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Enhancing Wheat Cultivation in Ethiopian Agriculture Through Row Planting

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Abstract
The widespread adoption of wheat row planting represents a promising agricultural innovation with far-reaching implications for enhancing wheat yield and productivity in Ethiopia. This practice, which has gained traction among farmers over the past several years, holds the potential to revolutionize wheat cultivation and contribute to food security and rural livelihoods. However, despite its growing popularity, there remains a notable dearth of empirical research examining the comparative impact of row planting versus conventional broadcast planting methods on wheat yield. Against this backdrop, this study seeks to fill this critical knowledge gap by rigorously evaluating the efficacy of wheat row planting in bolstering wheat yield among Ethiopian farmers. By conducting a comprehensive analysis of field data and employing robust statistical methodologies, the study endeavors to provide empirical insights into the tangible benefits of row planting vis-à-vis conventional broadcasting techniques. The findings of this research underscore the significant positive impact of wheat row planting on wheat yield, thereby validating the efficacy of this innovative farming practice. By meticulously arranging wheat seeds in rows, farmers can optimize plant spacing, minimize competition for resources, and promote more efficient nutrient uptake—factors that collectively contribute to enhanced crop vigor, yield, and overall productivity. Moreover, the study underscores the importance of integrating complementary agronomic practices in conjunction with wheat row planting to maximize its efficacy and scalability. By adopting a holistic approach that encompasses soil management, water conservation, crop rotation, and pest control strategies, farmers can unlock the full potential of row planting and achieve sustainable gains in wheat yield over the long term. In light of these findings, the study advocates for the concerted promotion, adoption, and scaling up of wheat row planting practices across Ethiopia's agricultural landscape. By disseminating evidence-based insights, providing targeted extension services, and fostering multi-stakeholder collaborations, policymakers, agricultural experts, and development practitioners can catalyze the widespread adoption of row planting, thereby empowering farmers to realize the full benefits of this transformative farming technique.
Keywords: Wheat Row Planting, Agricultural Innovation, Crop Yield, Farming Practices, Food Security
JEL Codes: Q12, Q16, O13

1. INTRODUCTION

Agricultural extension activities play a crucial role in promoting, adopting, and scaling up improved agricultural practices, including the adoption of good agronomic practices that contribute to enhancing wheat yields (Tesfay, 2021; Danso, 2022). In the context of wheat production, one such practice involves planting wheat in rows, which is widely recognized as a method to improve yield outcomes. Traditionally, broadcasting seeds by hand at high seed rates has been a common practice. However, this conventional method often leads to uneven distribution of seeds, making subsequent activities such as hand weeding and hoeing challenging. Moreover, the lack of uniformity in seed placement results in increased competition between wheat plants and weeds, thereby hampering wheat growth and tillering potential. As a consequence, wheat yields are adversely affected by these factors, ultimately leading to reduced productivity (Ahmad and Khan, 2021; Hossain, et al 2021). Recognizing the limitations of the traditional broadcasting approach, the adoption of row planting techniques offers several advantages. By planting wheat in rows, farmers can achieve more precise seed placement, ensuring better seed-to-soil contact and improved seedling emergence. This method facilitates easier weed management practices, as the organized layout of rows allows for more efficient weed control measures, such as mechanical weeding or herbicide application. Additionally, the reduced competition between wheat plants and weeds promotes optimal growth conditions, leading to enhanced tillering and ultimately higher wheat yields (Qasim and Tariq, 2019; Hendriks, et al 2022). Through agricultural extension efforts, farmers are educated and trained on the benefits of adopting row planting techniques as part of their wheat production practices. Extension services provide farmers with technical guidance, practical demonstrations, and access to improved seeds and equipment necessary for implementing row planting methods effectively

