Intensification of climate-smart agriculture technology in semi-arid regions of India

Working Paper No. 321

CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS)

Barun Deb Pal
Shreya Kapoor

RESEARCH PROGRAM ON
Climate Change, Agriculture and Food Security

CGIAR

CCAFS

Working Paper

Intensification of climate-smart agriculture technology in semi-arid regions of India

Determinants and impact

Working Paper No. 321

CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS)

Barun Deb Pal
Shreya Kapoor

To cite this working paper

Pal BD, Kapoor S. 2020. Intensification of climate-smart agriculture technology in semi-arid regions of India: Determinants and impact. CCAFS Working Paper no. 321. Wageningen, the Netherlands: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

About CCAFS working papers

Titles in this series aim to disseminate interim climate change, agriculture and food security research and practices and stimulate feedback from the scientific community.

About CCAFS

The CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) is led by the International Center for Tropical Agriculture (CIAT), part of the Alliance of Bioversity International and CIAT, and carried out with support from the CGIAR Trust Fund and through bilateral funding agreements. For more information, please visit https://ccafs.cgiar.org/donors.

Contact us

CCAFS Program Management Unit, Wageningen University & Research, Lumen building, Droevendaalsesteeg 3a, 6708 PB Wageningen, the Netherlands. Email: ccafs@cgiar.org

Abstract

Technology adoption has been proven to be an efficient way to improve agricultural productivity as well as farmers' income across the semi-arid regions of the globe. However, an upcoming method to improve food and livelihood security is through sustainable technology intensification. The study tries to assess the impact of climate-smart agriculture (CSA) technology intensification on farmers' income using inverse probability weighted regression adjustment method. The results show a rise in average income for high intensified farmers in comparison to the low intensified farmers. The results also show a rise in income for CSA intensified farmers in comparison to the farmers adopting only improved technologies. Therefore, technology intensification of CSA technologies has been found to be an effective way in ensuring income security to the farmers.

Keywords

Agriculture; climate change; climate-smart agriculture; technology intensification; food systems; food security; income security.

About the authors

Barun Deb Pal is a Project Manager at the International Food Policy Research Institute (IFPRI) South Asia.

Shreya Kapoor is a Research Analyst at the International Food Policy Research Institute (IFPRI) South Asia.

Acknowledgements

This study has been conducted with the financial support from both Department of Agriculture, Government of Karnataka (through ICRISAT, Hyderabad) and the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). Authors are deeply grateful to all the donors for adequate financial support for successful implementation of the primary survey and subsequent analysis. Last but not the least, we are thankful to all farmers and research staff of CGIAR institutions based in the study area for their cooperation and help.

Contents

Introduction

Climate change has severely hit agricultural production and welfare of farmers in South Asia (Arshad et al. 2017; Aryal et al. 2019). Low and erratic rainfall, unpredictable weather conditions and hardships of the farm households are contributing to lower agricultural yields and farmers' welfare. Recent development economics and agricultural economics literatures have focussed on the importance of the adoption of new agricultural technologies for the improvement in agricultural productivity and farmers' income (Pan et al. 2018; Asfaw et al. 2012, Pal et al. 2019). Various scientists have been proposing the use of climate-smart agriculture (CSA) technologies which are more effective and sustainable way of dealing with climate change adversities (Campbell et al. 2014; Dinesh et al. 2017; Sova et al. 2018). The use of such technologies not only increases crop yield and household incomes, but also enhances rural livelihoods and ease stress on natural resources (FAO 2013; Mendola 2008). CSA is an integrative approach to address three interlinked challenges of food security, climate change, and greenhouse gas mitigation (Aryal et al. 2020; Sapkota et al. 2015). In other words, it is an approach for transforming and reorienting agricultural development under the new realities of climate change (Lipper et al. 2014). Some of the methods that may be climate-smart, depending on context are, zero tillage, the making of broad bed furrows, micro-irrigation, intercropping, mulching, direct seeded rice, and laser land levelling, for example. Various adaption options have been suggested to date, but advancement and distribution of technologies is one of the most important solutions to confront the worsening impact of climate change on agriculture (UNFCCC 2006; Below et al. 2010; Lybbert and Summer 2010). The long-term adaptation strategy in agriculture depends on addressing similar issues in the short term, recognizing the fundamental truth that adaptation is a location-specific and continuous learning process (FAO 2008).

South Asian economies are agriculture based, so the land constitutes a valuable resource. The region shows extraordinarily diverse landforms due to the diverse climatic regimes, latitudes, altitudes and topography. Semi-arid region is one of the largest agroclimatic region in South Asia that spreads across India, Pakistan, Bangladesh and Sri Lanka. India, the largest country in South Asia, occupies the largest share of semi-arid region in South Asia. The semi-arid region occupies 34% of total geographical land in India where farming is largely dominated by monsoon rain. Water scarcity along with environmental stresses represent the most limiting factors for agricultural productivity in this agroclimatic region. Unpredictable weather, long dry seasons, inconsistent rainfall, and soils that are poor in nutrients make this region unique as compared to other agroclimatic region in India. Historically rise in average temperature along with declining trend of rainfall, the semi-arid region in India has been expanding. A recent study of Indian Institute of Tropical Meteorology (IITM), Pune has revealed that the semi-arid areas in India has been expanded by 10% during 1986-2005 than that was during 1950-1970.[1] On the other hand, the economic survey of India 2017-18 cited that the average increase in temperature in India between the most recent decade and the 1970s is about 0.45 degrees and 0.63 degrees in the kharif and rabi seasons, respectively. Between the same period the kharif rainfall patterns have declined on an average by 26 millimetres and rabi rainfall by 33 millimetres. Further, it has been projected from climate models associated with the Intergovernmental Panel on Climate Change (IPCC) that temperature in India is likely to rise between 3–4 degrees Celsius by the end of the 21st century, depending on greenhouse gas emissions. As a result, the semi-arid region will continue to expand, and agriculture sector will become more vulnerable if suitable adaptation measures are not implemented.

In this context, the government of the state Karnataka, one of the states located in the semi-arid region of India, played a pro-active role to demonstrate and scale up modern and improved technologies for the agriculture sector of this state. A consortium of CGIAR institutions, agriculture universities in this state and the Indian Council of Agricultural Research (ICAR), was formed in the year 2015 to identify and demonstrate locally suitable and economically viable technology for the principal crop grown in this state. Initially four districts have been selected to experiment the effectiveness of the modern technologies at the local level and farmers have been trained to adopt those technologies. In addition, the government of Karnataka provided subsidy to the farmers to adopt those modern technologies. Although, this program does not consider climate-smart technology explicitly

[1] Please see: https://timesofindia.indiatimes.com/city/pune/semi-arid-places-now-about-34-of-countrys-total-area/articleshow/65568752.cms#:~:text=Semi%2Darid%20places%20now%20about,Pune%20News%20%2D%20Times%20of%20India

but some of the modern technologies have potential to be climate-smart. Therefore, issue arises here whether the climate-smart technologies performed better than other improved technologies to enhance crop yield and farmers' income. What factors drive farmers to adopt climate-smart technologies voluntarily? What constraints the adoption of climate-smart technologies and how that can be mitigated to scale up climate-smart technology in the study state?

Given this backdrop, this study attempts to categorize the technologies that have been demonstrated through the above-mentioned program of the government of Karnataka and assess their impact on crop yield and farmers' income. A primary survey has been conducted with a sample of 1466 farmer households selected from the four districts where this program was implemented. Using multinomial logit model, this study explores various characteristics of farmers, which facilitate or obstruct the adoption of climate-smart agriculture techniques. The impact on farmers' income is evaluated by using Propensity Score Matching (PSM) and Inverse Probability Weighted Regression Adjustment (IPWRA). This method also helps us to do a comparative analysis between farmers' current practice, improved but not climate-smart practice and climate-smart practices. Therefore, this study provides an empirical evidence on the effectiveness of climate-smart technologies to enhance crop yield and farmers' income in the semi-arid region. This can help policy makers to take necessary steps for upscaling of the improved but climate-smart technology to adapt with the adverse agroclimatic condition and the negative impact of climate change in the long run.

