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Tackling Smallholder Farming Challenges through Climate-Smart Agriculture

Lavanya P*[1], DrRekha MM[2], SenthilKumar A[3], Archana J[4], Ashish Kaushal[5], Hala Baher[6]

*[1]Assistant Professor, Department of Physics and Electronics, Bhavan's Vivekananda College of Science, Humanities and Commerce, Hyderabad, Telangana, Mail id: lavanya.elec@bhavansvc.ac.in

[2]Assistant Professor, Department of Chemistry and Biochemistry, JAIN (Deemed to be University), Bangalore, Karnataka, India, Email Id:mm.rekha@jainuniversity.a.cin,Orcid Id-0000-0002-7371-6478

[3]Professor, Artificial intelligence, Shri Vishnu Engineering College for Women Email Id: drsenthilkumar.ai@svecw.edu.in,Orcid Id-orchid id : 0000-0003-2567-7950

[4]Assistant professor, B.tech Agricultural engineering, Bannari Amman Institute of technology, India. Email Id: archanaj@bitsathy.ac.in

[5] Jindal Global Business School, O P Jindal Global University, Sonipat, Haryana, Email: ashishkiitdelhi@gmail.com

[6]Department of Radiology and Ultrasonography Techniques, College of Medical Techniques, Al-Farahidi University, Baghdad, Iraq. Email Id: hala.baher@uoalfarahidi.edu.iq

Corresponding author (*): lavanya.elec@bhavansvc.ac.in

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Abstract

The nation's agricultural sector is crucial since millions of rural households depend on smallholder farming for their subsistence. However, smallholder farmers face many challenges that climate change has exacerbated, including erratic rainfall patterns, increased frequency of floods and droughts, and lower soil fertility. Climate-smart agriculture (CSA) theory has gained support to address these issues and advance sustainable agriculture. Data from 260 households were evaluated using the extended Roy model with a local instrumental variable (LIV) version utilizing a semi-parametric method and Propensity Score Matching (PSM). The PSM model's findings demonstrated the favorable and significant effects that adopting the row planting technique had on both consumption and income from agriculture per acre. The results are a direct consequence of the row planting method since variables have a uniform distribution, and the impact estimate is unaffected by hidden bias in selection. With a greater propensity for farmers to use climate-smart planting techniques, the marginal value of row planting grows. Implementing CSA might improve rural living, reduce environmental damage from agricultural development, and diminish the effects of climate change on smallholder agriculture.

Keywords: Climate-Smart Agriculture (CSA), Local Instrumental Variable (LIV), Propensity Score Matching (PSM).

1. Introduction

The India most recent prediction is that by 2050, there will be 9.6 billion people on the planet. The biggest problem facing the agri-food sector is food production. This necessitates tremendous efficiency increases since there is a limited amount of agricultural land accessible. Maximizing productivity with finite resources is necessary, which calls for a significant agricultural revolution (Abegunde *et al.,* 2019). However, special emphasis should be paid to the need to lessen climate change's consequences along with greenhouse gas

(GHG) emissions. Three times as much of it will be in the atmosphere by 2030, significantly raising global temperatures (Akinyi*et al.,* 2022). The impact on the world's agriculture sector is substantial. CSA, which uses cutting-edge technological developments to reduce global warming, connects these projects. According to the FAO, climate-smart agriculture "sustainably increases productivity, adaptation, reduces/removes GHGs, and enhances achievement of national food security and development goals" (Azadi*et al.,* 2021). CSA is more of a manufacturing mindset than a brand-new production technique. This depends on both new and innovative technology and the equipment and tools used in conventional agriculture. Nevertheless, fresh technology will expand throughout the agricultural sector as time passes (Barasa*et al.,* 2021). CSA is limited to two categories: precision agriculture and smart agriculture. What set them apart are their approaches. Precision agriculture is a management approach that ultimately focuses on input optimization, in contrast to smart agriculture, which aims to enhance the agricultural system as a whole. Furthermore, smart farming employs several datasets and data sources for comparison, including farm-level data and market and meteorological statistics (De Corato, 2020).

