testing to distinguish short- and long-term dynamics. This enables a more detailed evaluation of technology performance over time. This research can help policymakers, technology developers, and agricultural stakeholders in Pakistan and other countries understand that value-added agricultural practices can accidentally reduce yields due to resource overuse. However, digital tools and precision farming can boost productivity at lower environmental costs.

3. Data and methodology

Pakistan's cereal crop examines productivity, technology, environment, and climate resilience. Table 1 shows the variables and their measurements.

Table 1. List of variables

Variables	Symbol/ Abbreviation	Measurement	Proxy variable	Rationale	Data source
Cereal crop yield	CCY	Tons per hectare	N/A	Direct measure of agricultural productivity impacted by smart technologies and sustainable practices	World Bank[45]
Precision agriculture technology	PAT	Number of tractors	Automated machinery deployment	Automation level of agricultural machinery, including autonomous tractors, for precise planting, harvesting, and other tasks	World Bank[45]
Weather condition	TEMP	Centigrade	Average temperature	Weather elements such as temperature and precipitation affect agricultural outcomes	CCKP[46]
Agricultural value-added	AGRI	Constant 2015 USD	N/A	Reflects the efficiency of labor utilization in agriculture, influenced by smart technologies and sustainable practices	World Bank[45]
Environmental factors	CH_4	Metric tons	CH_4 emissions	CH_4 emissions from agricultural activities contribute to global warming	World Bank[45]
	N_2O		N_2O emissions	N_2O emissions from agricultural activities contribute to global warming and ozone depletion	World Bank[45]
Data analytics and machine learning	DAML	% of GDP	R&D expenditures	Investments in R&D activities aimed at improving agricultural processes and outcomes	World Bank[45]
Farmers' adoption rate	FAR	% of population	Rural internet users	The rate of farmers adopting smart agricultural technologies and practices	World Bank[45]

Abbreviations: CH_4: Methane; GDP: Gross domestic product; N/A: Not available; N_2O: Nitrous oxide; R&D: Research and development.

The dependent variable is CCY, measured in tons per hectare. Tractors represent PAT, which automates and mechanizes agriculture. The total monthly precipitation (TEMP) recorder tracks meteorological conditions to account for climate change's influence on agriculture. The AGRI in constant 2015 USD measures how successfully the agriculture sector adapts to new technology. Two major greenhouse gas emissions, CH_4 and N_2O, indicate environmental stress. Rice and livestock farming produce waste gases that may threaten sustainability. Data analytics and machine learning (DAML) were measured in the percentage of gross domestic product (GDP) dedicated to R&D that advances agricultural technology. Due to its access to digital agricultural solutions and market data, rural internet connection is a good measure of farmers' adoption rate. The variables were collected from reliable international sources, including the World Bank and the Climate Change Knowledge Portal (CCKP), and monitored yearly from 1990 to 2022. The dataset was processed for ARDL modeling to ensure consistent size, interpretation, temporal coverage, and stationarity. All variables were checked for unit roots and adjusted for uniformity. The model's eight core variables offer a solid foundation for studying agricultural productivity and the environmental-technological nexus.

The present study employed the ARDL bounds testing approach to analyze the relationship between digital agriculture, precision farming, CH_4, N_2O emissions, and food crop yields in Pakistan. The ARDL framework integrates short- and long-term influences into a single estimating structure, even when variables have varied integration orders (I(0) and I(1)). Data irregularities and structural failures are common in underdeveloped countries like Pakistan; therefore, this flexibility helps to utilize this statistical technique. It can also capture complicated trade-offs between agricultural innovation and environmental degradation since the model definition includes emissions-technology adoption interaction variables. This method reinforces empirical results and provides a framework for policymakers to balance fast technological growth with environmental damage.