Literature review

Impact of agricultural technologies on crop yield and farmers' welfare has been studied by various researchers across the globe. Evenson et al. 2003; Villano et al. 2015; Zeng et al. 2015; Bezu et al. 2014 have studied the effectiveness of adoption of improved varieties on crop yield and household income. According these studies, adoption of improved varieties which are developed to be suitable for local agro-climatic conditions are one of the most important means to boost crop yield and improve well-being. Apart from this, these studies have argued that age of farming experience, landholding size, level of education of farmer households and asset ownership are key factors behind the adoption of improved seed varieties. Using inverse probability weighted with regression adjustment (IPWRA) technique, Adolwa et al. (2019) has shown that adoption of integrated soil fertility management improves mazie yield by 27% in Tamale (Ghana) and 16% in Kakmega (Kenya). Kassie et al. (2011) has shown that adoption of improved pigeonpea varieties has positive and significant impact on consumption expenditure and negative and significant impact on poverty, reducing poverty in the range between 8-10 percentage points. Khonje et al. (2015) showed using propensity score matching (PSM) that adoption of improved maize varieties in eastern Zambia increased crop income per hectare ranging between USD 448 to USD 455, along with raising consumption expenditure per capita in the range between USD 52 to USD 59. Manda et al. (2019) analysed the impact of adoption of improved cowpea varieties in Nigeria, stating increase in houseold income by USD 0.22 per capita/day, equivalent to 17%.

Apart from the seed technology, there are studies that focus on adoption of farm management pratices to improve resource use efficiency. One such study has been conducted by Aryal et al. (2020) that have focused on the adoption of laser land levelling (LLL) and its impact on crop yield and farmers' income in the state Haryana in India. This study has shown that adoption of LLL technology improves rice and wheat yield by 14% and 11%, respectively, along with increasing net returns to rice and wheat farmers by 34% and 22%, respectively. Apart from the LLL technology, direct seeded rice (DSR) method of rice cultivation is gaining momentum over the puddled transplanted rice (PTR) method because of many advantages like narrowing soil erosion, reducing the loss of organic matter, alleviating water scarcity, and saving labour. Agronomic trials have stated that adoption of DSR method enhances land productivity and labour efficiency (Kumar and Ladha 2011). Adoption of DSR method has shown positive results for crop producing, indicating an increase in average treatment effect (ATT) of 3.1% in China (Sha et al. 2019) and 3.7% in eastern India (Mishra et al. 2017). On the other hand, the broad bed furrow (BBF) system helps in the soil in the preservation of water level for a longer duration and thus aids in stimulating crop growth. A field experiment was conducted in 2011-12 during the rabi and kharif season which showed the effect of BBF and nutrient management on maize crop recording productivity of 6.7 tonnes/ha for adopter farmers in comparison to 6.5 tonnes/ha for non-adopter farmers (Jnanesha et al. 2016).

In case of India, there are various studies that have evaluated the impact of different technological interventions on crop yields and/or farmers' income (Sahu and Das 2015; Kiresur et al. 2017; Wani et. al. 2017; Pingali et al. 2019). Several agro-ecological, socio-economic and cultural factors play an important role in the adoption of new agriculture technologies (Aryal et al. 2015; Teklewold et al. 2013; Asfaw et al. 2012). Adoption decisions by farmers are also influenced by risk, uncertainty, human capital, and social networks (Becerril and Abdulai 2010).

However, studies cited above consider either one technology or few individual technologies to asses their impact on crop yield, farmers' income and analyse key drivers of their adoption. But considering the agro-climatic conditions and climate change impact, the package of technologies may yield better than an individual technology. For example, adoption of laser land levelling with improved seed variet may yield better return even under adverse climate conditions. Again, intensification of technologies and crops has been seen as an important means of addressing the challenges faced by global food systems like food security, environmental degradation, and welfare concerns (Balaine et al. 2020). But, there is scarcity of literature that highlights the factors influencing the adoption of different intensification levels of technologies and hence it is a research gap that this study attempts to fill. Therefore, this study has analysed the level of intensification of climate-smart agriculture techniques in the context of the semi-arid region in India and assessed its impact on crop farmers' income.

Data and methods

Data

As described above, this study is based on the state of Karnataka in India. Agriculture in this state provides livelihood opportunity to nearly 57% of the state's workforce. Horticulture contributes 40% to the agricultural income, and 38% of the rural households have livestock and poultry, contributing significantly to their livelihoods (Ravindranath et al. 2014). The same study states that the state has warmed about 0.4 degrees Celsius, while rainfall trends indicate an overall decline in annual rainfall by 10%. Sorghum, millet, cowpea, chickpea, pigeon pea and groundnut are the principal crops that feed most people in this state. The sample districts chosen from the state for our study are Bidar, Chikballapur, Dharwad and Udupi. The selection of the districts is not random; rather they are the districts where the government of Karnataka implemented its flagship program to promote modern technology through the consortium of CGIAR institutions, agriculture universities and ICAR. A sample of 1466 farmer households has been selected and the primary survey was conducted using structured questionnaire in 2018-19. Among the selected sample farmer households, almost 50% are adopter farmers who have adopted improved technology in different scale. The adopters were selected purposively with the help of expert consultation among the government officials, CGIAR scientists, farmers and rural agriculture offices. On the other hand, the non-adopter farmers have been selected based on being neighbours of the adopter farmers. The survey aimed at capturing information from the farmers about their socio-demographic characteristics, technology adoption, assets ownership, farming activities, and revenue and cost associated with their farming activities. The details about the survey location and basic characteristics of the districts are described in the following paragraphs.

Bidar, a city in the north-eastern part of the Karnataka state has become vulnerable to climate change due to increased incidences of droughts, increases in temperatures, and erratic rainfall patterns. A study conducted by Banashree et al. (2019) illustrated that the farmers agreed that there has been change in rainfall patterns, increase in the number of dry spells in comparison to past years, uneven distribution of rainfall during different stages of crop growth, increase in temperature, depletion of groundwater obstructing irrigation by bore wells, and that return to investment has become uncertain in agriculture due to climate change.

Chikballapur is situated in the south-eastern portion of Karnataka state. The district has become vulnerable to climatic shocks like increasing temperatures, rising emissions, decreasing rainfall, and poor irrigation. The agricultural and livelihood vulnerability assessment has shown that households are in the ‘moderate’ to ‘high’ categories for both the indexes causing lack of diversity of sources of income (Ravindranath et al. 2014).

Dharwad is located in the north-western part of Karanataka state. Drought is the extreme climate shock along with other climatic factors experienced by the rainfed farmers in the district. Ashalatha et al. (2012) stated that yields of one of the major crops like cotton dropped by 60%, as cotton is highly susceptible to drought. Moreover, farmers from the district have reported that their farm income and crop yield had reduced over the years along with changes in climate and rainfall patterns (Ashalatha et al. 2012).

Udupi is a district in the southwest part of the state. The main staple crop of Udupi is paddy which is highly dependent on rainfall but the district has witnessed a reduction in rainfall of more than 10% in last 20 years (Ravindranath et al. 2014). Farmers have adopted various coping strategies to mitigate the negative impacts of climate change which include changes in cropping patterns, the adoption of intercropping, usage of drought resistance/tolerant seed varieties, etc. Figure 1 below illustrates the location of the four districts.