CSA fits within the smart agriculture category, where additional efforts are made to optimize farming systems. The wide definition of CSA encompasses integrating diverse farming/agronomic processes and procedures and enhancing input usage, including using seeds, pesticides, water, and other inputs. Because of how swiftly technology is developing, several cutting-edge CSA products related to the Internet of Things (IoT), artificial intelligence (AI), and robots are about to become commercially available. It is also important to highlight cloud-based computing, big data, and novel machine teaching (Jamil*et al.,* 2021). By enhancing the efficiency and precision of data collection and processing, these products can provide farmers access to more accurate information and advice. Farming chores like weeding and harvesting can be completed more swiftly and accurately. The direct effects of climate change on the entire agriculture industry might be beneficial or detrimental (Joung*et al.,* 2020). Agriculture accounts for a larger portion of its gross domestic product, and emerging nations are particularly affected. In addition, compared to wealthy countries, they are frequently more susceptible to such changes. Smallholder farms are the foundation of the global food chain, providing food and money for the majority of the world's poorest people. 84% of all farmers are small-scale, with the majority living in developing nations. They must be changed into a more effective, climatically robust unit with fewer GHG emissions. Raising their climate knowledge is essential since it influences their acceptance of CSA (Komarek*et al.,* 2020). The CSA may provide farms with more immediate advantages than its long-term promises. Small-scale producers especially depend on short-term gains since they lack the financial resources to make risky decisions. Smallholders choose CSA techniques that bring immediate advantages since agriculture has low-profit margins and considerable risks. To implement any CSA practices that could impact their financial situation, smallholdings typically require assurances and financial help. The three pillars of CSA may alter in favor of improved productivity, reduced GHG emissions, and higher resilience comes at a cost (Makate, 2019).

Makate C, (2020) suggests that for CSA to succeed in small-scale agriculture, a complete socioeconomic analysis must consider the diversity of the environment experienced by small farmers and the discovery and use of the farming families' potential for its acceptance and execution. Makate*et al.,* (2019) maintained to enhance CSA by including the undervalued but crucial component of "small-scale farmer" as well as developing Vulnerable-Smart Agriculture (VSA) as a full CSA replacement. The study's conclusions back up VSA's assertion that none of their programs can be workable and realistic as long as the opinions of farmers impacted by political decisions are not heard. Mazzocchi*et al.,* (2020) offered a multifaceted framework to assess how to distribute resources among competing options. The study used Cost-Benefit Analysis (CBA) to assess the methods' economic viability and identify the most significant climate-smart agricultural practices used by smallholder farmers in various value chains throughout Sub-Saharan Africa (SSA). This allowed for the development of a range of practical and affordable options.Mizik, (2021) examined the Regression adjustment with inverse probability weighting used in the investigation to determine how different adoption regimes affect agricultural output and income. Multinomial logistic regression is used to assess aspects of individual and multiple adoptions. The study by Phasinam*et al.,* (2022) suggests that to increase the study will investigate if local institutions (LI) can be expanded in scope and how indigenous knowledge (IK) may be integrated into climate change mitigation planning to scale the effectiveness of climate-smart agriculture technology. Soni*et al.,* (2020) provides Institutional Analysis and Development framework that serves as the basis for the article. It reviews existing research and considers potential CSA technology upscaling among smallholder farming groups that approaches/strategies, policy initiatives, and institutional needs may support.