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(Ahmad and Ali, 2016; Okori, et al 2022). By promoting the adoption of these agronomic practices, agricultural extension initiatives contribute to enhancing wheat productivity and improving livelihoods in farming communities. Row planting, when implemented with appropriate spacing between rows and optimal plant density, facilitates better aeration, moisture retention, sunlight exposure, and nutrient availability, all of which are conducive to the development of a healthy root system. In regions where this practice has been adopted, such as the United States, notable benefits have been observed. Research conducted in the United States, as cited by Lauren et al. (2012), illustrates the advantages of row planting combined with inter-row cultivation. By utilizing wide rows and implementing inter-row cultivation techniques, weed density was significantly reduced by 62 percent. This reduction in weed competition allowed wheat plants to thrive, resulting in a noteworthy increase in yield, up to 16 percent higher compared to traditional planting methods. These findings underscore the importance of proper row spacing and plant density in optimizing wheat production. By creating favorable growing conditions and minimizing weed interference, row planting techniques contribute to improved crop health, enhanced resource utilization, and ultimately higher yields (Rosembaum, and Rubin 1983; Ali and Zulfiqar, 2018). As such, adopting row planting practices represents a valuable strategy for farmers seeking to maximize wheat productivity and profitability. While agricultural extension offices have been actively promoting and scaling up manual wheat row planting in the study district for several years, the true impact of this planting method remains somewhat uncertain. Challenges related to program implementation, methodological issues, and perhaps an overly optimistic view of row planting's potential in real farm settings have been noted by Vandercasteelen et al. (2013). Despite these challenges, agricultural policy makers and extension personnel continue to view row planting as a best agronomic practice.

However, there is a notable gap in empirical research regarding the actual impact of wheat row planting on the yields of smallholder farmers. Without robust empirical studies to provide concrete evidence of its efficacy in diverse farm contexts, the true effectiveness of row planting as a yield-enhancing technique remains to be fully understood. Addressing this knowledge gap through rigorous empirical research could provide valuable insights for both policymakers and farmers, enabling more informed decision-making and more targeted agricultural extension efforts. This study aims to assess the effect of row planting on wheat yield among smallholder farmers. To achieve this goal, the study utilizes the propensity score matching method. By Jalan and Ravallion, (2003) employing this approach, the study seeks to provide valuable insights into the effectiveness of row planting techniques in wheat production within the study district. The findings of this study are expected to inform the development of agricultural policies and extension activities related to the promotion and scaling up of row planting practices. By offering empirical evidence on the impact of row planting on wheat yields among smallholder farmers, policymakers and extension personnel will be better equipped to design targeted interventions and support mechanisms. Ultimately, this research endeavors to contribute to the optimization of wheat production practices, thereby enhancing agricultural productivity and livelihoods within the study area (Okolie, et al 2022).

2. RESEARCH METHODOLOGY

The selection of Hetosa district through purposive sampling was driven by its prominence as a key hub for wheat production within the zone. Its strategic importance in contributing significantly to wheat production at various levels, coupled with the presence of well-established research and extension programs tailored to support wheat farmers, made it an ideal candidate for inclusion in the study. Moreover, Hetosa district's representation allows for insights that can be extrapolated to broader contexts within the zone and beyond. By focusing on a district with such attributes, the study aims to capture a comprehensive understanding of the impact of row planting on wheat yield, considering both local dynamics and broader agricultural frameworks. The deliberate dissemination of improved wheat varieties and row planting techniques within Hetosa district facilitated a conducive environment for evaluating the efficacy of wheat row planting on farmers' yields. This district served as a fertile ground for such an assessment due to the active adoption and practice of these advancements within the local agricultural landscape. To ensure a representative sample, a systematic approach was adopted in the selection process. Initially, a comprehensive list of kebeles, the primary administrative divisions associated with wheat cultivation, was compiled. Subsequently, employing simple random sampling, two kebeles were selected from this list, considering logistical constraints and resource availability.

In the final stage, within the chosen kebeles, a roster of wheat farmers was meticulously prepared. This meticulous compilation allowed for the systematic selection of participants, ensuring a diverse and inclusive representation within the study sample. The selection of sample farmers was carried out using a straightforward and unbiased approach known as simple random sampling. The determination of the sample size adhered to the formula established by Krejcie and Morgan (1970), Gujarati, (2004) and Dehejia and Wahba (2002) ensuring statistical robustness and reliability in the study's findings. To ensure equitable representation across kebeles, the allocation of the sample size was conducted in proportion to the population of farm household heads within each kebele. As a result, out of the total sample size of 133 randomly selected farmers, 107 were non-participants in row planting, while 26 were participants in the wheat row planting initiative during the 2012/13 cropping season. This distribution allowed for a balanced assessment of the impact of row planting on wheat yields across diverse farming contexts within the study area.