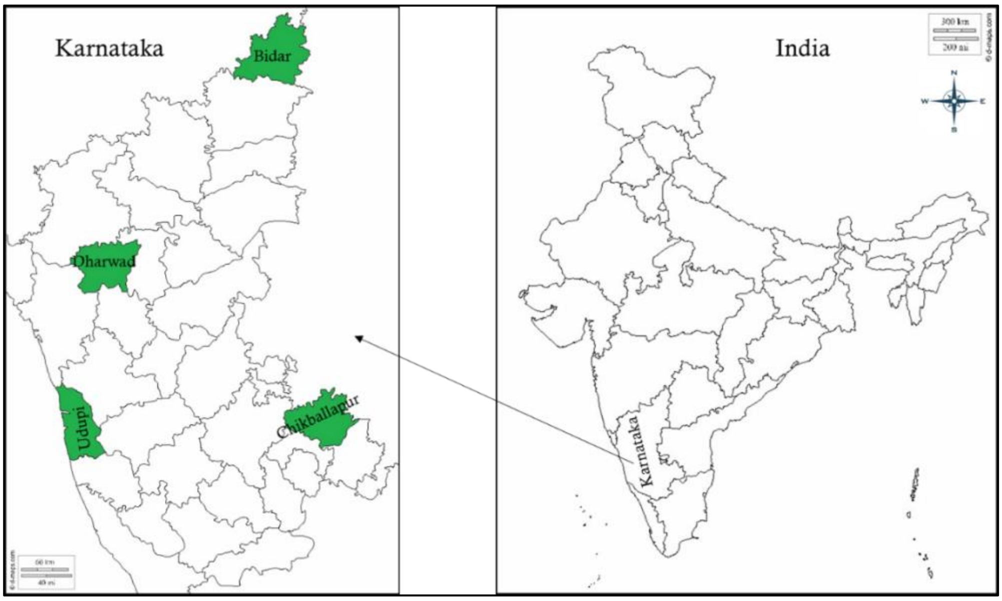

Figure 1. Study sites in Karnataka.

In the context of climate change, vulnerability refers to the propensity of the entity to face climate shock and suffer loss in production and/or income from agriculture (Kavi Kumar et al. 2007). McCarthy et al. (2001) defines vulnerability as the function of character, magnitude, and rate of climatic variation to which a system is exposed, its sensitivity, and its adaptive capacity. Exposure is defined as the nature and degree to which a system is exposed to significant climatic variations while sensitivity is defined as the degree to which a particular system is affected either adversely or beneficially by climate-related stimuli (Rama Rao et al. 2013). Exposure is related to the climate stress upon a certain unit of analysis (Gbetibouo and Ringler 2009). Sensitivity is determined by environmental and demographic conditions existing in a particular region. Adaptive capacity is the ability of a system to adjust to climate change, to neutralise potential damages, to take benefits of opportunities, and to cope with consequences (Rama Rao et al. 2013). Hence, adaptive capacity is a combination of wealth, technology, education, information, skills, infrastructure, access to resources, stability, and management capabilities (McCarthy et al. 2001). Table 1 depicts district-level analysis about their vulnerability to climate change.

Table 1. District-level analysis about climate change.

District	Vulnerability	Exposure factor	Sensitivity factor	Adaptive capacity factor
Bidar	Very high (35)	Projected rise in minimum temperature (161)	High NSA (156)	Low NIA (435)
Chikballapur	High (149)	Projected decrease in July rainfall (164)	Low rainfall (240)	Low groundwater availability (296)
Dharwad	Very high (108)	Projected decrease in total rainfall (179)	High NSA (248)	Low NIA (346)
Udupi	(566)	(510)	(486)	(194)

Source: Rama Rao et al. 2013.

Note: NSA – Net sown area; NIA – Net irrigated area; ranks in parenthesis.

The details of sample size and their distribution across districts, with respect to technology adoption are presented in Table 2. The sample consists of 56.82% of the adopters and 43.18% of the non-adopter farmer households. Altogether 12 technologies were considered which were categorised into improved and climate-smart based on the agronomic features of the technologies and farmers' evaluation. Improved technologies are those which increase yield but do not reduce use of ground water, nitrogen and energy. In contrast, climate-smart technologies are those tjat led to improvement in either water or nitrogen or energy input use even if crop yield does not increase. The detail classification of technologies is presented in Table 3 below.

Table 2. District-level selected sample.

District	Adopters		Non-adopters		Total
	Number	Percent	Number	Percent	
Bidar	340	40.82	163	25.75	503
Chikballapur	214	25.69	209	33.02	423
Dharwad	176	21.13	179	28.27	355
Udupi	103	12.36	82	12.95	185
Total	833	100	633	100	1466

Source: Authors' calculations based on IFPRI-GoK survey, 2018-19.

Table 3: Classification of technologies between improved and climate-smart.

Technologies	Type	Yield enhancement	Water efficient	Nitrogen efficient	Energy efficient
Broad bed furrow	Climate-smart	Yes	Yes	No	No
Laser land levelling	Climate-smart	Yes	Yes	No	Yes
Direct seeded rice	Climate-smart	No	Yes	No	Yes
Mulching	Climate-smart	No	Yes	Yes	No
Zero tillage	Climate-smart	No	No	Yes	Yes
Micro irrigation	Climate-smart	No	Yes	Yes	Yes
Intercropping (sugarcane with different crops; pigeon pea with finger millet)	Climate-smart	Yes	Yes	Yes	Yes
Integrated nutrient management	Climate-smart	Yes	No	Yes	No
Improved seeds	Improved	Yes	No	No	No
Integrated pest management	Improved	Yes	No	No	No
Nipping	Improved	Yes	No	No	No

Source: Authors' compilation using farmers' evaluation.

Further, the farmers who have adopted climate-smart technologies have been classified into three categories depending on the number of technologies they have adopted in the survey base year (i.e. 2018-19) and they are, namely, low, medium and highly intensified farmers. Low intensified farmers are recognized to be the farmer households adopting any 1 technology, medium intensified farmers are those adopting any 2 technologies, and highly intensified are those adopting more than 2 technologies. The district wise distribution of the technological intensified farmers is given in Table 4.

Table 4. Distribution of farmers based on technology adoption.

District	Improved	CSA			Total
		Low	Medium	High	
Bidar	115 (33.82)	6 (1.76)	62 (18.23)	157 (46.17)	340
Chikballapur	57 (26.63)	18 (8.41)	81 (37.85)	58 (27.10)	214
Dharwad	27 (15.34)	77 (43.75)	50 (28.41)	22 (12.5)	176
Udupi	19 (18.45)	4 (3.88)	29 (28.16)	51 (49.51)	103

Source: Authors' calculations based on IFPRI-GoK survey, 2018-19; percent values in parenthesis.

Econometric modelling

Multinomial logistic regression

The use of logistic regression model is consistent with the literature on adoption which describes the process of adoption as taking on a logistic nature (Simtowe et al. 2011). Logistic regression is a statistical model used to model a binary dependent variable. An extension of the binary logistic model is the multinomial logit model which models a non-dichotomous dependent variable. A logit model is used to estimate the key factors that affect the adoption of different levels of technology intensification. Here, the dependent variable has four classifications: improved, low CSA, medium CSA, and high CSA, and the explanatory variables are a combination of landholdings, education, and asset ownership. Hence, the multinomial logistic regression can be expressed as:

$$Y = log\left(\frac{p}{1-p}\right) = \beta_0 + \sum \beta_i X_i$$

where p is the probability of farmers adopting a certain level of technology intensification. These coefficients don't portray the true picture of the effect explanatory variables have on the adoption of technology intensification. The estimated coefficients obtained from multinomial logistic regression are in log-odds scale, which are sometimes difficult to interpret. Therefore, we use marginal effects to interpret the model results, or more accurately, model parameters. It is simpler to interpret the coefficients of marginal effects, since it gives estimates in probability scale. Hence, further calculations made to estimate marginal effects of each independent variable is computed as follows:

$$\frac{\delta Y}{\delta X_i} = \beta X_i * \frac{\exp{(z)}}{[1 + \exp(z)]^2}$$

where z is equal to the sum of coefficients multiplied by the means of their respective variables added to the constant term.

Adequate measuring of the impact of a program under a non-experimental setting is non-trivial and involves many challenges. The first of them is to have an appropriate counter-factual, that is, having observations where the adoption has not taken place. Since farmers are not randomly distributed across the two groups of adopters and the non-adopters, but rather they have been purposely selected by the program agencies based on their propensity to participate, the adopters and the non-adopters of the program are systematically different from each other. This gives rise to possible selection bias, which needs to be addressed if the results to be meaningfully interpreted. Propensity score matching (PSM) and inverse probability weighted with regression adjustment (IPWRA) were used to respond to the above issues. The different factors affecting adoption were obtained using the multinomial logit model.

