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ARTICLE

Toward Intelligent Agriculture: Quantifying the Impact of Key Agronomic Factors on Wheat Production in Pakistan

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ABSTRACT

Food security remains a critical global concern. The rising world population has led to a continuous increase in food demand. Wheat serves as a primary dietary component and its enhanced production is essential to mitigate the food availability challenge, especially in countries like Pakistan. The current study employs descriptive statistical analysis to explore and quantify the impact of various agronomic and input related factors on wheat production. The objective is to identify optimal levels of individual factors aiming to attain the intelligent agriculture practices that significantly contribute to yield improvement. Certified seed increases wheat yield by 25% compared to home-retained seed. A seed rate of 60 kg per acre, adopted by 48.3% of the farmers, is associated with improved productivity. Sowing wheat by mid-November ensures consistently higher yields. The use of 1 to 2 bags of DAP and 2 to 3 bags of urea per acre is associated with maximum yield gains. The use of other fertilizers contributes to a 12.02% increase in production. Pesticide applications for weed control are linked with a 17.11% enhancement in yield. Ploughing/rotavator operations demonstrate a positively increasing trend in yield. Wheat sown after cotton or sugarcane produced better wheat productivity. These findings highlight the critical role of agronomic practices and input management in achieving food security through increased wheat production. Policymakers and agricultural extension services should emphasize these statistically significant factors to support evidence based decision making among farmers. This study promotes intelligent agriculture practices and supports informed decisions for food sustainability.

Keywords: Food Availability; Wheat Production; Factors Effecting; Statistical Analysis; Yield Optimizations

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ARTICLE INFO
Received: 1 March 2025 | Revised: 17 March 2025 | Accepted: 20 March 2025 | Published Online: 25 March 2025
DOI: https://doi.org/10.36956/ia.v1i1.1826

CITATION
Islam, M., 2025. Toward Intelligent Agriculture: Quantifying the Impact of Key Agronomic Factors on Wheat Production in Pakistan. Intelligent Agriculture. 1(1): 1–14. DOI: https://doi.org/10.36956/ia.v1i1.1826

1. Introduction

Food is a fundamental and basic need of life and agriculture is the main stream for the food security and food availability [1]. The world's population is expected to reach 9.1 billion up to 2050 and the major contribution for this increase in the world population will come from developing countries [2,3]. Food production must increase by about 70 percent to meet this challenge and it will be double for the developing countries [2,4]. According to International Food Policy Research Institute (IFPRI) each day our world witnesses 800 million people go hungry and about 170 million children under 5 years of age suffer from malnourishment [5,6]. It is evident that growth rate of yield for major cereals is decreasing in the world [2,7] . Agriculture is the biggest sector of Pakistan, contributing about 21% of GDP and providing employment to 45% of Population [8]. Wheat, Rice, Maize, Jowar, Bajra and Barley are the food crops of Pakistan. Wheat is a staple food crop of Pakistan and it ranks first in acreage and production among all food crops [9,10]. According to FAO, Pakistan is 7th largest producer of wheat in the world [11]. Population growth rate in Pakistan is still high and production of wheat crop is still low as compared to other countries [12,13]. With the current rate of population growth, it is estimated that in 2050 Pakistan will attain the 4th position in terms of population in the world instead of 6th [14,15]. Wheat is the most vital staple food crop in Pakistan, serving as the primary source of calories and nutrition for the majority of the population. The overall compound growth rates for wheat area (1.207%) and yield (2.326%) remain lower than the population growth rate (2.839%) in Pakistan. Forecasts indicate that by 2030, wheat area, yield, and population in Pakistan are projected to increase by 12.7%, 25.5%, and 31.8%, respectively. By 2050, these figures are expected to raise further wheat area by 43%, yield by 97.8%, and population by 129% [16]. Wheat provides over 60% of daily caloric intake for an average Pakistani household, making it essential for national food security [17,18]. As the population grows, ensuring the consistent availability and affordability of wheat is critical to preventing hunger and malnutrition. Moreover, wheat cultivation supports the livelihoods of millions of farmers, contributes significantly to the national GDP, and plays a key role in the rural economy. To meet the needs of the growing population, it is imperative to enhance wheat productivity through modern agricultural practices, improved seed varieties, efficient irrigation, and robust data-driven policymaking [19,20]. Sustainable development in wheat production is not just an agricultural goal, but a national priority to ensure food security and economic stability in Pakistan. In Pakistan, the population is growing at an increasing rate, whereas the yield of the wheat crop is rising at a declining pace. This imbalance may lead to a gap between food production and demand, potentially resulting in food insecurity. To address this challenge, it is essential to enhance the per acre yield of wheat, especially in light of the rising population [21,22].

Qayyum and Pervaiz presented descriptive study of all the factors affecting the wheat yield in Punjab [23]. He studied the effects of variables, i.e., DAP, Urea, plough, level, water, source of seed, variety, spray, sowing time, harvesting time, rainfall and humidity and concluded the benchmarks to attain the better production. Bajkani et al. reported that traditional practice resulting the low production of wheat crop in Baluchistan [24]. Hussain et al. reported that by giving the better inputs food grain crop characterized increasing returns to scale in Swat, KPK [25]. Tariq et al. studied the climatic change on wheat crop and its per capita availability in Punjab and reported that in 2014 per capita availability of wheat is 198 kg per annum and it would be 105 kg per annum in 2031 and 84 kg per annum in 2050 due to rising trend of population and adverse climatic effect [26]. Islam et al. explored the study and found that food security has emerged as a critical global concern due to the continuous rise in population and the corresponding increase in food demand, which often surpasses the growth in agricultural production [7]. As a staple crop, wheat plays a central role in ensuring food availability worldwide. A study conducted using data from the Crop Reporting Service, Agriculture Department of Punjab, Pakistan, aimed to enhance wheat yield prediction by identifying the most informative data structures and exploring key agronomic and environmental factors associated with yield improvement.