3. DATA COLLECTION

The data collection process for this study involved a combination of primary and secondary sources. Primary data was gathered through a cross-sectional survey administered to randomly selected sample farmers. To ensure accuracy and relevance, a specially designed and pre-tested questionnaire, aligned with the study's objectives, was utilized. Trained data enumerators were employed to facilitate the collection process, which encompassed both quantitative and qualitative information. Various aspects of the farmers' demographic and socioeconomic characteristics, including family size, age and gender distribution, and educational background, were captured. Additionally, data on land holdings, input utilization (such as seeds, fertilizers, and pesticides), labor allocation, credit access, and extension services were collected to provide insights into agricultural practices. Moreover, information on farm outputs, input and output prices, agronomic techniques (including wheat row planting), and environmental factors such as rainfall patterns and temperature were documented. The survey was conducted during the months of May and June 2013, ensuring that seasonal variations and relevant agricultural activities were adequately captured. In parallel, secondary information on climate variables such as rainfall and temperature was sourced to complement the primary dataset, enriching the analysis and providing a comprehensive understanding of the factors influencing wheat yield outcomes.

4. ANALYTICAL METHODS

Participation in wheat row planting is not random, as it is influenced by various factors such as farm size, access to resources, and adoption of agricultural innovations. In the context of impact evaluation, propensity score matching (PSM) offers a valuable approach to address this issue. Unlike parametric regression models, which often require stringent assumptions and may not adequately account for non-random selection into treatment, PSM provides a more flexible and robust framework. By estimating the probability (propensity score) of treatment assignment based on observed covariates, PSM allows for the creation of a matched comparison group of non-participants who are similar to participants in terms of their propensity to adopt wheat row planting. This matching process helps to balance the distribution of observed characteristics between participants and non-participants, thereby reducing selection bias and enabling a more accurate estimation of the treatment effect. Moreover, PSM does not rely on specific functional forms or distributional assumptions, making it particularly well-suited for situations where the underlying data may not conform to parametric assumptions. Rosenbaum and Rubin's pioneering work on propensity score matching (PSM) in 1983 laid the foundation for its widespread adoption in social and economic program evaluation. In the absence of baseline data and when randomization is unlikely, PSM offers a powerful approach to estimate treatment effects. The essence of PSM lies in its ability to create a counterfactual comparison group by matching treated and untreated units based on their propensity scores, which represent the likelihood of receiving the treatment given observed covariates. By balancing the distribution of observed characteristics between treated and control groups, PSM allows for a more credible estimation of the causal effect of the treatment. One of the key strengths of PSM is its flexibility and robustness. Unlike parametric models that rely on specific functional forms and distributional assumptions, PSM does not impose such constraints, thereby offering a more data-driven and flexible approach to impact estimation. This makes PSM particularly well-suited for situations where the underlying data may not conform to parametric assumptions. Furthermore, PSM enables researchers to estimate treatment effects in a straightforward and intuitive manner, without the need for complex modeling techniques. By providing a transparent and interpretable framework for impact assessment, PSM facilitates a clearer understanding of the causal relationships between interventions and outcomes.