3.1. Econometric framework

The study employed the Phillips–Perron (PP) and Augmented Dickey–Fuller (ADF) unit root tests to determine stationary time-series data. These tests determine if a time series is stationary, a trait that could impact data predictability. The ADF test seeks a unit root to indicate non-stationarity. Like the ADF, the PP test finds unit roots by carefully examining the lagged variable's coefficient, but it detects heteroskedasticity better. Time-series data used in an economic model must fulfill both stationarity and consistency conditions. Equations I to VIII show the estimated ADF unit root test equations:

$$\Delta(CCY)_t = \phi + \vartheta\,(TIME) + \zeta\,(CCY)_{t-1} + \zeta_1\Delta\,(CCY)_{t-1} + \ldots + \zeta_{p-1}\Delta\,(CCY)_{t-p-1} + \varepsilon_t \quad (1)$$

$$\Delta\,(PAT)_t = \phi + \vartheta\,(TIME) + \zeta\,(PAT)_{t-1} + \zeta_1\Delta\,(PAT)_{t-1} + \ldots + \zeta_{p-1}\Delta\,(PAT)_{t-p-1} + \varepsilon_t \quad (II)$$

$$\Delta\,(TEMP)_t = \phi + \vartheta\,(TIME) + \zeta\,(TEMP)_{t-1} + \zeta_1\Delta\,(TEMP)_{t-1} + \ldots + \zeta_{p-1}\Delta\,(TEMP)_{t-p-1} + \varepsilon_t \quad (III)$$

$$\Delta\,(AGRI)_t = \phi + \vartheta\,(TIME) + \zeta\,(AGRI)_{t-1} + \zeta_1\Delta\,(AGRI)_{t-1} + \ldots + \zeta_{p-1}\Delta\,(AGRI)_{t-p-1} + \varepsilon_t \quad (IV)$$

$$\Delta\,(CH_4)_t = \phi + \vartheta\,(TIME) + \zeta\,(CH_4)_{t-1} + \zeta_1\Delta\,(CH_4)_{t-1} + \ldots + \zeta_{p-1}\Delta\,(CH_4)_{t-p-1} + \varepsilon_t \quad (V)$$

$$\Delta\,(N_2O)_t = \phi + \vartheta\,(TIME) + \zeta\,(N_2O)_{t-1} + \zeta_1\Delta\,(N_2O)_{t-1} + \ldots + \zeta_{p-1}\Delta\,(N_2O)_{t-p-1} + \varepsilon_t \quad (VI)$$

$$\Delta\,(DAML)_t = \phi + \vartheta\,(TIME) + \zeta\,(DAML)_{t-1} + \zeta_1\Delta\,(DAML)_{t-1} + \ldots + \zeta_{p-1}\Delta\,(DAML)_{t-p-1} + \varepsilon_t \quad (VII)$$

$$\Delta\,(FAR)_t = \phi + \vartheta\,(TIME) + \zeta\,(FAR)_{t-1} + \zeta_1\Delta\,(FAR)_{t-1} + \ldots + \zeta_{p-1}\Delta\,(FAR)_{t-p-1} + \varepsilon_t \quad (VIII)$$

Where CCY = Cereal crop yield; PAT = Precision agriculture technology; TEMP = Temperature; AGRI = Agriculture value-added; CH_4 = Methane emissions; N_2O = Nitrous oxide emissions; DAML = Data analytics and machine learning; FAR = Farmer's adoption rate; Δ, t, and ε denote difference operator, time, and error term, respectively.

The ARDL bounds testing approach developed by Pesaran *et al*.[47] is a robust method for co-integration analysis. Superior to Johansen and Engle–Granger tests, ARDL permits the inclusion of deterministic and non-stationary variables along with their lagged values in the model. Researchers ascertain co-integration by employing least squares regression to assess the ARDL model and comparing the F-statistic with critical values. ARDL's equations incorporate short- and long-term dynamics to depict both immediate and equilibrium interactions between variables, making it the preferred method for econometric analysis, especially in complex economic systems. Equation IX shows the ARDL model specification with error correction term:

$$\begin{aligned}\ln(CCY)_t = {} & \alpha_0 + \sum_{i=1}^{p}\varphi_i\Delta\ln(CCY)_{t-i} + \sum_{i=0}^{q}\theta_i\Delta\ln(PAT)_{t-i} \\ & + \sum_{i=0}^{r}\theta_i\Delta\ln(TEMP)_{t-i} + \sum_{i=0}^{t}\phi_i\Delta\ln n(AGRI)_{t-i} \\ & + \sum_{i=0}^{v}\phi_i\Delta\ln(CH4)_{t-i} + \sum_{i=0}^{w}\phi_i\Delta\ln(N2O)_{t-i} + \\ & \sum_{i=0}^{x}\phi_i\Delta\ln(DAML)_{t-i} + \sum_{i=0}^{y}\phi_i\Delta\ln(FAR)_{t-i} + \\ & \delta_1\ln(PAT)_t + \delta_2\ln(TEMP)_t + \delta_3\ln(AGRI)_t \\ & + \delta_4\ln(CH4)_t + \delta_5\ln(N2O)_t + \delta_6\ln(DAML)_t \\ & + \delta_7\ln(FAR)_t + \rho(ECT)_{t-1} + \varepsilon_t\end{aligned} \quad (IX)$$

Where Δ denotes difference operator.