Hierarchical regression analysis was employed, and additional data clusters were created from the original dataset to evaluate the predictive performance of various models. A similar study was conducted by Hameed et al. on Cotton crop production [27]. This study aims to identify key variables that influence cotton productivity and propose yield enhancement practices. The analysis is based on a dataset comprising 12,504 crop-cut experiments collected by the Crop Reporting Service, Punjab, spanning from 2018 to 2021. Wheat production remains a cornerstone of food security, particularly in agrarian economies like Pakistan. While traditional agronomic practices have long been recognized for their role in yield optimization, recent advancements emphasize the growing importance of precision agriculture, climate-smart strategies and big data analytics in transforming wheat farming. Precision agriculture (PA) leverages data driven technologies such as GPS-guided equipment, remote sensing, and variable rate application systems to enhance input use efficiency and crop productivity. Research by Wang et al. and Zhang et al. underscores that PA significantly improves resource utilization, enabling farmers to apply the right input at the right time and place, thereby increasing wheat yields while minimizing environmental impact [28,29]. Similarly, Tey and Brindal noted that PA technologies can enhance nitrogen use efficiency and soil fertility [30], particularly when integrated with real-time monitoring systems. Climate-smart agriculture (CSA) has also gained traction as a strategy to build resilience against climate change while promoting sustainable production. According to Lipper et al. [31], CSA incorporates improved seed varieties, optimized planting dates and conservation tillage to enhance productivity under variable climatic conditions. The integration of big data and machine learning in agriculture represents a paradigm shift in yield forecasting and input optimization. A study by Kamilaris et al. highlighted the potential of predictive models using satellite imagery, weather data, and on-ground sensor inputs to inform evidence based decisions [32]. In Pakistan, Islam et al. demonstrated that combining statistical and machine learning techniques can accurately predict wheat output based on agronomic inputs and climatic variables, offering a cost-effective decision support system for policymakers and farmers alike [2].

Wheat production is influenced by a wide range of agronomic and management practices, including fertilizer use, pesticide application, sowing and harvesting periods, seed varieties, seed treatment, irrigation and land preparation techniques. While previous studies have attempted to explore the effects of these factors, they often examined them in isolation or without considering the varying levels at which each factor operates. This limits our understanding of how different levels of each factor contribute individually to wheat yield enhancement. There is a need for a more detailed analysis using robust statistical techniques to identify and quantify the individual contribution of each factor and its levels to wheat production. Present study is designed to analyze the impact of various agronomic and management factors on wheat crop production using descriptive statistical tools and techniques such as probability share, average, standard deviation, coefficients of variations, and normality in the data, etc. This study is determining the individual contribution of each factor such as fertilizer type, pesticide usage, sowing and harvesting periods, seed quantity, seed treatment, irrigation and soil type, etc., on wheat yield to attain the pathway toward intelligent agriculture by quantifying the impact of key agronomic factors on wheat production in Pakistan. The objective is to identify optimal levels of individual factors that significantly contribute towards the intelligent agriculture for yield improvement. It also assessed the effect of different levels of each factor on wheat production in order to identify optimal combinations that maximize yield to provide statistically sound recommendations for improving wheat productivity through better management of input factors.

2. Materials and Methods

For the present study secondary data is collected from Crop Reporting Service (CRS) of district Bahawalpur, Punjab, Pakistan from 2007–08 to 2013–14. The Crop Reporting Service (CRS) of the Agriculture Department, Punjab, Pakistan, operates within the domain of agricultural statistics, with a primary focus on the collection, analysis, and dissemination of accurate and timely crop-related data. Its core objective is to support agricultural planning, policy formulation and decision-making by providing reliable estimates of crop acreage, yield and production across the province. The CRS conducts systematic field surveys, including Girdawri (crop inspection) to monitor the area under cultivation for various crops during different seasons such as Rabi and Kharif. It also evaluates crop conditions, assesses the impact of weather, pests, and diseases, and forecasts expected outputs using scientific and statistical methods. Furthermore, the service plays a vital role in ensuring food security, supporting price stabilization policies, and guiding resource allocation by offering data-driven insights to the government and stakeholders in the agricultural sector. About 795 fields and 19875 entries are analyzed there in SPSS for the current study. Descriptive statistical analysis is presented with tabulation and graphical presentation of individual factor with its level and combined effect of factors with their levels. Statistical tools are used as mean yield, standard deviation, coefficient of variation, correlation coefficients, % share and % increase/decrease, etc.; normality analysis is performed using the graphical method [33,34].