2. Materials and methods

Teff production and variety overview

Farmers' main crop for food production is Teff. Teff cultivation is estimated to be practiced by 6.4 million farmers worldwide, or around one-fifth of all agricultural land. Two out of every three people consume Teff every day. It is the go-to grain for over 50 million people and controls the market. Teff is expanding as a global crop because it is gluten-free and beneficial for those with celiac disease or gluten sensitivity. Its production and consumption are only surpassed by maize. Teff is a crop with a lower risk than other cereals since it can endure bad weather. The crop may also grow in swampy situations and has only a limited number of disease and insect issues. Teff may grow in a variety of agroecology. Although it is also grown in select places during the brief wet season, teff is normally grown during the major rainy season. Improved teff genotypes and farming methods are gaining traction in the main Teflon-producing regions. However, acceptance is still limited. Most planting employs manual broadcasting, which takes much more seed and yields substantially less than contemporary techniques. Instead, row planting is a climate-smart farming method that improves spacing, uses fewer seeds, and is simple to weed, harvest, and control illnesses and pests, ultimately leading to a significant boost in output. Presently uses manual broadcasting for most planting, which uses much more seed and produces far lower yields than modern methods. On the other hand, row planting is a climate-smart farming technique that increases spacing and uses fewer seeds, eventually leading to a significant increase in production. Mechanical planting techniques can increase yield by employing the right seed rates and spacing. Teff plants grow better when planted in rows than the conventional broadcasting approach when the per-hectare seed rate is reduced from 35 kg to 10 kg. This is true because there is less competition for nutrients in the soil, water, and sunshine. Since every plant generates more stalks, the potential net earnings are substantially larger, and grains per stalk, in addition to the cost savings from using fewer inputs. Climate-smart farming practices are advantageous where food poverty has long been a major problem. Numerous factors contribute to food insecurity, including poor agricultural productivity, frequent droughts, environmental degradation, rural-urban movement, and population pressures. Climate Resilient Green Economy (CRGE) plan was disclosed in 2011 and one of its goals is to increase farmer income and provide food security while reducing sector emissions. This immediately calls for using agricultural methods that improve productivity while being climate conscious. To support ongoing agricultural expansion and assure national food security, it must increase its usage of yield-increasing technological advancements due to a need for more arable land and a fast-growing population. As part of these initiatives, tripling Teff's grain and straw yields would have a huge positive impact on food safety and the economy. Empirical research is crucial to follow the GTP and CRGE implementation processes and other national policies.

Research region and the data

Teff, sorghum, maize, horse beans, chickpeas, haricot beans, and other annual crops are grown, and commercial crops like onion and pepper are grown. The primary cereal crop produced there is Teff, and as a consequence of a recent government program, many farmers are now employing improved Teff seed types and row planting methods. These factors led to the region being picked as a study location. The structured questionnaire inquires about each household's socioeconomic standing, including the age and the family head's gender, their degree of schooling, the number of family members they have, and how they employ agricultural inputs like fertilizer and superior seeds. Additionally, it inquires about their opinions of the novel row planting techniques. The study gathered additional information regarding consumption expenditure and social capital, including association membership for farmers, income level, and source of revenue.

Empirical approaches

Finding a reliable assessment of counterfactual analysis, or what would have occurred to participating units if they had not attended, is the major problem in assessing any intervention or program. As a result, the foundation of an effective impact evaluation is the identification of the counterfactual. If treatment is administered randomly, the results of persons not receiving treatment can provide a reliable counterfactual assessment. However, comparing the results across the two groups will produce inaccurate estimates if the treated households have features different from the untreated ones. The largest challenge is to identify a valid evaluation. Imagine what might have happened to participating troops if they had yet to participate in the exercise in assessing any intervention or program. Therefore, identifying the counterfactual is the key to a fruitful impact analysis. If administered randomly, the results of individuals who do not undergo therapy can provide a reliable counterfactual assessment. Estimates that need to be adjusted will arise from comparing the results between the two groups if the treated households have features that set them apart from the untreated ones. To fully capture the effects of unobserved heterogeneity, propensity score matching must advance. Along with PSM results, selection on returns is applied to the average treatment impact and the marginal extended treatment impact, and unobservables are computed using Roy's local instrumental variable (LIV) semiparametric.