4. Results and discussion

Table 2 shows the descriptive statistics of the variables. Crop yield represents the production of cereal crops per unit of land. In our dataset, the average yield for cereal crops is 1983.552 tons per hectare, ranging from a maximum of 1429.200 tons to a minimum of 3564.900 tons. The standard deviation of 840 indicates variability in cereal crop production across different regions and time periods. Skewness and kurtosis values of 1129.717 and 0.592 suggest a positively skewed and flat distribution of yield data, respectively.

Table 2. Descriptive statistics

Methods	CCY (tons per hectare)	AGRI (constant 2015 USD)	TEMP (centigrade)	CH_4 (metric tons)	N_2O (metric tons)	PAT (number of tractors)	FAR (% of population)	DAML (% of GDP)
Mean	1983.552	7.64E+10	21.062	97.936	89.760	8.73E+12	74.673	0.291
Maximum	1429.200	7.76E+10	20.840	97.364	89.189	8.79E+12	75.173	0.292
Minimum	3564.900	7.76E+10	21.900	128.366	120.189	8.79E+12	91.943	0.632
Standard deviation	840	6.31E+10	20.550	74.368	66.189	7.76E+12	58.959	0.164
Skewness	1129.717	3.58E+09	0.443	17.487	17.483	2.15E+11	9.527	0.131
Kurtosis	0.592	−2.734	0.526	0.121	0.121	−3.416	−0.023	0.554

Source: Author's estimates.

Abbreviations: AGRI: Agriculture value-added; CH_4: Methane emissions; CCY: Cereal crop yield; DAML: Data analytics and machine learning; FAR: Farmer's adoption rate; GDP: Gross domestic product; N_2O: Nitrous oxide emissions; PAT: Precision agriculture technology; TEMP: Temperature.

The average AGRI is 7.64E+10 units, ranging from 7.76E+10 to 7.76E+10 units. The standard deviation of 6.31E+10 shows the variability of AGRI across different geographical regions and historical periods. Kurtosis of −2.734 and skewness of 3.58E+09 imply a leptokurtic distribution of the AGRI data. TEMPs range from a minimum of 21.900°C to a maximum of 20.840°C, with an average TEMP of around 21.062°C. The standard deviation of 20.550 indicates TEMP variation across different time periods and regions. Skewness of 0.443 and kurtosis of 0.526 suggest a somewhat positively skewed and relatively flat distribution of TEMP data. Agricultural processes release methane gas into the atmosphere. Mean methane emissions in our dataset are 97.936 units, with a maximum of 97.364 units and a minimum of 128.366 units. The standard deviation of 74.368 shows variability in methane emissions across different time periods and regions. Methane emissions data exhibit a positively skewed distribution with a skewness of 17.487 and a relatively flat distribution with a kurtosis of 0.121. Agricultural processes also emit N_2O gas into the atmosphere. Average N_2O emissions in our dataset are 89.760 units, with a maximum of 89.189 units and a minimum of 120.189 units. The standard deviation of 66.189 emissions indicates variability in N_2O emissions across different time periods and regions. Skewness of 17.483 and kurtosis of 0.121 illustrate a positively skewed and relatively flat distribution of the N_2O emissions data. The mean value of PAT in terms of number of tractors is 8.73E+12. The nation's GDP is 0.291% of the data analytics. Table 3 shows the unit root estimates for ready reference.

According to the unit root test results, AGRI, CH_4, N_2O, and PAT are level-stationary variables, confirming that these variables do not adhere to the random walk hypothesis, and their order of integration is zero, *i.e.*, I(0) variables. On the other hand, the remaining variables are first-difference stationary, following the random walk hypothesis, and having an order of integration of one, *i.e.*, I(1) variables. The combination of I(0) and I(1) variables provides a strong rationale for utilizing the ARDL bounds testing approach for short- and long-term parameter estimates. Table 4 shows the lag length selection criteria.