Ravallion's, (2005) insight underscores the importance of understanding the limitations and advantages of different impact evaluation techniques. While regression models utilize the full sample and may provide estimates based on unmatched data, propensity score matching (PSM) focuses on the matched sample, which lies within the region of common support. By restricting the analysis to the matched sample, PSM ensures that treated and control units are comparable in terms of observed covariates, thereby reducing the potential for bias due to differences in characteristics between the two groups. This approach enhances the robustness of impact estimates, particularly in situations where the treatment assignment may be non-random or affected by selection bias. In contrast, regression models that rely on the full sample may yield biased estimates if the underlying assumptions of the model are violated or if there are unobserved differences between treated and control units. Moreover, such models may be less robust to misspecification of regression functions, leading to potentially unreliable inference about the causal effects of the treatment. By acknowledging the strengths and limitations of both regression models and propensity score matching, researchers can make informed decisions about the most appropriate methodological approach for their specific evaluation context. In situations where non-random treatment assignment is a concern, PSM offers a valuable tool for obtaining credible estimates of treatment effects while mitigating the risk of bias and misspecification. Janan and Ravallion's, (2005), Caliendo and Kopeinig (2008) work highlights the versatility and applicability of propensity score matching (PSM) across various fields within the social sciences, particularly in the evaluation of public programs and policies. By employing PSM, researchers can effectively compare the outcomes of participating and non-participating households, thereby providing valuable insights into the impact of interventions.

The fundamental principle behind PSM is to create pairs of participating and non-participating households that are similar in terms of relevant characteristics prior to the intervention. This matching process ensures that the treatment group (i.e., adopters of row planting) is comparable to the control group (i.e., non-adopters) with respect to observed covariates, thereby allowing for a more rigorous assessment of the treatment effect. By identifying non-adopter households that closely resemble adopter households in terms of their propensity to participate in row planting, PSM enables researchers to isolate the causal effect of the intervention from confounding factors. This methodological approach enhances the credibility and validity of impact evaluations, providing policymakers and practitioners with actionable insights into the effectiveness of public programs and policies. Greene's, (2012) explanation succinctly outlines the core objective of propensity score matching (PSM) methodology in impact evaluation studies. The primary goal of matching is to identify a comparison group from a pool of nonparticipants that closely resembles the group of program participants. This similarity is determined based on observable characteristics, such as demographic variables, socioeconomic status, or other relevant covariates. The concept of "closeness" is operationalized through propensity scores, which represent the likelihood or propensity of each individual to receive the treatment (i.e., participate in the program) based on their observed characteristics. By estimating these propensity scores, researchers can effectively rank individuals according to their likelihood of treatment assignment. Once propensity scores are computed, individuals with similar scores are paired together, forming matched pairs of participants and nonparticipants. The pairing process ensures that each participant is matched with a nonparticipant who has a similar propensity to participate in the program, thereby creating comparable treatment and control groups. After matching is completed, the average treatment effect is estimated by comparing the outcomes of the matched pairs. The difference in outcomes between participants and their matched counterparts from the control group provides an estimate of the average treatment effect, capturing the causal impact of the program or intervention. By leveraging propensity scores and matching techniques, PSM allows researchers to account for selection bias and confounding factors, thereby enabling more robust and credible evaluations of program impacts. This methodological approach enhances the validity and reliability of impact assessments, ultimately informing evidence-based policymaking and program design.

5. RESULTS AND DISCUSSION

The table 1 offers insights into the distribution of wheat planting methods among a selected group of farmers. The two primary methods observed are Broadcast and In Row planting. Broadcast planting, utilized by the majority of farmers in the sample, was adopted by 107 out of 133 farmers, representing approximately 80.45% of the total sample. This method involves scattering seeds evenly across the entire planting area, providing uniform coverage but potentially requiring more seeds. In contrast, the In Row planting method was less commonly practiced, with only 26 farmers, comprising 19.55% of the sample, employing this technique. In Row planting involves placing seeds in rows with defined spacing between them, allowing for easier management of crops but potentially requiring more labor during planting. The data suggests a preference for the Broadcast method among the sampled farmers, likely influenced by factors such as ease of implementation, resource availability, and traditional farming practices. Understanding these preferences can inform agricultural extension services and policymaking aimed at promoting efficient and sustainable farming practices.