Propensity score matching (PSM)

Propensity score matching is used to evaluate the impact of CSA technology intensification on farmers' net income. The main motive behind using PSM was introduced by Rosenbaum and Rubin (1983) who observed that self-selection bias can be reduced through matching the propensity scores between the treated (intensified) and untreated (non-intensified) groups. PSM has been applied to various other impact assessment studies (Asfaw et al. 2012; Khonje et al. 2015; Villano et al. 2015; Ali et al. 2016) to control for selection bias. In our study we apply PSM because the adoption of CSA technologies is not random but based on farmers' decisions. Therefore, farmers who are highly intensified may differ from low intensified farmers based on key characteristics like landholdings, education, and assets ownership. Thus, the self-selection problem can be solved by implementing the PSM model which involves a binary choice model to generate propensity scores for each individual in the study (Bello et al. 2020). PSM is used to match the households and rank them based on their behaviour towards technology intensification to ascertain that the effects are evaluated among a group of farmers possessing similar characteristics (Mendola 2007). This method controls for self-selection bias arising due to unobserved characteristics and making comparison between treatment and control groups in the region of common support (Becker and Ichino 2002; Villano et al. 2015). The balancing property indicates the matching quality of the samples (Bello et al. 2020). We have used the standard bias method to observe the matching quality which calculates mean difference of covariates between treatment and control group after matching.

Rosenbaum and Rubin (1985) defined propensity score as the conditional probability of receiving a treatment which can be expressed as:

$$e(x) = Pr(W_i == 1|X_i = x) = E[W_i|X_i = x]$$

where W_i is the binary indicator; 1 = adopters and 0 = non-adopter, and X_i is a vector of covariates including landholdings, education, and asset ownership. After the propensity scores have been evaluated, the causal effect of the technology intensification on farmers' net income is calculated using the average treatment effect on the treated (ATT). ATT is computed as the difference between the treatment group matched with the control group who are balanced on the propensity scores and fall within the region of common support (Bello et al. 2020). The ATT is expressed as:

$$ATT = E(Y_1|W = 1) - E(Y_0|W = 0)$$

where Y_1 and Y_0 are the net income for the treatment and control groups, respectively. There are three different algorithms for running propensity scores: kernel bandwidth matching, nearest neighbourhood matching, and radius caliper method. In our analysis we used the nearest neighbourhood matching method to calculate the average treatment effect on the treated. PSM is often used for impact assessment studies to evaluate the effect of participation on certain outcomes like adoption. However, sometimes PSM fails to account for unobserved differences between adopters and non-adopters and hence produce biased estimates of the treatment effect (Abdulai and Huffman 2014). Therefore, to check for robustness of the estimates, we used another econometric method, IPWRA.

Inverse probability weighted with regression adjustment (IPWRA)

The estimators obtained from IPWRA method estimates for both the outcome and treatment variables to account for selection bias or non-random treatment assignment (Tambo and Mockshell 2018). The Inverse probability weighing (IPW) estimator can be used to demonstrate causality when it is not possible to conduct a controlled experiment but there are observed data to model. Regression adjustment (RA) estimators involve separate regressions being run for each treatment level to predict potential outcomes (i.e., the data that we wish we had to estimate the causal treatment effects) (Pomeans) and the difference between the 'Pomeans' is used to estimate the average treatment effect on the treated (ATT).

IPWRA uses weighted regression coefficients to compute treatment effects where the weights are the estimated inverse probabilities of treatment (Wooldridge 2010). It is considered to be a double robust estimator because even if one of the models (treatment/outcome) is wrongly specified, the estimator is still consistent. RA and IPW estimators model the outcome and treatment, respectively, to explain the non-random treatment assignment (Huber 2015). On the other hand, IPWRA estimates model both the outcome and the treatment to account for the biased treatment assignment.

Following Manda et al. (2018), we use inverse weights equal to 1 for the treated and $\frac{\bar{p}(x)}{1-\bar{p}(x)}$ for the untreated, then following Hirano and Imbens (2001) propensity weights are defined as:

$$W_i = T_i + (1 - T_i)\frac{\bar{p}(x)}{1 - \bar{p}(x)}$$

where $\bar{p}(x)$ are the estimated propensity scores. In contrast to the above IPW estimator, the RA estimator uses a linear regression model for treated and untreated units and averages the predicted outcomes to obtain the treatment effects (Manda et al. 2018). According to Wooldridge, (2010), the ATT for the RA model can be expressed as:

$$ATET_{RA} = n_A^{-1} \sum_{i=1}^{n} T_i [r_A(X, \delta_A) - r_N(X, \delta_N)]$$

where n_A is the number of technology adopters (A) and r_i (X) is the postulated regression model for the adopters and non-adopters (N) based on the covariates X and the parameter $\delta_i = (\alpha_i, \beta_i)$. The IPWRA estimator is obtained by combining the RA equation with the weighting equation. Hence, ATT for the IPWRA estimator can be expressed as:

$$ATET_{IPWRA} = n_A^{-1} \sum_{i=1}^{n} T_i [r_A^* (X, \delta_A^*) - r_N^*(X, \delta_N^*)]$$

Adolwa et al. (2019) states that to get unbiased estimates from IPWRA model, the analysis has to satisfy three assumptions:

- Conditional independence, which implies that once we have controlled for all the observable variables, potential outcomes are not correlated with the treatment.
- Overlap assumption, which signifies that each unit has non-zero probability of receiving the treatment. Manda et al. (2018) states that this assumption holds true when for each adopting farmer in the sample we observe non-adopter farmers with similar characteristics.
- The sample is assumed to be independently and identically distributed. This ensures that the outcome and treatment status of the farmers are independent of output and treatment status of other farmers in the sample (Adolwa et al. 2019).

Results and discussion

Descriptive statistics

Table 5 shows the descriptive statistics of the key variables used in our study. The following table depicts the mean and standard deviation for each variable for four different categories, i.e., improved, low, medium, and high intensification of CSA. Landholdings were categorised into four groups, marginal (<1 ha), small (1–2 ha), medium (2–4 ha), and large (>4 ha). Education level was been divided into four sub-groups: illiterate, primary, secondary, and higher-secondary and above. Improved technology adopters possessed 41% of marginal landholdings, 44% of small landholdings, 9% of medium landholdings, and 6% of large landholdings. The share of low intensified CSA farmers in marginal, small, medium, and large landholdings was 21%, 40%, 26%, and 13%, respectively. Medium CSA intensified farmers possessed 26% marginal, 50% small, 16% medium, and 85 large landholdings. Highly intensified CSA farmers owned 24%, 47%, 17%, and 12% marginal, small, medium, and large landholdings, respectively. The largest proportion of illiterate farmers had adopted improved technology (29%), while the lowest proportion was of highly intensified CSA adopters.

Primary education was equal for low and medium CSA intensified farmers, each being around 28%, respectively. Highly CSA intensified farmer adopters had the highest secondary (30%) and higher-secondary and above (24%) levels of education. Livestock was owned by 54% of improved technology adopters and by 68%, 66%, and 74% of low, medium, and highly CSA intensified farmers, respectively. Average ownership of a pumpset and tractor for improved technology adopters was 54% and 5%, respectively. Average ownership of a pumpset and tractor by low CSA intensified was 56% and 17%, respectively. Some 70% of medium CSA intensified farmers owned a pumpset and 13% of them possessed tractors. A pumpset and tractor were owned by 89% and 17%, respectively, of highly CSA intensified farmers.

Table 5. Descriptive statistics of key variables.

Variable	Improved (N = 218)	Low CSA (N =105)	Medium CSA (N = 222)	High CSA (N = 288)
Landholding				
Marginal	0.408	0.209	0.261	0.236
Small	0.436	0.400	0.500	0.469
Medium	0.092	0.257	0.158	0.170
Large	0.064	0.133	0.081	0.125
Education				
Illiterate	0.294	0.295	0.252	0.208
Primary	0.266	0.276	0.279	0.246
Secondary	0.243	0.219	0.256	0.305
Higher-secondary and above	0.197	0.209	0.212	0.239
Asset ownership (Yes = 1, No = 0)				
Livestock	0.541	0.676	0.657	0.736
Pumpset	0.536	0.562	0.698	0.885
Tractor	0.050	0.171	0.126	0.167

Source: Authors' calculations based on IFPRI-GoK survey, 2018-19.