Based on the lag length criterion of the Akaike information criterion, a lag length of 4 is deemed optimal for ARDL estimations. Similarly, the lag length criteria of final prediction error and Hannan–Quinn criterion also indicate the same optimal lag length value, while Schwarz criterion suggests the use of a third lag length. Therefore, the study concluded that a lag length of 4 is optimal for ARDL estimation. Table 5 shows the ARDL estimates for ready reference.

Dynamic factor interactions have major implications for Pakistan's agriculture policy and long-term survival. The short- and long-term connections between AGRI and CCY are negative. This suggests agricultural inefficiency and misallocating land, labor, and capital, which may explain why value addition does not always increase yields.[48] Inefficient input utilization, outdated farming practices, and inadequate infrastructure are plausible factors. Intensive farming may also decrease soil fertility and diminish agricultural production due to water management concerns and pesticide and fertilizer overuse.[49] These findings highlight systemic industry concerns, including infrastructure, extension, and agricultural R&D underfunding. These systemic inefficiencies must be addressed to boost agricultural output and growth.[50]

Table 3. Unit root estimates

Variables	Level		First difference		Decision
	Intercept	Intercept and trend	Intercept	Intercept and trend	
CCY	−2.027 (0.274)	−1.733 (0.724)	−7.639 (0.000)	−7.724 (0.000)	I (1), *i.e.,* first-difference stationary
AGRI	−4.847 (0.000)	−4.758 (0.001)	−2.445 (0.134)	−2.635 (0.266)	I (0) level stationary
TEMP	−1.170 (0.997)	−1.794 (0.695)	−2.921 (0.049)	−3.546 (0.044)	I (1), *i.e.,* first-difference stationary
CH_4	−1.062 (0.954)	−5.376 (0.000)	−4.853 (0.000)	−2.352 (0.402)	I (0), *i.e.,* level stationary
N_2O	7.398 (0.955)	−5.376 (0.000)	−2.732 (0.074)	−2.352 (0.4002)	I (0), *i.e.,* level stationary
PAT	−4.312 (0.000)	−3.987 (0.000)	−7.101 (0.000)	−6.670 (0.000)	I (0), *i.e.,* level stationary
FAR	−2.040 (0.269)	−2.526 (0.314)	−8.008 (0.000)	−7.940 (0.000)	I (1), *i.e.,* first-difference stationary
DAML	−1.802 (0.376)	−2.029 (0.573)	−7.776 (0.000)	−7.711 (0.000)	I (1), *i.e.,* first-difference stationary

Source: Author's estimate. Note: Small bracket shows probability value.
Abbreviations: AGRI: Agriculture value-added; CH_4: Methane emissions; CCY: Cereal crop yield; DAML: Data analytics and machine learning; FAR: Farmer's adoption rate; N_2O: Nitrous oxide emissions; PAT: Precision agriculture technology; TEMP: Temperature.

Table 4. Lag length selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	−1955.827	NA	1.59e+23	67.61472	67.79234	67.68391
1	−1660.686	529.2175	1.44e+19	58.29953	59.36527	58.71466
2	−1600.655	97.29230	4.39e+18	57.09155	59.04542	57.85262
3	−1539.557	88.48697	1.33e+18	55.84678	58.68877*	56.95380
4	−1489.183	64.27038*	6.11e+17*	54.97181*	58.70193	56.42477*

Source: Author's estimate. Note: * indicates lag order selected by the criterion.
Abbreviations: AIC: Akaike information criterion; FPE: Final prediction error; HQ: Hannan–Quinn criterion; LogL: Log-likelihood; LR: Likelihood ratio; SC: Schwarz criterion.

On the other hand, data analytics have drastically increased cereal crop output in the short term, supporting the growing body of studies on digital farming's revolutionary potential.[51,52] Farmers may optimize crop management, resource allocation, and production using data-driven options. Through targeted planting, watering, fertilizing, and pest control using real-time data, crop yields can be quickly increased.[53] Predictive analytics may help farmers anticipate weather and market trends and monitor soil and crop health to respond quickly to developing threats.[54] Data analytics provide short-term productivity gains and verifiable returns on low costs, encouraging greater adoption. Technological diffusion, accelerating innovation when an early adopter group benefits disproportionately, matches this phenomenon.[55] Thus, data analytics boost yields, efficiency, inventiveness, and farmer curiosity.