Table 1: Sample farmers wheat planting methods

Planting method	Frequency	Percent
Broadcast	107	80.45
In Row	26	19.55
Total	133	100

The table 2 presents the average wheat yield, measured in quintals per hectare (q/ha), for the two planting methods observed among the sampled farmers. For the Broadcast planting method, the data shows that the average yield across 107 observations is 30.14 q/ha, with a standard deviation of 7.63. The yield ranged from a minimum of 16.00 q/ha to a maximum of 54.67 q/ha. On the other hand, the In Row planting method yielded an average of 41.23 q/ha based on 26 observations, with a slightly higher standard deviation of 9.83. The range of yields for this method was from a minimum of 30.00 q/ha to a maximum of 66.67 q/ha. When considering the total sample of 133 observations, the average wheat yield was calculated at 32.30 q/ha, with a standard deviation of 9.20. The overall yield ranged from 16.00 q/ha to 66.67 q/ha. These findings indicate that, on average, the In Row planting method resulted in higher wheat yields compared to the Broadcast method. However, both methods exhibited variability in yields, with some farmers achieving higher yields than others within each method.

The significant F-statistic in the ANOVA table 3 suggests that there are notable differences in mean wheat yields between the Broadcast and In Row planting methods. This finding indicates that the choice of planting method has a discernible impact on the wheat yield among the sampled farmers. The higher mean yield associated with the In Row planting method compared to the Broadcast method aligns with agricultural practices that emphasize precision planting and spacing. Moreover, the ANOVA table highlights that a substantial portion of the total variation in wheat yields can be attributed to differences between the two planting methods. This underscores the importance of selecting the appropriate planting method to optimize crop productivity. Farmers may consider factors such as soil conditions, available resources, and equipment when deciding on the most suitable planting method for their agricultural operations. Overall, the results of the ANOVA analysis provide valuable insights into the effectiveness of different wheat planting methods in terms of yield outcomes. Further research could delve into additional factors influencing yield variability and explore potential strategies for improving wheat production efficiency based on the choice of planting method.

Table 2: Average wheat yield of planting methods (q/ha)

Planting method	Obs	Mean	Std.dev	Minimum	Maximum
Broadcast	107	30.14	7.63	16.00	54.67
In row	26	41.23	9.83	30.00	66.67
Total	133	32.30	9.20	16.00	66.67

Table 3: Analysis of variance for mean yield difference of planting methods

	Analysis of variance				
Source of variation	SS	df	MS	F	Prob > F
Between groups	10.30	45	0.23	1.88*	0.0061
Within groups	10.62	87	0.12		
Total	20.92	132	0.16		

Source: Computation from own data; *P < 0.01 significance level.

Table 4: Logit estimate for propensity score for study district

Variables	Coef.	Std.error	z	P>z
Age	-0.037	0.062	-0.59	0.553
Education	-0.052	0.078	-0.67	0.506
Experience	-0.008	0.063	-0.13	0.895
Land holding	-0.573	0.452	-1.27	0.205
Crops	0.104	0.232	0.45	0.653
Rotation	1.293	0.686	1.88*	0.060
Credit	-1.860	1.185	-1.57	0.116
Seed	-2.209	0.913	-2.42**	0.015
Household size	0.048	0.187	0.26	0.796
Livestock holding	0.374	0.129	2.9***	0.004
Income	0.051	0.060	0.86	0.390
Constant	-0.204	2.013	-0.1	0.919
Number of obs	=	133		
LR chi2(11)	=	49.62***		
Prob > chi2	=	0.0000		
Pseudo R2	=	0.378		
Log likelihood	=	-40.902		

In Table 4, the logit estimate for the propensity score for the study district reveals the coefficients, standard errors, z-values, and p-values associated with various predictor variables. Each coefficient represents the estimated effect of the corresponding predictor variable on the log-odds of being in the treatment group (or possessing a certain characteristic). Among the predictor variables, livestock holding shows a statistically significant positive relationship with the log-odds of being in the treatment group, as indicated by its coefficient of 0.374 ($z = 2.9$, $p = 0.004$). This suggests that households with higher livestock holdings are more likely to be in the treatment group, relative to those with lower livestock holdings. Similarly, the variable "Seed" also demonstrates a statistically significant negative association with the log-odds of being in the treatment group, with a coefficient of -2.209 ($z = -2.42$, $p = 0.015$). This implies that households with certain characteristics related to seed usage are less likely to be in the treatment group. Other variables, such as rotation, show a trend towards significance ($z = 1.88$, $p = 0.060$), indicating that they may have some influence on the propensity score, albeit not at a statistically significant level. The overall model fit is assessed through the LR chi-squared test, which yields a statistically significant result (chi2(11) = 49.62, $p < 0.0001$), suggesting that the model as a whole significantly predicts the probability of being in the treatment group. The pseudo R-squared value of 0.378 indicates that the model accounts for a considerable portion of the variability in the outcome variable, while the log likelihood provides a measure of how well the model fits the observed data, with a value of -40.902.