3. Results and Discussion

Descriptive statistics

Based on the body of research in the area, the factors employed in this study were selected. (**Table 1**) below gives an overview of the variables utilized in the empirical research. Row planting was used by 40% of the sample's households to plant and harvest teff during the 2012 growing season. The sample houses' average sex composition is 89% male-headed, with no obvious difference between those who adopt and those who do not. Table 1 shows noticeable mean differences in socioeconomic factors between users of the novel planting technique and non-users. Between adopters and nonadopters, there is a significant disparity in education, cell phone ownership, livestock ownership, and money made by growing other crops. Row planting technology users and non-users differ considerably in family size, radio/television ownership, the number of oxen a farmer owns, their interactions with

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government extension agents, their involvement in farmers' groups, their proximity to a key road, and their non-farm income. Comparatively, to those who do not utilize the technology, Row planters are often more educated, male-headed, younger, and have larger families. The household head's average education is around four years for adopters and three years for nonadopters.

Table 1: An overview of the descriptive data for the sample households

Variable name	Acceptors (n = 104) Mean(SE)	Difference (=mean of NA-Mean of Ad)	Nonadopters (n = 156) Mean (SE)
Gender of the head of the home (1 for men, 0 for women)	0.92 (0.029)	-0.05	0.88 (0.028)
The number of adults in a household	4.33 (0.130)	-0.67*	4.68 (0.89)
If the household owns a mobile device, the value is 1. Otherwise, it is 0.	0.83 (0.039)	-0.126**	0.70 (0.038)
Ownership of additional cattle	0.66 (0.057)	-0.069	0.59 (0.049)
Government extension contact information In the event of contact, 1; otherwise, 0.	0.99 (0.011)	-0.22*	0.79 (0.034)
Credit availability (1 if true, 0 otherwise)	0.91 (0.030)	0.059	0.847 (0.030)
Minutes needed to go to the main market	54.81 (2.57)	-0.87	53.96 (2.84)
Minutes it takes to get to the major road.	029.95 (2.72)	14.51*	44.46 (3.24)
Other sources of income	4051 (702.3)	-2451*	1599.63 (335.2)
Seniority of the head of the family	47.9 (1.08)	1.95	49.77 (1.18)
Head of household education (in years)	4.06 (0.34)	-0.959**	3.10 (0.280)
possession of a radio or television	0.77 (0.043)	-0.18*	0.59 (0.05)
Owned oxen: number	1.29 (0.07)	-0.27*	1.03 (0.06)
Application of pesticides (yes = 1, 0 otherwise)	0.55 (0.06)	-0.052	0.49 (0.05)
The revenue from other crops	7187 (524.81)	-1211.2**	5976.21 (348.98)
Association with farmers (= 1 if a member, 0 otherwise)	0.91 (0.030)	-0.17*	0.75 (0.036)
Minutes needed to go to the extension office	33.59 (2.89)	1.37	34.96 (2.3)
Conservation of soil and water (= 1 if true, 0 otherwise)	0.98 (0.017)	-0.07***	0.92 (0.024)
Size of the farm in hectares	0.455 (0.018)	-0.002	0.454 (0.017)

Note: *, **, and ***, reflect significance levels at 1%, 5%, and 10%, respectively.

Higher education makes it easier for farming households to employ modern agricultural technology. Adopting families own more radio/television, mobile phones, oxen, and other animals than nonadopters. According to the Ministry of Health, the sample homes' average household size is around four individuals, less than the 4.7 national averages. Increased access to finance institutions, more income, and better informational resources enable farmers to embrace modern farming methods. The other important factor is per capita consumption, the relevant outcome variable. Agricultural homes were chosen as a sample to determine their opinions on the row planting technique. Accordingly, 96% of homes that had adopted the technology said it was done so for its increased productivity. No lodging is the second most significant justification for utilizing the row planting technique (81%). Crop lodging, which reduces crop output, is the act of a crop falling over when it is mature. Teff's long, fragile stems, which are prone to falling over, make it the most problematic crop for farmers, especially those who grow Teff. The nonadopters about why they prefer row planting over the conventional broadcasting technique. Row planting is work intensive, according to most nonadopters who responded (92%). This shows the need to consider less labor-intensive technologies to reduce the labor shortage issue certain families face and boost the technology's adoption rate. Additionally, 18% of those who did not embrace row planting did not think it would produce a higher yield than the conventional broadcasting approach. Time constraints (46.7%) and lack of technological understanding (23.7% of nonadopters) were the additional reasons for not employing the row planting approach. This may imply that more knowledge about the technology may persuade those who still need to adopt it to do so.