The data generated by the Crop Reporting Service (CRS), Punjab, is widely regarded as reliable and credible due to its scientifically designed methodologies, regular field surveys, and rigorous verification processes. Trained field staff conducts ground-based assessments, including Girdawri and acreage surveys under the direct supervision of experienced officers. The CRS employs standardized statistical techniques to ensure data accuracy which supports policy formulation, resource allocation, and food security planning at the provincial and national levels. The variables are analyzed in the current studies as:

(1) Source of seed, dummy variable used 0=home seed, 1=certified seed)
(2) Quantity of seed used per acre or seed rate
(3) Sowing time
(4) Fertilizers DAP and Urea in bags (each bag contains 50 kg)
(5) Other fertilizers, dummy variable used 0 for no other fertilizers use and 1 for use of other fertilizers
(6) Pesticides, dummy variable used 0 for no use of pesticides and 1 for use of pesticides
(7) No. of plough/rotavators
(8) Soil type (1=chikni loom 2=sandy loom 3= kalrathi (partially)
(9) Seed treatment, seed are properly poisoned or not, dummy variable used 0 for no treatment and 1 for seed treatment
(10) Last crop sown

The statistical techniques are applied to provide both foundational insights and to detect variability within the data as:

- Mean yield is calculated to establish average productivity of different levels of the agronomic factors.
- Standard deviation (SD) and coefficient of variation (CV) are employed to assess the extent of yield variability across different levels of the agronomic factors.
- Percentage share is used to quantify the proportional contribution of different agronomic factors to identify trends of the farmers.
- Normality analysis is carried out using graphical methods such as histograms with normal curve and P-P plots to ensure the validity of parametric statistical tools.

The rationale for using these techniques lies in their suitability for agricultural datasets where the understanding of central tendency, dispersion, and inter variable relationships are crucial for informing policy, resource allocation and adaptive strategies in crop management. This study will help to promote evidence based practices, support the transition toward intelligent agriculture and enable informed decision making for achieving sustainable food security.

3. Limitations and Future Research Directions

While this study utilizes secondary data to assess the influence of key agronomic factors on intelligent agriculture practices aimed at enhancing wheat yields, we acknowledge the limitations associated with the use of historical datasets. Although the dataset may be dated, it retains analytical value due to the consistent patterns observed in wheat cultivation practices and the relatively slow pace of change in certain foundational agronomic variables. Furthermore, the data provides a historical baseline that is essential for identifying long term trends, benchmarking productivity levels, and understanding the cumulative impact of agronomic interventions. It is important to recognize that the dataset may not fully capture recent advancements in technology, shifts in policy or abrupt environmental changes such as those induced by climate variability or global market disruptions. These factors can introduce biases or limit the generalizability of findings to current conditions. Therefore, a more nuanced discussion of external variables such as climate change, water resource availability, and input price fluctuations should be integrated into the interpretation of results. To address these limitations, future research should prioritize the incorporation of mixed methods, including panel data analysis and multivariate regression techniques to better capture temporal dynamics and causal linkages. The use of primary data collected through farm level longitudinal surveys would also enhance the granularity and contextual accuracy of the findings. Such approaches would support more tailored data driven policy recommendations and promote sustainable wheat production practices that are resilient to ongoing environmental and economic changes.

4. Results

4.1. Normality Analysis

It is evident from **Figures 1** and **2**, normality through histogram and P-P plot of pooled data of wheat crop showing complete linear and normal behavior.

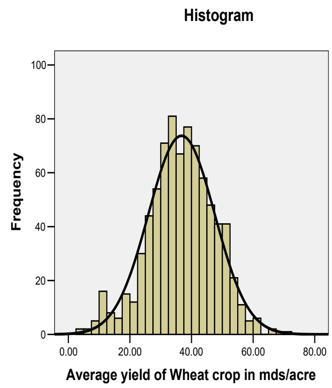

Figure 1. Histogram with Normal Curve.

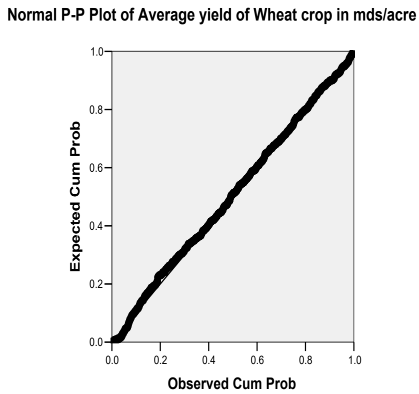

Figure 2. P-P Plot.

4.2. Effect of Different Factors with Their Levels

Seed rate mean seed quantity used per acre. Seed rate and sowing time are important factors to enhance the wheat production. **Table 1** presents data on the quantity of wheat seed used per acre (in kilograms) and its corresponding impact on the average yield (in maunds per acre) based on sample points collected during the survey. The table includes key statistical measures such as the number of sample points, percentage share of each seed rate, average yield, standard deviation (S.D), and coefficient of variation (C.V%). The most frequently used seed rate is 60 kg/acre, applied in 48.3% of the sample points (384 out of 795), which also results in the highest average yield of 37.7 maunds/acre, with a relatively low variability (C.V = 27.28%). Seed rates of 50 kg and 70 kg per acre are also widely adopted, used in 19.5% and 17.86% of the sample points respectively. Both show average yields of 36.0 and 36.9 maunds/acre, suggesting stable performance with moderate variability (C.V = 36.95% and 24.9%). The lowest average yield (30.0 maunds/acre) is observed with the 65 kg/acre seed rate, although this rate is only used in 2.138% of the samples, showing high variability (C.V = 44.46%). Conversely, the 75 kg/acre rate shows a decent average yield of 34.6 maunds/acre with the lowest variability (C.V = 17.6%), though it is used in just 2.516% of the samples points. Overall, the data suggests that the 60 kg/acre seed rate is the most effective and widely used, balancing high yield with relatively low variation across the sampled wheat fields. These insights are especially valuable for formulating precision input recommendations, particularly within the framework of intelligent agriculture practices, where optimizing seed rate plays a crucial role in enhancing both productivity and sustainability.