Factors affecting technology intensification - multinomial logit regression

Table 6 displays the key factors affecting the adoption behaviour of different groups of intensified farmers. Here, we present the coefficients of marginal effects (dy/dx) obtained after running the multinomial logistic regression. We observe that the level of intensification increases with the landholding size. Small scale farmers are more likely to adopt medium and high intensification of technology in comparison to the non-adopters and low and improved technology adopters. There is a 4.1% and 4.8% chance that small landholders are likely to adopt medium and high technology intensification, respectively. Medium landholder farmers are 3% more likely to adopt low level of technology intensification in comparison to other farmers. On the other hand, large farmers have a 8.6% chance of adopting high level of technology intensification. One interesting point that we can witness here is that small, medium, and large landholders have negative coefficient for improved level of technology which means that marginal farmers are more likely to adopt improved technology methods. Landholding size has direct relation with the adoption of technology and is similar to the results obtained by Hussain (2012) for Pakistan.

Education is positively correlated with level of adoption of technology intensification. The higher the education, the higher the awareness is of farmers regarding the innovative methods of cultivation. Farmers with secondary education have 4.4% more chance of adopting high level of intensification in comparison to other farmers. Similarly, farmers having education level of higher-secondary and above have 3% and 7% more chance of adopting improved technology and high technology intensification, respectively. This result is consistent with the findings obtained by Buriro et al. (2014) for Sindh, Pakistan and Hasnain et al. (2015) for Bangladesh.

Asset ownership plays a significant role in determining the adoption of climate-smart agriculture technology intensification. Livestock ownership increases a 2% chance of adopting low level of intensification and a 8% chance of adopting high level of intensification. Ownership of pumpset raises the adoption by 7% for medium technology intensification and by 20% for high technology intensification. There is a 13% likelihood of increasing high level of technology intensification for farmers possessing tractors. The results of asset ownership confirm with the results obtained by Ali et al. (2014) and Ali and Khan (2013) in Pakistan for livestock ownership.

The Wald chi2 (296.50) estimate obtained from the model helps us to state that the model is a good fit. The log-likelihood ratio (LR) is found to be significant at 1 percent level of significance which implies that all the explanatory variables included in the model jointly influence farmer’ probability of adoption of different levels of technology intensification.

Hence, given this goodness of fit measures, it can be concluded that logit model employed in the study has integrity and is appropriate.

Table 6. Estimates from multinomial logit model.

	Marginal effects (dy/dx)				
Variables	**Non-adopters**	**Improved**	**Low**	**Medium**	**High**
Land category (Base: Marginal)					
Small	-0.052*	-0.034	-0.003	0.041**	0.048*
	(0.029)	(0.023)	(0.010)	(0.014)	(0.025)
Medium	-0.0318	-0.079**	0.026*	0.022	0.048
	(0.055)	(0.034)	(0.014)	(0.025)	(0.041)
Large	-0.055	-0.043***	0.003	0.009	0.086***
	(0.040)	(0.010)	(0.014)	(0.023)	(0.014)
Education (Base: Illiterate)					
Primary	-0.072*	0.030	0.001	0.024	0.018
	(0.041)	(0.039)	(0.024)	(0.023)	(0.014)
Secondary	-0.080***	0.019	0.002	0.015	0.044***
	(0.020)	(0.020)	(0.016)	(0.018)	(0.011)
Higher-secondary and above	-0.136***	0.027**	0.008	0.032	0.069**
	(0.034)	(0.011)	(0.016)	(0.033)	(0.040)
Asset ownership (Yes = 1, No = 0)					
Livestock	-0.110**	-0.003	0.020***	0.011	0.076***
	(0.018)	(0.025)	(0.005)	(0.010)	(0.018)
Pumpset	-0.286***	-0.010	0.028	0.066***	0.203***
	(0.013)	(0.042)	(0.022)	(0.025)	(0.012)
Tractor	-0.122***	-0.033	0.001	0.024	0.131***
	(0.055)	(0.044)	(0.017)	(0.041)	(0.031)

Source: Authors' calculation based on IFPRI-GoK survey, 2018-19; Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Impact of technology adoption on farmers' net income—PSM and IPWARA

Estimates from propensity score

Table 7 displays the results for treatment effects obtained from propensity score matching for climate-smart agriculture intensified farmers in comparison to the farmers adopting improved technologies. The detailed results of PSM are attached in the appendix. The assumption of common support has been satisfied which is well justifiable from Figures A1, A2, and A3. The upper half of the graphs shows propensity scores for treated individuals while the lower half displays the propensity scores for the control group. Tables A1, A2, and A3 depict the balance test for covariates before and after matching. There is significant reduction in bias after the matching has been implemented. It is evident from the results that CSA intensified farmers are better off than the farmers adopting only improved technologies. The results show that low intensified CSA farmer households have an additional income of Rs. 4772 in comparison to improved farmer households. Medium and highly intensified CSA farmers gain an additional Rs. 7091 and Rs. 8795, respectively in comparison to the improved farmers. Thus, the results clearly depict that as the level of technology intensification increases from improved level to low, medium, and high CSA, the level of income also increases.

Table 7. Estimates from PSM model - Net Income.

Category	Observations in common support		ATT (Rupees)	Standard error
	Adopters	Non-adopters		
Low	96	218	4772.058***	1563.448
Medium	204	218	7091.483***	1060.854
High	278	218	8795.491***	1099.566

Source: Authors' calculations based on IFPRI-GoK survey, 2018-19; *** p<0.01.

Estimates from IPWRA

Next, after obtaining the results from PSM, we employed the IPWRA method to check for robustness of our results. IPWRA is considered a powerful estimator for observational data. One of its merits is that it provides for more robust results to misspecification (Curtis et al. 2007). We implemented a test to check whether the matched samples are balanced or not. This helped us to ascertain that the matched samples are properly balanced. Figures in the appendix show that all the covariates are balanced since there are no signs of change in distribution of the raw and weighted scores.

Table 8 presents treatment effects for different levels of CSA intensified farmers with respect to farmers adopting only improved technology. The potential net income for farmer households adopting improved technologies is Rs. 6961. The average treatment effect on treated group of low, medium, and high intensified CSA farmer households is Rs. 4845, Rs.

6801, and Rs. 7858, respectively. This clearly shows that CSA intensified farmers are more better off than improved technology farmers. The results also show that under CSA intensification, the level of income increases from low to medium to high intensified farmer households.

Table 8. Treatment effect for different levels of technology intensification.

Outcome – Net Income	Coefficient	Standard error
ATET		
Low	4845.877***	1170.367
Medium	6801.697***	1026.571
High	7858.08***	1253.486
Pomeans		
Improved	6961.258***	695.316

Source: Authors' calculation based on IFPRI-GoK survey, 2018-19; *** p<0.01.

Table 9 displays results of treatment effects for CSA intensified farmers with reference to low intensified CSA farmer households. The potential output for low intensified CSA farmers comes out to be Rs. 10691 and the average treatment effect on the treated medium and high intensified CSA farmer households is Rs. 3907 and Rs. 4463, respectively. This result also indicates that as the intensification of CSA technologies increase, the net income earned by those group of farmer households also rises. Hence, we can state that CSA technologies are more efficient and effective in increasing farmers' income and higher the degree of CSA intensification, the higher the level of income is.

Table 9. Treatment effect for different levels of CSA technology intensification.

Outcome – Net income	Coefficient	Standard error
ATET		
Medium	3907.008***	1256.04
High	4463.854***	1272.845
Pomeans		
Low	10691.6***	1075.029

Source: Authors' calculation based on IFPRI-GoK survey, 2018-19; *** p<0.01.

Discussion

Karnataka state has approximately 7.5 million hectares of rainfed area with diverse agro-ecological features. The state is susceptibe to intermittent rounds of floods and droughts leading to crop failure, creating food and income insecurity. In the year 2016, the government of Karnataka introduced a flagship program named Bhoosamrudhi for the welfare of the agriculture community on a pilot basis in four districts. The program aimed at boosting crop productivity of the rainfed agriculture through the introdcution of science-led interventions. The key objectives of the program were mechanization, crop intensification and diversification, water management, nutrient management, feeder and fodder management. The main technologies demonstrated to the farmers include laser land levelling, direct seeded rice, broad bed furrow, mulching, nipping, etc. Adoption of technology has become high in India and other developing nations, but what is more important now is technology intensification. Intensification of technology can be defined as the application of multiple technologies by the farmers on their farms to boost crop as well as land productivity, demanding high net returns in the end. Technology distribution is one side of the coin, but adoption and effectiveness remains another side which requires extensive analysis to justify its impact.