Estimating propensity scores and matching

There are two reasons why estimating is important for the propensity score. Calculating the average treatment treated (ATT) is the first step. Getting matching treated and untreated agricultural households is the second step. The propensity scores are estimated using logistic regression.

Estimation findings of the adoption determinants

(Table 2) lists the logit estimations' findings of the matching procedure's variables and teff's row planting technique. The balance attribute was established and met, and the overlap requirement was applied. Conversely, the expected propensity score for row planters varies from 0.0768 to 0.978 with a mean of 0.55, whereas it ranges from 0.0025 to 0.915 with a mean of 0.33 for broadcasters. Since 35 data were lost since the row planting method was not used, the common support requirement is fulfilled close to [0.0769, 0.978]. The model has a log-likelihood value of -142 and a pseudo-R2 value of 0.189. Numerous covariates have coefficients that show the expected patterns, including radio ownership, household size, interaction with government extension workers, and proximity to a major road, among other things. Family size is found to have a positive and statistically significant coefficient of 1%, which is utilized as a stand-in for the availability of labor in the home. Larger households imply more labor being available, which can aid in adopting agricultural technologies. Dinku and Beyene's latest research (2019) found a significant correlation between family size and acceptance of wheat growing in rows. The benefits of owning a radio are good but could be stronger. As anticipated, a positive and substantial correlation exists between row planting adoption, and the family's interaction with government extension agents since getting technology knowledge is simpler. A crucial factor that has a favorable and large impact on adoption is non-farm income. Farmers take more risks and adopt new technologies when their income from sources other than agriculture increases. So, a household's income can be increased by non-farm revenue, affecting the decision to adopt and the household's spending habits.

Table 2: Estimation inside the logit framework

Changeables	**Approximations**
Sex of the head of the household	-0.1021 (0.504)
Household size	0.441*** (0.137)
Mobile ownership	-0.0287 (0.375)
Owned oxen: number	0.2966 (0.283)
Income from other crops	0.00003 (0.0001)
Participation in a farmers' association	0.0658 (0.472)
conservation of soil and water	0.961 (0.7544)
Pseudo R2	0.20
Seniority of the head of the family	-0.0079 (0.015)
Education of the head of the household	0.0341 (0.534)
Ownership of radio/television	0.543 (0.327)
Government extension contact information	3.18*** (1.053)
Livestock ownership(TLU)	-0.2835 (0.287)
Access to credit	0.6742 (0.458)
Location of the extension office	0.0010 (0.008)
Non-farm income	0.0002** (0.0001)
Number of Observation	261

Note: ***, ** relate to 1% and 5% significance levels, respectively.

The mismatched raw data show substantially larger sample differences than matched case samples. Row planters and broadcasters are thus more evenly distributed across the covariates due to the matching procedure. Two additional balancing signals were employed additionally to the conventional bias evaluation. Two of these indicators were the likelihood ratio test and the pseudo R^2 from the logit of treatment status on covariates before and following matching on matched samples. After checking, there should not be a consistent difference between the two groups' covariate distributions; as a result, the combined significance of all variables should not be accepted, and there should be a low pseudo R^2. Because of this, it can be shown that covariates are distributed equally among the two groups of farming families by looking at the covariate distribution, the low pseudo R^2 following matching (0.015), and the probability ratio's negligible p-value (0.996). The common support graphing in **(Figure 1)** also demonstrates a large overlap between users of the row planting technique and non-users.