Table 1. Seed Quantity Used in kg and Average Yield of Wheat Crop.

Seed Qty	No. of Sample Point	% Share	Avg yield mds/acre	S.D	C.V%
45	3	0.377	35.2	13.398	38.04
50	155	19.5	36.0	13.286	36.95
55	14	1.761	33.4	9.9782	29.87
60	384	48.3	37.7	10.288	27.28
65	17	2.138	30.0	13.349	44.46
70	142	17.86	36.9	9.1985	24.9
75	20	2.516	34.6	6.0878	17.6
80	60	7.547	35.8	9.6218	26.86

Table 2 presents the distribution of wheat sowing times across different sample points along with their respective average yields, standard deviation (S.D), and coefficient of variation (C.V%). The data highlights the relationship between sowing time and wheat productivity. Only 0.377% of the sample points sowed wheat up to October 1st. The highest proportion of wheat sowing (39.25%) was observed during November 16–30, with an average yield of 37.9 mds/acre and a coefficient of variation of 27.77%. Wheat sown between November 1–15 (22.89% of sample points) had a slightly higher average yield (41.1 mds/acre) compared to late November, indicating that early November is optimal for higher productivity with lower yield variability (C.V% = 25.19). As sowing is delayed, a decline in yield is observed. Crops sown during December 1–15 (29.69%) had an average yield of 33.5 mds/acre with a higher variability (C.V% = 29.49). The lowest yield of 30.3 mds/acre was recorded in fields sown from December 16 onwards, which comprised 7.799% of the sample. This group also showed the highest variability in yield (C.V% = 32.03). Overall, the data indicates a clear negative impact of delayed sowing on wheat yield, with early November sowing (especially up to November 15) appearing to be the most favorable in terms of achieving higher and more stable yields. These insights can be leveraged to inform intelligent agriculture practices for optimized sowing strategies.

Table 3 presents the relationship between the quantity of DAP (Di-Ammonium Phosphate) fertilizer used and the average wheat yield per acre across different sample points. The data are categorized into four distinct groups based on the number of DAP bags used: *No DAP*, *1 or less bag*, *1 to 2 bags*, and *2 to 3 bags*. Each category shows the number of sample points, percentage share of the total samples, average yield in mds per acre, standard deviation (S.D), and coefficient of variation (C.V %), which is a measure of relative dispersion. The largest proportion of the sample (80.75%) falls under the category of *1 or less bag* of DAP, with 642 sample points. This group recorded an average yield of 36.8 mds/acre, with a standard deviation of 10.25, resulting in a coefficient of variation of 27.88%, indicating moderate variability in yield. The *No DAP* group comprises 66 sample points (8.302% of the total) and shows a significantly lower average yield of 29.6 mds/acre. The standard deviation here is 13.11, with a high C.V. of 44.32%, suggesting considerable yield variability and potential instability in production without DAP application. The category *1 to 2 bags* includes 86 sample points (10.82%) and demonstrates the highest average

Table 2. Sowing Time of Wheat Crop and Average Yield of Wheat Crop.

Sowing Time	No. of Sample point	% Share	Avg yield mds/acre	S.D	C.V%
up to 1st Oct	3	0.377	42.2	11.272	26.71
November 1–15	182	22.89	41.1	10.364	25.19
Nov 16–30	312	39.25	37.9	10.519	27.77
Dec 1–15	236	29.69	33.5	9.8934	29.49
From 16 Dec & later	62	7.799	30.3	9.6981	32.03

yield at 42.2 mds/acre. This group also exhibits the lowest C.V. of 21.99%, implying relatively stable and higher productivity with moderate DAP usage. The data suggests a positive association between DAP application and wheat yield up to a certain level. The highest yield and stability were observed in the *1 to 2 bags* group. Conversely, the absence of DAP not only resulted in lower yields but also showed high variability, reflecting the importance of balanced fertilizer use in achieving optimal wheat production. These findings on the balanced use of DAP fertilizer underscore the potential of intelligent agriculture to optimize input utilization and improve yield stability.

Table 3. Use of DAP and Wheat Yield.

DAP Use in Bags	No. of Sample Point	% Share	Avg Yield mds/acre	S.D	C.V %
No DAP	66	8.302	29.6	13.11	44.32
1or less bag	642	80.75	36.8	10.25	27.88
1 to 2 bags	86	10.82	42.2	9.28	21.99
2 to 3 bags	1	0.126	38		