Whenever any innovation is made, efforts are required to increase its adoption. Despite the government trying to disburse the technologies to the farmers, the adoption of mordern and innovative methods has remained low. We analysed the key characteristics such as the size of landholdings, education, and asset ownership of the farmers to understand how these parameters affect the adoption of the technology intensification. We observe that landholding size has a positive correlation with the degree of technology intensification. As the landholding size increases, there is higher technology adoption and vice versa. Similar case is observed with the level of educational qualifications. This is true because as the level of knowledge increases, farmers' awareness increases regarding modern and innovative methods of farming. Higher degree of literacy escalates the probability of farmers in adopting higher intensification of technologies. This result corroborates with the ones obtained by Yamano et al. (2018) for Bangladesh and Kassie et al. (2013) for rural Tanzania. Following our discussion on key factors deciding farmers' adoption, we also witness that possession of livestock, pumpset, and tractors also has a positive effect in determining the adoption of different levels of CSA technology intensification.

Further, we examined the effectiveness of the technology intensification on the farmers' income, especially climate-smart agriculture technologies. Adoption of climate-smart agricultural techniques is strengthening across the globe to make agriculture adaptive to climate change without compromising on food and income security to the world citizens. We used PSM and IPWRA methods to match for the treatment and control groups and compute the average treatment effect of the adoption of varied levels of intensification on the farmers' net returns. We found that as the intensification of CSA technologies increases, the net income generated to the farmers also increases. Under PSM method, we see that low, medium, and high CSA intensified farmers gain by Rs.4772, Rs. 7091, and Rs. 8795, respectively, in comparison to the farmers adopting only improved technologies. Subsequently we used IPWRA method to check for robustness of the results and to control for unobserved endogeneity and selection bias; we notice that incomes for low, medium, and high CSA intensified farmers rise by Rs.4845, Rs.6801, and Rs.7858, respectively, in comparison to farmers adopting just improved technologies. Lastly, to check for the effectiveness among the CSA intensified farmers, we find an increase of RS.3900 and Rs.4463 for medium and high CSA intensified farmers over the low CSA intensified farmers. Given this background, we see a positive impact of CSA intensification on the monetary welfare of the farmer households, but perceive that adoption still remains very low among the farmers. There are many reasons which can be attributed to non-adoption of modern technologies. Adesina and Zinnah (1993) highlight that lack of access to capital and land can act as major obstruction in adoption decisions. Further, awareness regarding new methods of farming also act as an obstruction in technology adoption (Soni et al. 2000). Moreover, Truong (2008) pointed out that mobility of machines to the fields becomes another constraint in technology adoption. On organising focussed group discussions with the farmers in the sample districts, we discover that unawareness and illiteracy about the technologies is the main cause of non-adoption among the farmers. Secondly, small landholding size also hinders high intensification of CSA technologies since farmers are not able to achieve economies of scale on small farms. Lastly, lack of infrastructure also impedes adoption of

CSA technologies because farmers complained about unavailability of machines in the custom hiring centres in their respective districts.

Conclusion

Climate change has devastating impacts on agriculture both in terms of food security as well as farmers' livelihoods. Technology adoption has been identified to be one of the most promising and effective methods to tackle the adverse effects of climate change on agriculture. Various climate-smart agriculture technologies have been identified by the agronomists across the world to deal with the situations like drought, flood, pests, temperature change, and many others. Literature has established that CSA technologies have been effective in improving crop productivity and farmers' income across the globe. Nonetheless, new approaches to agriculture are required if we want to move towards sustainability along with feeding the population with sufficient quantity and diversity of nutritious and safe food. Hence, technological intensification is seen as a viable approach towards achieving sustainability in agriculture along with increasing crop yield and welfare of the farmers. Intensification of CSA techniques is a more effective and efficient way to achieve the desired results for the economy and environment. CSA methods have the benefits of increasing food production without further diminishing the soil and water resources, restoring soil fertility, increasing farmers' adaptation capacity to climate change, and building resilience to climatic shocks.

Therefore, this study attempts to assess the main factors affecting farmers' decisions to adopt different levels of climate-smart agricultural technological intensification along with its impact on farmers' livelihoods. The findings of the study clearly establish that landholding, education, and asset ownership of the farmers play a significant role in the adoption of CSA techniques. This helps us to establish the positive relationship between risk bearing ability and the adoption of CSA methods. As farmers' awareness and access to information are directly related to their educational level, it plays a crucial role in determining the adoption of CSA technologies. The results further show that there is a significant rise in the average income of the medium and highly intensified farmer households in comparison to the households that are low intensified. Hence, our null hypothesis fails to get rejected that the higher the technological intervention is, the higher the monetary benefit is to the farmers.

Therefore, vigorous efforts should be made to target medium and large farmer households having large asset base for adopting large-scale intensification of climate-smart agriculture methods. Small and marginal landholders should be encouraged to adopt only one CSA technology initially, which can be further intensified slowly and gradually. Education is another important factor affecting the adoption, so minimum level of education should be made mandatory for all the people in the rural areas at a subsidized cost by the government to make education easily affordable. Skill development should be propagated to the farmers to enhance their technical abilities to operate highly methodical machines. Training programs can be organised to impart knowledge and training to the farmers to make them skilful in implementing CSA technologies. Moreover, availability of machines at the custom hiring centres should be increased to encourage adoption of technologies by the farmers. Along with increasing availability of machines, new centres should be opened in each village to increase farmers' accessibility to such centres.

One drawback of our study is that we are not able to factor in the price aspect which acts as an important agent in determining the income of the farmers. Price is instrumental in influencing the demand and supply forces in a free market economy. Price elasticity and income elasticity affects demand for different products. Price is an important determinant in protecting the homeland farmers from the competition that they might face from low-priced imports. Hence, a uniform price system may help farmers in securing their incomes by selling their products in the market. Differences in prices among the farmers can induce changes in income pattern in a given geographical space leading to varying results. If we factor in price and then capture the effect of intensification, it would give a clearer picture on the income of the farmers.

References

Abdulai A, Huffman W. 2014. The adoption and impact of soil and water conservation technology: An endogenous switching regression application. *Land Economics* 90:26-43.

Adesina AA, Zinnah MM. 1993. Technology characteristics, farmers' perceptions and adoption decisions: A tobit model application in Sierra Leone. *Agriculture Economics* 9: 297-311.

Adolwa LS, Schwarze S, Buekert A. 2019. Impacts of soil fertility management on yield and household income:The case of Tamale (Ghana) and Kakamega (Kenya). *Ecological Economics* 161:186-192.

Ali A, Erenstein O, Rahut DB. 2014. Impact of direct rice-sowing technology on rice producers' earnings: Empirical evidence from Pakistan. *Development Studies Research* 1(1): 244-254.

Ali A, Khan M. 2013. Livestock ownership in ensuring rural household food security in Pakistan. *The Journal of Animal & Plant Sciences* 313-318.

Ali A, Rahut DB, Behera B. 2016. Factors influencing famers' adoption of energy-based water pumps and impacts on crop productivity and household income in Pakistan. *Renewable and Sustainable Energy Reviews* 54:48-57.

Arshad M, Amjath-Babu TS, Krupnik TJ, Aravindakshan S, Abbas A, Kachele H, Muller K. 2017. Climate variability and yield risk in South Aisa's rice-wheat systems:Emerging evidence from Pakistan. *Paddy and Water Environment* 15:249-261.

Aryal JP, Mehrotra M, Jat ML, Sidhu HS. 2015. Impacts of laser land leveling in rice-wheat systems of the north-western Indo-gangetic plains of India. *Food Security* 7(3):1-15.

Aryal JP, Sapkota TB, Rahut DB, Jat ML. 2020. Agricultural sustainability undr emerging climatic variability: The role of climate-smart agriculture and relevant policies in India. *International Journal of Innovation and Sustainable Development* 14:219-245.