The study shows a positive association between technology adoption and cereal crop production in the short and long terms. This shows how technological advances boost agriculture productivity. Modern agricultural technology improves seed kinds, efficiency, and resource management in the short term,[56] whereas investments in technology may improve agricultural performance and production in the long run.[5] In addition, digital infrastructure and R&D expenditures may boost innovation and speed the adoption of breakthrough agricultural technologies. These findings emphasize the

Table 5. ARDL estimates

Dependent variable: CCY				
Variables	**Coefficient**	**Standard error**	**t-Statistic**	**Probability**
Δ(AGRI)	−0.014	0.002	−5.801	0.000
Δ(TEMP)	−180.128	198.039	−0.909	0.367
Δ(DAML)	3971.774	1568.494	2.532	0.014
Δ(FAR)	24.330	11.244	2.163	0.034
Δ(CH_4)	50.567	23.435	2.145	0.045
Δ(N_2O)	48.356	37.546	2.457	0.053
Δ(PAT)	0.048	0.012	3.840	0.000
CointEq(−1)	−0.362	0.148	−2.443	0.017
Long run coefficients				
Variables	**Coefficient**	**Standard error**	**t-Statistic**	**Probability**
AGRI	−0.028	0.010	2.801	0.035
TEMP	−497.536	499.057	−0.996	0.323
DAML	3163.687	2299.048	1.376	0.174
FAR	67.203	26.846	2.5031	0.015
CH_4	58.562	28.096	2.573	0.013
N_2O	56.203	30.326	2.952	0.016
PAT	0.147	0.052	2.826	0.035
Constant	21865.514	10810.553	2.022	0.048

Source: Author's estimate.

Abbreviations: AGRI: Agriculture value-added; CH_4: Methane emissions; CCY: Cereal crop yield; DAML: Data analytics and machine learning; FAR: Farmer's adoption rate; N_2O: Nitrous oxide emissions; PAT: Precision agriculture technology; TEMP: Temperature.

importance of policy frameworks, extension services, and institutional capacity in technology transmission and farmer training.[57]

The ARDL results indicate a positive relationship between CH_4 and N_2O emissions and CCYs in the short and long run. This shows that intensive agricultural practices increase emissions and food output. However, this association highlights an essential cost-benefit analysis: agricultural intensification improves yields and greenhouse gas emissions, threatening environmental sustainability. These findings demonstrate the necessity to include precision farming technology that maximizes input use and reduces environmental impacts into productivity gains to reduce emissions. Further, the findings reveal that productivity advantages and environmental externalities are traded off since more emissions are generated in exchange for higher yields, which are not achieved in a more sustainable manner. Conversely, CH_4 and N_2O emissions may enhance plant growth and soil fertility in some situations.[58] These gases enhance plant growth and output and are usually produced by microbial activities in the soil.[59] These emissions are indicative of more nutrient-rich soil, which is crucial for increasing agricultural production.[60] This relationship emphasizes the necessity for data-driven solutions and precision agriculture to strike a balance between crop production and greenhouse gas emissions.

Precise agriculture technology can aid in the rapid enhancement of CCYs over time, boosting agricultural efficiency and sustainability. Data analytics, GPS-guided devices, and remote sensing provide accurate resource management, site-specific interventions, and real-time monitoring.[61] These technologies provide personalized input applications for crop and soil conditions, improving yields with minimal waste and environmental impact. It has been demonstrated that long-term output and resilience can be increased through the implementation of strategies informed by data collected from multiple growing seasons.[30] In addition, precision agriculture may strengthen agricultural systems, protect biodiversity, and improve soil health, enabling sustainability in agriculture.

Table 6 shows that diagnostic testing confirmed the ARDL model's robustness. The Breusch–Godfrey

Table 6. Diagnostic test estimates

Test	Statistic	*p*-value	Conclusion
Breusch–Godfrey LM (serial correlation)	1.84	0.17	No serial correlation
Breusch–Pagan–Godfrey (heteroskedasticity)	2.15	0.14	No heteroskedasticity
Jarque–Bera (Normality)	1.73	0.42	Residuals are normally distributed
Ramsey RESET (specification)	1.92	0.16	Model is correctly specified
CUSUM	—	—	Stable within 5% significance bounds
CUSUMSQ	—	—	Stable within 5% significance bounds

Source: Author's estimate.
Abbreviations: CUSUM: Cumulative sum; CUSUMSQ: Cumulative sum of squares.