Table 4 presents the distribution of sample points based on urea fertilizer application and its relationship with average yield mds per acre, standard deviation (S.D), and coefficient of variation (C.V%). Only 2 sample points (0.252% share) reported no urea usage. The average yield in this group was 31.3 mds/acre, with a relatively high standard deviation of 18.95, resulting in a coefficient of variation of 60.48%, indicating significant variability in yield without urea application. This category includes 135 sample points (16.98% share), showing an average yield of 31.2 mds/acre. The standard deviation was 11.75, and the C.V% stood at 37.72, suggesting moderate variation in yield with low urea usage. The majority of the sample (500 points, 62.89%) falls in this category. The average yield increased to 37.1 mds/acre, with a lower standard deviation of 10.35, and a C.V% of 27.92, reflecting improved yield stability with optimal urea use. With 146 sample points (18.36% share), this group achieved the highest average yield of 40.8 mds/acre. The standard deviation was 8.50, and the C.V% was the lowest at 20.84, indicating the most consistent and efficient yield performance among all categories. This group comprised only 12 sample points (1.509%). The average yield was 37.9 mds/acre, with a higher standard deviation of 14.30 and a C.V% of 37.79, suggesting increased variability in yield at higher levels of urea application. The data suggests that moderate use of urea (1 to 3 bags per acre) is associated with higher and more stable crop yields, while both insufficient and excessive application leads to increased yield variability. The 2 to 3 bags category appears to be the most efficient and consistent in terms of yield performance, highlighting the potential role of data driven input optimization in advancing intelligent agriculture.

Table 4. Use of Urea and Wheat Yield.

Urea Use in Bags	No. of Sample Point	% Share	Avg Yield mds/acre	S.D	C.V%
No urea	2	0.252	31.3	18.95	60.48
1 or less bags	135	16.98	31.2	11.75	37.72
1 to 2 bags	500	62.89	37.1	10.35	27.92
2 to 3 bags	146	18.36	40.8	8.500	20.84
3 to 4 bags	12	1.509	37.9	14.30	37.79

Table 5 presents a comparative analysis of wheat yield between sample points where other fertilizers were used and where they were not used. Out of the total sample points, the 89.18% reported no use of other fertilizers. The average wheat yield in these areas was 36.28 mds per acre, with a standard deviation (S.D) of 10.79, indicating moderate variability. The coefficient of variation (C.V) was 29.74%, reflecting a relatively higher dispersion in yield among these points. In contrast, the 10.82% reported the use of other fertilizers. The average yield in these areas was significantly higher at 40.64 mds per acre, with a lower standard deviation of 9.63. The C.V was 23.69%, suggesting more consistency in yield where other fertilizers were applied. The data

Table 5. Use of Other Fertilizers and Wheat Yield.

No					Yes				
No. of Sample Point	%Share	Avg Yield mds/acre	S.D	C.V %	No. of Sample Point	%Share	Avg Yield mds/acre	S.D	C.V %
709	89.18	36.28	10.79	29.74	86	10.82	40.64	9.63	23.69

suggest a positive association between the use of other fertilizers and increased wheat yield, with reduced variability among users compared to non-users, highlighting the potential role other fertilizers towards intelligent agriculture in optimizing input use for improved and consistent crop performance.

Table 6 presents the relationship between the number of plough/rotavator uses and the corresponding wheat yield per acre, based on data collected from various sample points. The table includes five categories based on the frequency of land preparation (from 2 to 6 times). Two-time ploughing was practiced at 64 sample points, accounting for 8.05% of the total. The average wheat yield observed was 34.8 mds/acre, with a standard deviation of 9.36, resulting in a coefficient of variation (C.V) of 26.90%, indicating moderate variability in yield. Three-time ploughing was the second most common practice, recorded at 290 sample points (36.48%). The average yield was 35.9 mds/acre, with higher yield variation (S.D = 10.67, C.V = 29.69%). The four-time ploughing category had the highest number of sample points (307), contributing 38.62% to the sample. The average yield increased slightly to 36.5 mds/acre, but also showed increased variability (S.D = 11.27, C.V = 30.88%), suggesting inconsistency in yield outcomes. Five-time ploughing, practiced at 113 points (14.21%), showed a notable improvement in yield (39.6 mds/acre) and lower variability (S.D = 9.37, C.V = 23.68%), indicating more consistent and favorable results. Six-time ploughing, though the least common (only 21 points, 2.64%), resulted in the highest average yield of 43.3 mds/acre, with a standard deviation of 11.24 and C.V of 25.96%, demonstrating both high productivity and relatively stable outcomes. The data suggests a positive relationship between the number of plough/rotavator uses and wheat yield, with increased frequency generally leading to higher average yields. However, variability in yield (as indicated by S.D and C.V%) also tends to increase with more frequent tillage, except in the five-time category, which offers both high and consistent yield, potentially indicating an optimal level. This analysis highlights how optimizing land preparation frequency can enhance yield outcomes, supporting data driven decision making in intelligent agriculture.

Table 6. No. of Plough/Rotavator Use and Wheat Yield.

Number of Plough/ Rotavator	No. of Sample Point	% Share	Avg Yield mds/acre	S.D	C.V%
2	64	8.05	34.8	9.3563	26.90
3	290	36.48	35.9	10.671	29.69
4	307	38.62	36.5	11.266	30.88
5	113	14.21	39.6	9.3662	23.68
6	21	2.642	43.3	11.24	25.96

Table 7 presents a comparative statistical analysis of wheat yield based on harvesting time. The data are divided into two distinct harvesting periods: Up to 15 April and from 16 April to the start of May. A total of 266 sample points (33.46%) were harvested by 15 April. The average yield recorded during this early harvesting period was 34.42 mds per acre. The standard deviation (S.D) of yield was 11.5, indicating moderate variability in yield among the samples. The coefficient of variation (C.V%) was 33.4%, suggesting a relatively higher dispersion of yield values around the mean. A total of 529 sample points (66.54%) were harvested after 15 April. The average yield during this later harvesting period was 37.93 mds per acre, which is noticeably higher than the earlier period. The standard deviation was 10.2, slightly lower than the earlier period, indicating more consistency in yield. The coefficient of variation was 26.83%, showing reduced relative variability compared to the earlier harvesting group. Wheat harvested after 15 April demonstrated a higher average yield and lower variability, both in absolute and relative terms, compared to wheat harvested earlier. This analysis highlights the potential of intelligent agriculture systems to optimize harvest timing and predict yield outcomes, enhancing overall crop management and efficiency.