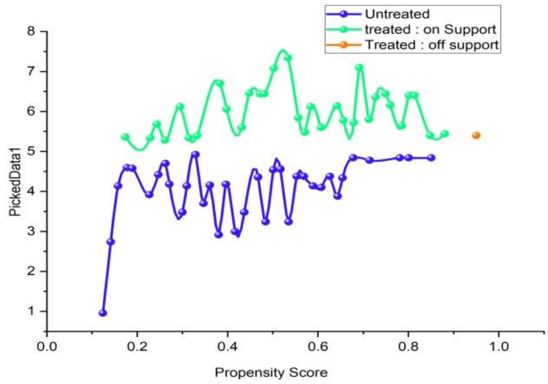

Figure 1: Distribution of propensity scores and common evidence for propensity score estimate

Estimation of treatment effects

For agricultural households growing teff, three distinct matching algorithms are employed. Row planting technology's effects on consumer expenditure per capita and agricultural income per hectare are assessed, and ATT is contrasted between several approaches. The matching methods include kernel, radius, and closest neighbor matching. Based on 100 replications, bootstrap standard errors are employed. According to all three matching algorithms, the row planting technique significantly and favorably impacted per capita consumption and agricultural revenue. (**Table 3)** and **(Figure 2)** display the three matching approaches' estimated effects of conventional therapy on the ATT. The result variable is the consumption per person log.12 Row planting households sees a 12.3% to 18.4% larger rise in per capita consumption broadcasters than. This is a typical example of a per capita consumption imbalance across comparable agricultural families with various treatment statuses. Row planting in the highlands resulted in a wheat yield almost 14% higher than broadcasting. Our results show that row planting did not significantly boost Teff's production.

Table 3: A row-planted Teffcultivar and its effects on per-person consumption are estimated using ATT.

	Nearest neighbor	**Radius(0.1)**	**Kernal**
ATT	18.5	12.4	13.5
Treated	105	105	10
Control	55	123	123

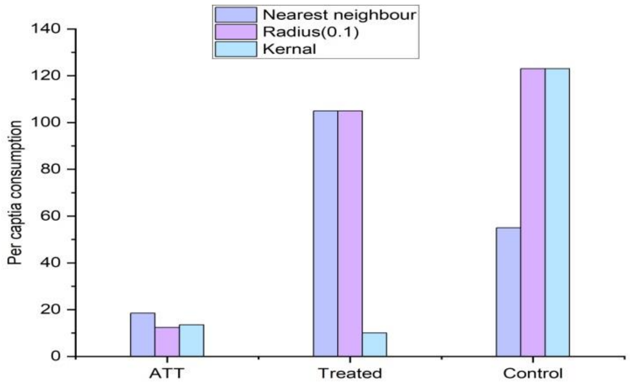

Figure 2: *Consumption of per capita*

According to **(Table 4)** and **(Figure 3)**, Crop income per hectare is also positively and significantly impacted by the row planting method. The users of the row planting method have larger crop incomes than nonadopters. This specific conclusion on agricultural revenue is congruent, who found that row planting increased crop production.

Table 4: Estimation of ATT: Crop revenue per hectare

	Nearest neighbor	**Radius(0.1)**	**Kernal**
ATT	2116.6	1323.2	1541
Treated	105	105	105
Control	55	123	123

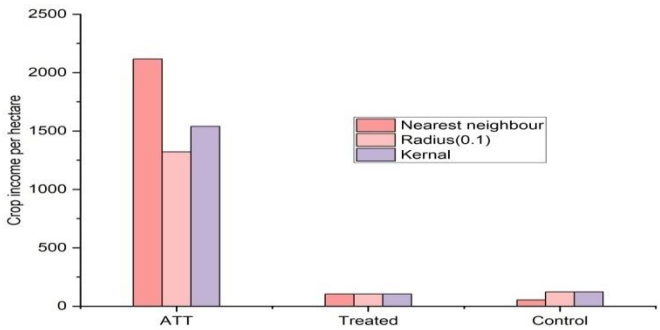

Figure 3: *Crop income per hectare*

This may infer from the conclusions in **(Tables 5 and 6)** that adopting row planting directly impacts the ATT calculations. The results are consistent with propensity score matching and show favorable average treatment effects. Additionally, since families are more likely to adopt the treatment status or row planting, the marginal treatment impact is growing.