The table 5 provides a summary of propensity scores for participant and non-participant farmers based on their planting methods. The "Obs" column represents the number of observations for each category. For row planting, there were 26 observations, with a mean propensity score of 0.5167 and a standard deviation of 0.2796. The minimum propensity score observed for row planting was 0.0028, while the maximum score was 0.9905. In contrast, for broadcast planting, there were 107 observations, with a lower mean propensity score of 0.1174 and a slightly smaller standard deviation of 0.1631. The minimum propensity score observed for broadcast planting was 0.0007, and the maximum score was 0.7212. Considering all planting methods together (total), which includes both row planting and broadcast planting, there were 133 observations in total. The mean propensity score for all planting methods combined was 0.1955, with a standard deviation of 0.2478. The minimum propensity score observed across all planting methods was 0.0007, while the maximum score was 0.9905.

Table 5: Summary of propensity scores for participant and non-participant farmers

Variable (planting method)	Obs	Mean	Std.dev	Minimum	Maximum
Row planting	26	0.5167	0.2796	0.0028	0.9905
Broadcast	107	0.1174	0.1631	0.0007	0.7212
Total	133	0.1955	0.2478	0.0007	0.9905

The table 6 presents the performance of different matching estimators for the study district, evaluated based on various criteria including balancing tests, pseudo R2, and matched sample size. For the nearest neighbor matching estimator, two different specifications are considered: Neighbor (1) and Neighbor (2). Both specifications involve 11 balancing tests and result in pseudo R2 values of 0.443 and 0.134, respectively. The matched sample size for both Neighbor (1) and Neighbor (2) is 120. Next, the performance of caliper matching estimators is assessed using two different caliper values: Caliper (0.01) and Caliper (0.25). For Caliper (0.01), 11 balancing tests are conducted, and the pseudo R2 value is 1.000, indicating a high level of explanatory power. However, the matched sample size is relatively small at 20. On the other hand, Caliper (0.25) also involves 11 balancing tests but yields a lower pseudo R2 value of 0.226 with a larger matched sample size of 38. Lastly, the table includes the performance of kernel matching estimators with three different bandwidth values: Bandwidth (0.25), Bandwidth (0.1), and Bandwidth (0.5). All three specifications involve 11 balancing tests. The pseudo R2 values for Bandwidth (0.25), Bandwidth (0.1), and Bandwidth (0.5) are 0.021, 0.024, and 0.118, respectively. The matched sample size is consistent across all three bandwidth specifications, with 120 observations in each case.

Table 6: Performance of matching estimators for the study district

		Performance criteria		
S.N.	Matching estimator	Balancing test*	Pseudo R2	Matched sample size
1.	Nearest neighbor			
	Neighbor (1)	10	0.443	120
	Neighbor (2)	11	0.134	120
2.	Caliper matching			
	Caliper (0.01)	11	1.000	20
	Caliper (0.25)	11	0.226	38
3.	Kernel matching			
	Bandwidth (0.25)	11	0.021	120
	Bandwidth (0.1)	11	0.024	120
	Bandwidth (0.5)	11	0.118	120

The table 7 presents estimates of average treatment effects for two groups of farmers based on the outcome indicator of wheat yield. Under the "Unmatched" sample, the average yield for treated farmers is 30.135, while for control farmers, it is 41.231. The difference in yield between the two groups is 11.096, with a standard error of 1.771 and a t-statistic of 6.27. Considering the "ATT" (Average Treatment Effect on the Treated), the estimated average yield for treated farmers is 33.819, whereas for controls, it is 39.583. The difference in yield is 5.765, with a standard error of 2.345 and a t-statistic of 2.46, indicating statistical significance at the 5% level. The table also indicates the Average Treatment Effect on the Untreated (ATU) and the Average Treatment Effect (ATE), although the specific values for these parameters are not provided in the table.