Table 7. Statistical Analysis of Harvesting Time and Wheat Production.

Up to 15 April					From 16 April and Start of May				
No. Of Sample Point	% Share	Avg Yield mds/acre	S.D	C.V %	No. of Sample Point	% Share	Avg Yield mds/acre	S.D	C.V %
266	33.46	34.42	11.5	33.4	529	66.54	37.93	10.2	26.83

Table 8 presents the relationship between the crop sown prior to wheat and its subsequent production in terms of average yield in mds per acre. Cotton was the most common preceding crop, observed at 626 sample points, comprising 78.74% of the total. The average wheat yield after cotton was 37.14 mds/acre with a standard deviation of 10.33 and a coefficient of variation of 27.80%, indicating moderate variability in yield. Rice preceded wheat at 43 sample points (5.41%), with a similar average wheat yield of 37.03 mds/acre, but a higher variability (S.D. 11.71, C.V. 31.63%). Sugarcane was observed in 15 cases (1.89%) and resulted in the highest average wheat yield of 40.70 mds/acre. It also had the lowest variability among all categories (S.D. 7.55, C.V. 18.54%), suggesting more consistent wheat production after sugarcane. Fodder was grown before wheat at 29 points (3.65%), with a significantly lower average wheat yield of 31.79 mds/acre and a high C.V. of 35.26%, showing high yield variability. Fallow Land, observed in 65 cases (8.18%), resulted in an average wheat yield of 34.49 mds/acre. However, it exhibited the highest variability among all categories with a C.V. of 38.22%. Others, including miscellaneous crops, were reported in 17 cases (2.14%), with an average yield of 35.68 mds/acre and a relatively high variability (C.V. 35.99%). Sugarcane as the preceding crop yielded the highest and most stable wheat production, while fodder and fallow land resulted in relatively lower and more variable yields. Cotton, although the most prevalent preceding crop, provided a moderate average yield with moderate variability. This analysis highlights the variability in wheat production based on preceding crops, emphasizing the potential for intelligent agricultural practices to optimize crop rotation and improve yield stability.

Table 9 summarizes the relationship between soil type and wheat yield. Chikni loam, covering 72.2% of sample points, shows the highest average yield (39.4 mds/acre) with moderate variability (C.V. 25.16%). Sandy loam, with 21.51% share, has a lower yield (31.76 mds/acre) and slightly higher variability (C.V. 26.99%). Kalrathi (partially), though only 6.29% of samples, records the lowest yield (23.54 mds/acre) and highest variability (C.V. 47.1 This findings highlights the need for intelligent agriculture systems that can tailor practices to specific soil types, optimizing yield potential and minimizing variability through data driven management techniques.

Table 8. Last Crop Sown Before Wheat Crop and Wheat Production.

Last Crop	No. of Sample Point	% Share	Avg Yield mds/acre	S.D	C.V%
Cotton	626	78.74	37.143	10.33	27.80
Rice	43	5.41	37.027	11.71	31.63
Sugar Cane	15	1.89	40.697	7.545	18.54
Fodder	29	3.65	31.788	11.21	35.26
Fallow Land	65	8.18	34.493	13.18	38.22
Others	17	2.14	35.677	12.84	35.99

Table 9. Type of Soil and Wheat Production.

Soil Type	No. of Sample Point	% Share	Avg Yield mds/acre	S.D	C.V%
Chikni loom	574	72.20	39.4	9.913	25.16
Sandy loom	171	21.51	31.76	8.571	26.99
Kalrathi (partially)	50	6.29	23.54	11.09	47.12

Table 10 provides a comparison of wheat yield based on the source of seed used by farmers. It highlights the significant differences between the performance of certified seeds and home-grown seeds. Farmers who used certified seeds, accounting for only 10.44% of the sample, achieved an average yield of 44.87 mds per acre. This group also exhibited a relatively lower variability in yield, with a coefficient of variation (C.V.) of 21.5%, indicating more consistency in their crop production. In contrast, the majority of farmers (89.56% of the sample) relied on home-grown seed, which resulted in a considerably lower average yield of 35.82 mds per acre. These farmers experienced higher yield variability as reflected by a higher coefficient of variation of 26.99% suggesting that their crop production was less consistent. This data underscores the potential benefits of using certified seed, both in terms of higher average yield and lower yield variability, suggesting that certified seeds might offer more reliable and productive outcomes compared to home-grown alternatives. This analysis emphasizes the role of data driven decisions and technological advancements

such as intelligent agriculture practices to optimize seed selection and improve crop yields through more consistent and reliable production strategies.