Aryal JP, Sapkota TB, Khurana R, Khatri-Chhetri A, Rahut DB, Jat ML. 2019. Climate change and agriculture in South Asia: Adaptation options in smallholder production systems. *Environment, Development and Sustainability* 22:5045-5075.

Asfaw S, Shiferaw B, Simtowe F, Lipper L. 2012. Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy* 37(3):283-295.

Ashalatha KV, Gopinath M, Bhat AR. 2012. Impact of climate change on rainfed agriculture in India: A case study of Dharwad. *International Journal of Environmental Science and Development* 3(4):368-371.

Balaine L, Dillon EJ, Lapple D, Lynch L. 2020. Can technology help achieve sustainable intensification? Evidence from milk recording on Irish dairy Farms. *Land Use Policy* 92:1-12.

Banashree B, Maraddi GN, Shanwad UK. 2019. Study of farmers' perception on climate change: A case study of Raichur and Bidar districts of Karnataka. *Journal of Pharmacognosy and Phytochemistry* 2:168-172.

Becerril J, Abdulai A. 2010. The impact of improved maize varieties on poverty in Mexico: A propensity score matching approach. *World Development* 38(7):1024-1035.

Becker OS, Ichino A. 2002. Estimation of average treatment effects based on propensity score. *Stata Journal* 2(4):358-377.

Bello LO, Baiyegunhi LJ, Danso-Abbeam D. 2020. Productivity impact of improved rice varieties' adoption: case of smallholder rice farmers in Nigeria. *Economics of Innovation and New Technology* 1-18.

Below T, Artner A, Siebert R, Sieber S. 2010. Micro-level practices to adapt to climate change for African small-scale farmers. *IFPRI Discussion Paper 00953*, 1-28.

Bezu S, Kassie GT, Shiferaw B, Ricker-Gilbert J. 2014. Impact of improved maize adoption on welfare of farm households in Malawi: A panel data analysis. *World Development* 59:120-131.

Buriro RA, Khooharo AA, Talpur GH. 2015. Technical efficiency of rice production Sindh (Pakistan): A statistical analysis. *Science International* 27(6): 6225-6230.

Campbell BM, Thornton P, Zougmore R, Asten PV, Lipper L. 2014. Sustainable intensification: What is its role in climate smart agriculture? *Current opinion in Environmental Sustainability* 8:39-43.

Curtis LH, Hammil BG, Eisenstein E L, Kramer JM, Anstrom KJ. 2007. Using inverse probability-weighted estimators in comparative effectiveness analyses with observational databases. *Medical Care* 45(10):103-107.

Dinesh D, Aggarwal P, Khatri-Chhetri A, Rodriguez AM, Mungai C, Radeny M, Sebastian L, Zougmore R. 2017. The rise in climate-smart agriculture strategies, policies, partnerships and investments across the globe. *Agriculture for Development* 30:4-9.

Evenson RE, Gollin D. 2003. Crop variety improvement and its effect on productivity. In *The impact of international agricultural research*. Wallingford: CABI Publishing.

FAO. 2008. Climate Change and Food Security: A Framework Document. 1-107. Rome: Food and Agriculture Organization of the United Nations.

FAO. 2013. Climate Samrt Agriculture: Sourcebook. Rome: Food and Agriculture Organisation of the United Nations.

Gbetibouo GA, Ringler C. 2009. Mapping South African farming sector vulnerability to climate change and variability: A sub-national assessment. IFPRI Discussion Paper 00885. Washington D.C., USA: International Food Policy Research Institute.

Hasnain Md. N, Hossain Md. E, Islam Md. K. 2015. Technical efficiency of boro rice production in Meherpur district of Bangladesh: A stochastic frontier approach. *American Journal of Agriculture and Forestry* 3(2):31-37.

Hirano K, Imbens GW. 2001. Estimation of causal effects using propensity score weighing: An application to data on right heart catherization. *Heath Services and Outcomes Research Methodology* 2:259-278.

Huber C. 2015. Introduction to treatment effects in Stata: Part 1. The Stata Blog.

Hussain A. 2012. Impact of credit disbursement, area under cultivation, fertiliser consumption and water availability on rice production in Pakistan (1988-2010). *Sarhad Journal of Agriculture* 28(1):95-101.

Jnanesha AC, Alagundagi SC, Mansur CP, Kumar A. 2016. Effect of broad bed furrow and integrated nutrient management practices on growth and yield of maize. *National Conference on Harmony with Nature in context of Resource Conservation and Climate Change.* Hazaribag.

Kassie M, Jaleta M, Shiferaw B, Mmbando F, Mekuria M. 2013. Adoption of interrelated sustainable agricultural practices in smallholder systems: Evidence from rural Tanzania. *Technological Forecasting and Social Change* 80(3):525-540.

Kassie M, Shiferaw B, Muricho G. 2011. Agricultural technology, crop income, and poverty alleviation in Uganda. *World Development* 39(10):1784-1795.

Kavi Kumar KS, Klein RJ, Ionescu C, Hinkel J, Klein R. 2007. Vulnerability to poverty and vulnerability to climate change: Conceptual Framework, Measurement and Synergies in Policy. Working Paper 19/2007. Madras School of Economics.

Khonje M, Manda J, Alene AD, Kassie M. 2015. Analysis of adoption and impacts of improved maize varieties in Eastern Zambia. World Development 66:695-706.

Kiresur VR, Nayak MR, Gaddi GM, Khyadagi KS. 2017. Improved farm technology adoption and its role in doubling farmers' income: A case of dry zones in Karnataka. *Agricultural Economics Research Review* 30:217-231.

Kumar V, Ladha JK. 2011. Chapter six- Direct seeding of rice: Recent developments and future research needs. In *Advances in Agronomy*, by D. L. Sparks, 297-413. Academic Press.

Lipper L, Thornton P, Campbell BM, Baedeker T, Braimoh A, Bwalya M, Caron P, Cattaneo A, Garrity D, Henry K, Hottle R, Jackson L, Jarvis A, Kossam F, Mann W, McCarthy N, Meybeck A, Neufeldt H, Remington T, Sen PT, Sessa R, Shula R, Tibu A, Torquebiau EF. 2014. Climate-smart agriculture for food security. Nature Climate Change 4:1068–1072

Lybbert T, Summer D. 2010. Agriculture technologies for climate change mitigation and adaptation in developing countries: Policy options for innovation and technology diffusion. International Center for Trade and Sustainable Developement (ICTSD) and International Food and Agriculture Trade Policy Council (IPC).

Manda J, Alene AD, Tufa AH, Abdoulaye T, Wossen T, Chikoye D, Manyong V. 2019. The poverty impacts of improved cowpea varieties in Nigeria: A counterfactual analysis. *World Development* 122: 261-271.

Manda J, Gardebroek C, Kuntashula E, Alene AD. 2018. Impact of improved maize varieties on food security in eastern Zambia: a double robust analysis. *Review of Development Economics* 22(4):1709-1728.

McCarthy JJ, Canziani OF, Lear NA, Dok Ken DJ, White KS. 2001. Climate change 2001: Impacts, Adaptation, and Vulnerability. Cambridge University, Press.

Mendola M. 2007. Agricultural technology adoption & poverty reduction: A propensity score matching analysis for rural Bangladesh. *Food Policy* 32:372-393.

Mendola M. 2008. Migration and technological change in rural households: Complementsor substitutes? *Journal of Development Economics* 85(1-2):150-175.

Mishra AK, Khanal AR, Pede VO. 2017. Is direct seeded rice a boon for economic performance? Empirical evidence from India. *Food Policy* 73:10-18.

Pal BD, Kishore A, Joshi, PK, Tyagi NK. 2019. *Climate Smart Agriculture in South Asia: Technologies, Policies and Institutions.* Springer.

Pan Y, Smith S, Sulaiman M. 2018. Agricultural extension and technology adoption for food security: Evidence from Uganda. *American Journal of Agricultural Economics* 100(4):1012-1031.

Pingali P, Aiyar A, Abraham M, Rahman A. 2019. Agricultural technology for increasing competitveness of small holders. In: Pingali P, Aiyar A, Abraham M, Rahman A. *Transforming Food Systems for Rising India.*

Rama Rao CA, Raju BM, Subba Rao AV, Rao VU, Kausalya R, Venkateswarlu B, Sikka AK. 2013. Atlas on Vulnerability of Indian Agriculture to Climate Change. Hyderabad: Central Research Institute for Dryland Agriculture.