Table 5: Results of a sensitivity analysis utilizing the per-person consumption log and Rosenbaum bounds

Rosenbaum sets limits for the expenditure and consumption log (N=260 paired pairs)						
Gamma	Sig + upper limit degree of	Sig- lower limit degree of	t-that + upper bound Point estimation by	The lower limit, t-that Hodges-	Confidence interval + upper limit	Confidence at the lower bound

	importance	importance	HodgesLehman	Lehman juncture	(a=.95)	intervals - (CI) (a=.95)
1	0	0	8.69927	8.899927	8.666399	8001
1.26	0	0	8.67108	8.72693	8.63273	8401
1.6	0	0	8.64688	8.75148	8.60916	8801
1.76	0	0	8.62672	8.77075	8.58835	9333.44
3	0	0	8.6102	8.7887	8.57064	9700

Table 6: Results Calculating agricultural revenue per hectare using Rosenbaum limits for sensitivity analysis

Rosenbaum sets limits for the expenditure and consumption log(N=260 paired pairs)						
Gamma	Sig + upper limit degree of importance	Sig- lower limit degree of importance	t-that + upper bound Point estimation by HodgesLehman	The lower limit, t-that Hodges-Lehman juncture	Confidence interval + upper limit (a=.95)	Confidence intervals at the lower bound - (CI) (a=.95)
1	0	0	7467.68	7467.67	6934.34	9000
1.26	0	0	7121	8001	6401	8500
1.6	0	0	6666.68	8001	6401	8900
1.76	0	0	6401	8533.34	6133.34	9333.34
3	0	0	6401	8801	5866.68	9700

4. Conclusion

There is little empirical data to support the complex link between rural farming households' well-being and climate-smart agricultural methods. Even though the beneficial influence of agricultural technology on well-being is generally acknowledged, it can be difficult to evaluate the acceptance of agricultural technology's effects on small-scale farming because it can be difficult to discover methodologies suitable to measure the influence of agricultural technology. The study assesses how the row planting technique affects prosperity estimated by combining a semi-parametric LIV method with propensity score matching of rural families based on consumer spending and agricultural revenue per capita. Assessing the ability of the Rosenbaum limits method to consider the expected effect of a hidden bias in adoption choosing. The study's findings demonstrate that the row planting technique significantly and favorably affects income from crops and consumption per person in farming families. Families who embraced row planting may have had greater per capita consumption and agricultural revenue than houses that watched television, per the analysis of the causal influence using propensity score matching. The anticipated treatment impact is insensitive to unobserved variability, according to the findings of the sensitivity analysis, demonstrating how the practice of row planting results in higher consumption expenses and lower levels of hunger and poverty. The semi-parametric LIV model also indicates that increased propensities to adopt the row planting technique are associated with increased marginal treatment impact on crop revenue. Farmers might be able to achieve food security and spread the practice to other areas; people won't be as vulnerable to the consequences of climate change. However, several significant obstacles must be overcome before adopting such techniques. Furthermore, because the impact of such technology may vary depending on the setting, it is important to avoid extrapolating our results to all rural. The study's findings support the idea that the climate-smart agriculture practice of row planting may help farming communities become more resilient and improve their quality of life. Future research may examine the long-term impacts of the row planting method in addition to cross-sectional data. A deeper understanding of the economics of row planting in the region may be obtained by modeling it with various combined CSA techniques that farmers use concurrently. Finally, greater empirical research is required to fully understand the function of biophysical elements and how they interact with the socioeconomic context.

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