Table 11 provides a detailed summary of the impact of pesticide/weedicide spray and seed treatment on wheat yield, highlighting the differences in yield and variability between treated and untreated fields. In the fields where pesticide or weedicide spray was applied, the average yield was significantly higher at 40.64 mds/acre, accompanied by a lower coefficient of variation (C.V) of 23.6%, indicating a relatively stable and consistent yield. In contrast, the fields that did not receive spray treatments had a lower average yield of 34.7 mds/acre, with a higher yield variability (C.V = 32.2%). Similarly, seed treatment showed a clear positive effect on wheat yield. While the number of seed-treated plots was relatively smaller, these fields produced a higher average yield of 43.66 mds/acre with a lower variability (C.V = 23.4%) when compared to untreated fields. The untreated plots had an average yield of 36.52 mds/acre and a higher yield variability (C.V = 29.2%). These findings suggest that both pesticide/weedicide spray and seed treatment practices have a positive influence on wheat yield, enhancing not only the overall yield but also its consistency. The reduced variability in the treated fields implies that these practices may contribute to more predictable and reliable wheat production. These findings underscore the potential of integrating intelligent agriculture technologies such as precision pesticide application and seed treatment to optimize yield and reduce variability ensuring more consistent and reliable wheat production.

5. Discussions

The empirical findings of this study reaffirm and expand upon the existing body of literature concerning the multifaceted determinants of wheat productivity in Pakistan. For instance, Qayyum and Pervaiz conducted a descriptive analysis highlighting the influence of critical factors such as DAP, urea, water availability, seed quality, sowing and harvesting times and weather conditions elements that are echoed in our study [23]. The observed enhancement in wheat yield due to the timely sowing (particularly by mid-November), certified seed usage, and the application of optimal fertilizer combinations (1–2 bags of DAP and 2–3 bags of urea) aligns closely with their established benchmarks. Our findings demonstrate the importance of integrated weed and pest management strategies as supported by the 17.11% yield increase observed through spray applications. This corroborates earlier insights by Bajkani et al. [24], who attributed low wheat productivity in Baluchistan to the persistence of traditional farming methods, which often overlook such critical input optimizations. The relevance of input quality is further substantiated by Hussain et al. [25], who reported increasing returns to scale in food grain crops like wheat when better-quality inputs were used. Our results echo this assertion particularly in relation to certified seed use, fertilizer regimes, and supplementary nutrient applications, all of which significantly boosted yield outcomes. In terms of broader environmental and socio-economic implications, the projected decline in per capita wheat availability reported by Tariq et al. and Tabasam under-

Table 10. Source of Seed and Wheat Yield Analysis.

Own Home Seed					Certified Seed				
No. of Sample Point	% Share	Avg Yield mds/acre	S.D	C.V %	No. of Sample Point	% Share	Avg Yield mds/acre	S.D	C.V %
712	89.56	35.815	10.48	26.99	83	10.44	44.87	9.65	21.5

Table 11. Use Pesticides/Weedicides Spray and Seed Treatment Effects on Wheat Yield.

Factors	No					Yes				
	No. of Sample Point	%Share	AvYield mds/acre	S.D	C.V %	No. of Sample Point	%Share	Avg Yield mds/acre	S.D	C.V %
Spray	438	55.09	34.7	11.20	32.2	357	44.9	40.64	9.6	23.6
Seed Treatment	769	96.73	36.52	10.70	29.2	26	3.27	43.66	10.2	23.4

lines the urgency of adopting climate-resilient and efficient production techniques [26]. As their study suggests, wheat availability could fall dramatically by 2050 due to population growth and adverse climatic effects. Our study responds directly to this concern by identifying key agronomic interventions such as optimal sowing windows, soil specific cultivation strategies and timely harvesting that can contribute to sustainable production increases. The integration of advanced data analytics, as demonstrated by Islam et al. [7], further reinforces the value of predictive modeling in guiding agricultural decisions. Our study, which utilized large scale survey data and analytical techniques to evaluate the impact of various agronomic practices, aligns with this approach. These findings also find support in the broader global discourse on precision agriculture (PA) and climate-smart agriculture (CSA). Wang et al., Zhang et al., and Tey and Brindal have collectively shown that technologies such as GPS-guided tools, remote sensing and real time monitoring can dramatically enhance resource use efficiency principles that mirror the data-driven recommendations of our research [28–30]. Moreover, CSA strategies, as noted by Lipper et al. [31], advocate for optimized planting schedules, resilient seed varieties, and conservation practices. Our study's emphasis on mid-November sowing and specific crop rotation patterns (notably cotton-wheat and sugarcane-wheat sequences) complements these recommendations by demonstrating their tangible yield benefits under local conditions. Finally, the integration of big data and machine learning in agricultural planning as highlighted by Tey and Brindal and demonstrated in Pakistan by Islam offers a forward looking pathway to agricultural transformation [2,30]. Our findings provide practical, evidence based guidelines that can feed into such systems enhancing the accuracy of yield forecasting and the efficiency of input management. In summary, this study substantiates the claims of earlier research while contributing new insights into the contextual application of agronomic best practices in Punjab, Pakistan. The results emphasize that strategic interventions, supported by empirical data and technological innovation, can not only play the role of intelligent agriculture to enhance the wheat productivity but also bolster national food security and economic resilience in the face of environmental and demographic pressures.