Table 7. ARDL bounds estimates

Test statistic	Value	k
F-statistic	10.43256	7
	Critical value bounds	
Significance	**I (0) Bound**	**I (1) Bound**
10%	2.45	3.52
5%	2.86	4.01
2.5%	3.25	4.49
1%	3.74	5.06

Source: Author's estimate.

LM serial correlation test yielded a p=0.17 and found no residual autocorrelation. The residuals were homoscedastic, according to the Breusch–Pagan–Godfrey heteroskedasticity test with a p=0.14. The Jarque–Bera normality test validated the residuals' normal distribution with a p=0.42. The estimated model's stability was confirmed by the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ), which were inside the critical bounds at 5% significance. These results suggest that the estimated ARDL model is stable and statistically sound.

Table 7 presents the ARDL bounds estimates, revealing an F-statistic of 10.432. This value exceeds the critical bounds for I(1), indicating a significant dependency among the model variables. Co-integration, signifying a long-term equilibrium relationship between variables despite short-term fluctuations, was observed.

5. Conclusions and policy recommendation

The current study showed how Pakistan's environmental conditions, agricultural production, and adoption of AgriTech are interconnected. The adoption of data analytics, precision agriculture, and technology can boost grain crop yields. However, the association between CH_4 and N_2O emissions and yields is attributed to the intensified agricultural techniques rather than the environmental benefits. An increase in production may harm the environment, suggesting a productivity-environment trade-off. Furthermore, the inconsistent influence of AGRI on yields suggests systemic inefficiencies and the need for more consistent investment and policy. The study showed that prudent scaling of digital tools and climate-smart technology may decouple productivity from environmental impact, underlining the need to promote precision-based interventions, sustainable intensification, and data-driven decision-making to boost yields and climate resilience in Pakistan through revisions of the agricultural policy. Future research may incorporate farmer's behavior, financing techniques, and regional comparisons into analysis to enhance policy relevance.

Pakistan's policymakers should focus on agricultural sector efficiency and resource allocation to reduce the detrimental effects of agricultural value addition on CCYs. To this end, robust agricultural extension services, sophisticated farming methods, and rural infrastructure are needed. Policy measures that make high-quality inputs and new equipment more accessible, inexpensive, and simple to use should be encouraged to accelerate agricultural technology adoption. At this point, it should be noted that sustainable agricultural practices, efficient land use, adequate labor, and capital utilization are factors that increase productivity while preventing environmental degradation and preserving soil fertility. In addition, farmers must be given reliable access to real-time agricultural data so that they can interpret and apply data to make informed choices. Actions from public and private sectors may be required to promote data analytics and precision agriculture's digital infrastructure. Besides, farmers should be educated about modern farming techniques and extension services that employ sustainable methods and precision technology to assist farmers in increasing yields and reducing environmental impact.

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This study revealed that the usage of digital technology and precision agriculture can enhance crop yields. However, the positive relationship between emissions and productivity highlights the serious environmental impacts arising from agricultural activities that must be controlled. Furthermore, our results suggested that value-added agriculture may have uneven effects on crop yields in the short and long terms. Future research should incorporate AgriTech solutions with improved environmental monitoring systems to reduce emissions. Further studies on Pakistan's policy frameworks that encourage sustainable agriculture without compromising food security are also warranted.

The utilization of only secondary data, devoid of the comprehensive cereal crop production characteristics, is the primary limitation of this study. Future research should incorporate socioeconomic status, soil health, and water usage practices to provide a full picture. Further, it should examine the long-term implications of data analytics and new agricultural technologies on Pakistan's crops and farming methods. Studies that combine agricultural knowledge with cutting-edge technology may lead to sustainable development. Regional environmental, economic, and social variances must be considered for the effective customization of interventions. More importantly, collaboration among academics, policymakers, and practitioners in translating research findings into transformative, sustainable agricultural approaches is highly desired.

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Conflict of interest

The authors declare that they have no competing interests.

Author contributions

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Writing–review & editing: All authors

Availability of data

The data are freely available from the World Development Indicators published by the World Bank (2023) at https://databank.worldbank.org/source/world-development-indicators and CCKP (2023) at https://climateknowledgeportal.worldbank.org/country/pakistan (accessed on January 15, 2025).

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