Overall, the estimates suggest that there is a significant difference in wheat yield between treated and control farmers, with the treated group generally exhibiting higher yields compared to the controls.

Table 7: Estimates of average treatment effects for the two groups of farmers

Outcome indicator	Sample	Treated	Controls	Difference	S.E.	T-stat
	Unmatched	41.231	30.135	11.096	1.771	6.27
Wheat yield	ATT	39.583	33.819	5.765	2.345	2.46*
	ATU	30.505	39.067	8.563	.	.
	ATE	8.096	.	.		

6. CONCLUSIONS

The aim of this research was to assess how the adoption of wheat row planting practices affects the yield of smallholder farmers in the Arsi zone of Ethiopia. To achieve this objective, the study employed a combination of methodologies, including propensity score matching (PSM), binary logit regression, and cross-sectional survey data analysis. Propensity score matching was utilized as the primary analytical approach to evaluate the impact of wheat row planting on yield outcomes. This method allowed the researchers to address potential selection bias by matching participants who adopted wheat row planting with similar nonparticipants based on observable characteristics. By creating comparable groups, the study aimed to isolate the causal effect of wheat row planting on yield outcomes. In addition to propensity score matching, binary logit regression analysis was employed to explore the determinants of wheat row planting adoption among smallholder farmers in the Arsi zone. This statistical technique enabled the researchers to identify factors associated with the likelihood of adopting wheat row planting practices, providing valuable insights into the decision-making process of farmers. Furthermore, the study utilized cross-sectional survey data collected from smallholder farmers in the Arsi zone. This data provided information on various demographic, socioeconomic, and agricultural factors relevant to the adoption of wheat row planting and its impact on yield outcomes. By analyzing this survey data, the researchers were able to contextualize their findings within the broader socio-economic and agricultural landscape of the study area. The data analysis revealed a significant positive impact on wheat yield among farmers who adopted wheat row planting compared to those utilizing the conventional broadcast planting method. However, it's important to note that the mere act of placing wheat seeds in rows may not solely account for this yield advantage over the broadcast planting method. Other agronomic factors, such as row and seed spacing, seed and fertilizer rates, early hand weeding and hoeing, as well as additional agronomic and management practices, likely contribute to the observed differences in yield. Indeed, the effectiveness of wheat row planting in enhancing yield outcomes is likely influenced by a combination of factors, including the overall management practices employed by farmers. Optimal row and seed spacing, appropriate rates of seed and fertilizer application, timely weed control measures, and other agronomic interventions are all integral components that interact synergistically to maximize the yield potential of wheat crops. Therefore, while wheat row planting may serve as a fundamental agronomic practice, its full impact on yield can only be realized when implemented alongside a comprehensive set of agronomic and management strategies. Future research and extension efforts should consider these multifaceted factors to better understand and harness the potential benefits of row planting for wheat production, ultimately enhancing agricultural productivity and food security in the region. The study underscores the importance of integrating additional agronomic practices alongside wheat row planting to maximize wheat yield. Agricultural research and extension activities should focus on promoting a holistic approach that combines row planting with complementary agronomic interventions. By considering factors such as optimal seed and fertilizer rates, appropriate spacing, effective weed management, and timely agronomic practices, farmers can unlock the full potential of wheat row planting and achieve higher yields. Furthermore, successful promotion, adoption, and scaling up of wheat row planting practices hinge on the dissemination of comprehensive agronomic knowledge and practices through extension services. Extension agents play a crucial role in providing farmers with the necessary information, training, and support to implement row planting effectively. Additionally, collaborative efforts between agricultural researchers, extension workers, and farmers' groups can facilitate the adoption of integrated agronomic strategies tailored to local agroecological conditions. In essence, the study recommends a holistic approach to wheat production that emphasizes the synergistic effects of multiple agronomic practices, including row planting. By adopting such an approach, farmers can enhance wheat yields, improve food security, and promote sustainable agricultural development in the region.

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