6. Policy Implications

The conclusions presented offer a strong foundation for shaping evidence-based agricultural policy, but to maximize their impact, specific and actionable policy recommendations are necessary. Given the clear yield advantages linked to certified seed usage, timely sowing, optimal fertilizer regimes, integrated weed management and strategic crop rotations, it is imperative for policymakers to promote the large-scale adoption of these agronomic practices through targeted support mechanisms. At the national and regional levels, agricultural extension services should be strengthened and better funded to provide hands-on training and awareness campaigns focused on the identified best practices. Furthermore, subsidies or credit schemes could be introduced to make certified seeds and balanced fertilizer inputs more accessible, especially for smallholder farmers who face economic constraints. Investment in infrastructure for timely seed and input delivery, along with the promotion of agro-based cooperatives, can further ease the adoption of these methods. Policies should also encourage soil testing and crop planning services to guide farmers in optimizing land use according to soil texture and previous crop sequences. Additionally, incentivizing mechanized land preparation and timely harvesting could significantly boost productivity. These recommendations not only aim to increase wheat production but also contribute to enhancing food security, reducing reliance on imports, and building a more climate-resilient and economically viable agricultural sector in Pakistan.

7. Economic Feasibility of Policy Recommendations towards Intelligent Agriculture

The transition toward intelligent agriculture requires a comprehensive and pragmatic assessment of the economic feasibility of the proposed policy recommendations. While interventions such as the use of certified seeds, timely sowing, optimized fertilizer regimes, integrated weed management and strategic crop rotations offer long term benefits, their initial implementation demands financial investments that may be challenging for smallholder farmers. Therefore, policy support should prioritize mechanisms that reduce entry barriers such as input subsidies, access to affordable credit and public-private partnerships to enhance service delivery at the grassroots level. To ensure the broader scalability of these recommendations, particularly in resource-constrained settings, it is crucial to tailor strategies to local contexts and capacities. Demonstration projects, farmer field schools, and capacity-building programs can facilitate knowledge transfer and build confidence in adopting intelligent agricultural practice. The economic feasibility of these practices extends beyond individual farms. At the macroeconomic level, improved productivity can reduce reliance on costly imports, stabilize domestic food markets, enhance trade balances and stimulate rural economies which ultimately contribute to national food security. However, potential barriers such as limited access to technology, fragmented land holdings, weak extension services, and climate related risks must be acknowledged. Addressing these challenges requires an integrated policy approach that promotes institutional coordination, strengthens rural infrastructure and supports adaptive research and development. In conclusion, while upfront costs and implementation challenges exist, the long term benefits of intelligent agriculture in terms of yield improvement, climate resilience and economic sustainability underscore the importance of targeted public investment and inclusive policy frameworks to support a more productive and equitable agricultural future in Pakistan.

8. Conclusions

With the increase of population, demand for wheat being an important and staple food crop is increasing rapidly while its production is not enough to meet the challenge of food availability. It is necessary to analyze the different factors with aims to find the pathway towards intelligent agriculture system to enhance the wheat production. Empirical findings indicate that farmers utilizing certified seed consistently achieve approximately 25% higher yields compared to those using home-retained seed. Among surveyed farmers, 48.3% adopted a seed rate of 60 kg per acre, which corresponded with significantly improved production outcomes. Wheat sown by mid-November produced statistically consistent and reliable yield increase. In terms of fertilizer application, the combination of 1–2 bags of DAP and 2–3 bags of urea per acre was associated with maximum yield outputs, establishing this regime as a statistically optimal fertilizer practice. Supplementary use of other fertilizers demonstrated a yield enhancement of up to 12.017%, indicating the potential for synergistic nutrient effects. The application of sprays was found to improve wheat yields by up to 17.11%, underscoring the significance of integrated weed management. Similarly, pre sowing land preparation techniques such as ploughing/rotavator exhibited a positive yield. Soil texture analysis revealed that chikni loam soils provided the most conducive environment for wheat cultivation, contributing to a yield increase of up to 24.05% and 67.37%, when compared to sandy loam and kalrathi soils, respectively. Crop rotation patterns also influenced yield outcomes. Wheat sown after cotton and sugarcane showed superior productivity, with the cotton-wheat sequence yielding more reliable and sugarcane-wheat sequence yielding more consistent production gains. Additionally, timely harvesting (post mid-April) further contributed to yield optimization. These findings underscore the critical need for the adoption of evidence based agronomic practices to improve wheat production in Pakistan, particularly in key areas such as seed selection, sowing time, fertilizer application, weed control, and crop sequencing. By utilizing scientific research and data-driven strategies, farmers can optimize their input usage, enhance crop yields, and minimize resource wastage. This approach will not only ensure more efficient agricultural practices but also help mitigate the challenges posed by climate change, resource constraints, and fluctuating market conditions. Moreover, it will contribute significantly to addressing Pakistan's growing food security concerns by boosting wheat production, a staple food crop, and strengthening the country's agricultural resilience. Implementing these practices at scale could lead to more sustainable farming systems, reducing dependency on imported wheat and improving the overall stability of the national food supply chain. Ultimately, evidence-based agronomy offers a path to securing a stable, affordable food supply for the population, ensuring long-term agricultural sustainability and enhancing rural livelihoods across the country. This finding highlights the critical role of intelligent agriculture practices in optimizing wheat production through data driven and evidence based strategies that enhance productivity, sustainability and resilience in the face of growing food security challenges.

Funding

This work received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

The author would like to appreciate the strong data collection mechanisms and efforts of all the team of CRS is considerable good asset for our sweet homeland Pakistan.

Conflicts of interest

The author declares no conflict of interest.

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