Ravindranath NH, Bala G, Murthy IK, ..., Ravindranath D. 2014. Transitioning towards climate resilient development in Karnataka. Bangaluru: Centre for Sustainable Technologies, Indian Institute of Science.

Rosenbaum PR, Rubin DB. 1983. The central role of propensity score in observational studies for causal effects. Biometrika 70(1):41-55.

Rosenbaum PR, Rubin DB. 1985. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. The American Statistician 29(1):33-38.

Sahu SK, Das S. 2015. Impact of agricultural related technology adoption on poverty:A study of select households in India. *Working paper 131/2015*. Madras School of Economics.

Sapkota TB, Jat ML, Aryal JP, Jat RK, Khatri-Chhetri A. 2015. Climate change adaptation, greenhouse gas mitigation and economic profitability of conservation agriculture: Some examples from cereal systems of Indo-Gangetic Plains. Journal of Integrative Agriculture 14:1524-1533.

Sha W, Chen F, Mishra AK. 2019. Adoption of direct seeded rice, land use and enterprise income: Evidence from Chinese rice producers. *Land Use Policy* 83:564-570.

Simtowe F, Kassie M, Diagne A, Asfaw S, Shiferaw B, Silim S, Muange E. 2011. "Determinants of agricultural technology adoption: The case of improved pigeonpea varieties in Tanzania." *Quaterly Journal of International Agriculture* 50 (4):325-345.

Sova CA, Grosjean G, Baedeker T, Nguyen TN, Wallner M, Nowak A, Corner-Dolloff C, Girvetz E, Laderach P, Lizarazo M. 2018. Bringing the concept of climate-smart agriculture to life: Insights from CSA country profiles across Africa, Asia and Latin America. Washington D.C.: World Bank, and the International Centre for Tropical Agriculture.

Tambo JA, Mockshell J. 2018. Differential impacts of conservation agriculture technology options on household income in Sub-Saharan Africa. Ecological Economics 151:95-105.

Teklewold H, Kassie M, & Shiferaw B. 2013. Adoption of multiple sustainable agricultural practices in rural Ethiopia. *Journal of Agriculture Economics* 64(3):597-623.

Truong TNC. 2008. Factors affecting technology adoption among rice farmers in the Mekong Delta through the lens of local authorial managers: An analysis of qualitative data. *Omonrice* 16:107-112.

UNFCCC. 2006. Technologies for adaptation to climate change. United Nations Framework Convention on Climate Change.

Villano R, Bravo-Ureta B, Solis D, Fleming E. 2015. Modern rice technologies and productivity in the Philippines: Disentangling technology from managerial gaps. Journal of Agricultural Economics 66(1):129-154.

Wani SP, Chander G, Anantha KH. 2017. Enhancing resource use efficiency through soil management for improving livelihoods.

Wooldridge JM. 2010. Econometric analysis of cross-section and panel data. 2nd Ed. MIT Press, Cambridge, MA.

Yamano T, Luz M, Habib A, Kumar S. 2018. Neighbors follow early adopters uner stress: Panel data analysis od submergence-tolerant rice in northern Bangladesh. *Agricultural Economics* 49:313-323.

Zeng D, Alwang J, Norton GW, Shiferaw B, Jaleta M, Yirga C. 2015. Ex post impacts of improved maize varieties on poverty in rural Ethiopia. *Agricultural Economics* 46(4):515-526.

Appendix

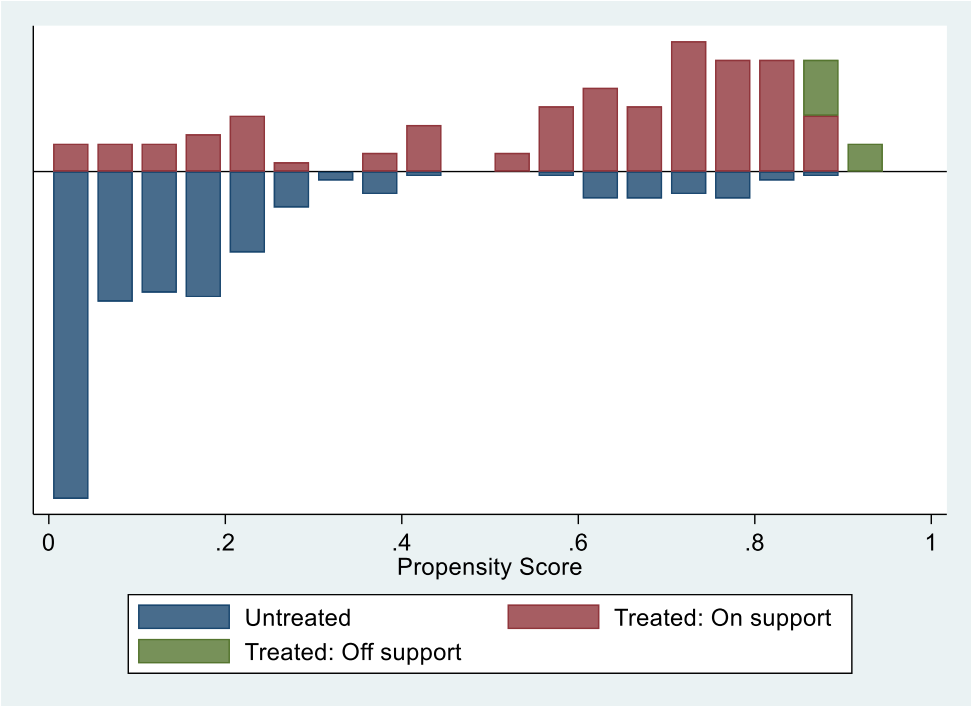

Figure A1. Common support for low vs improved.

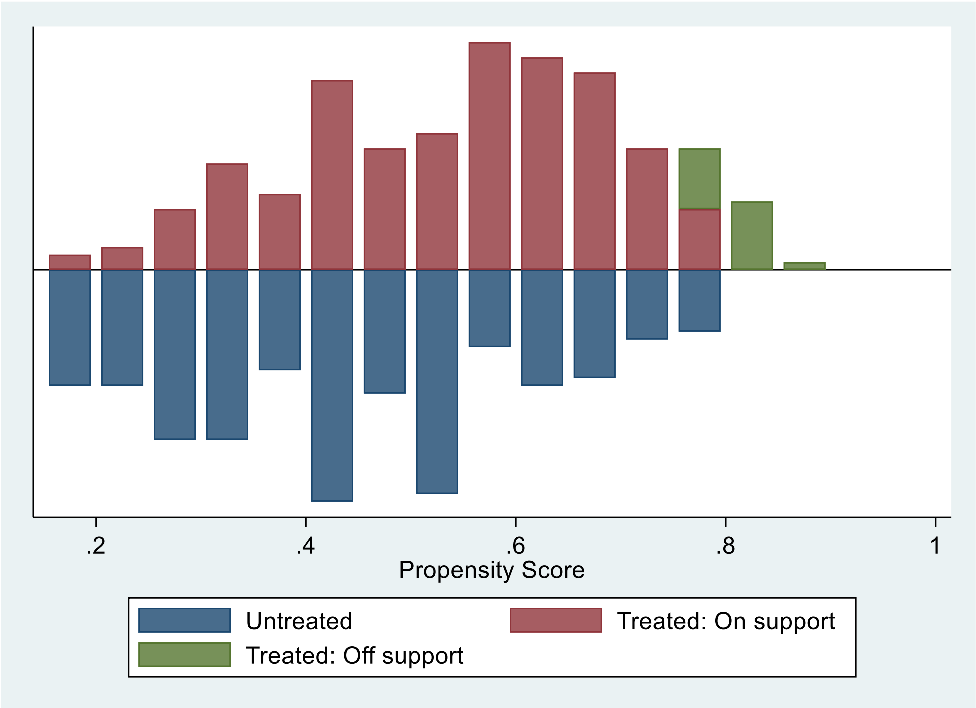

Figure A2. Common support for medium vs improved.

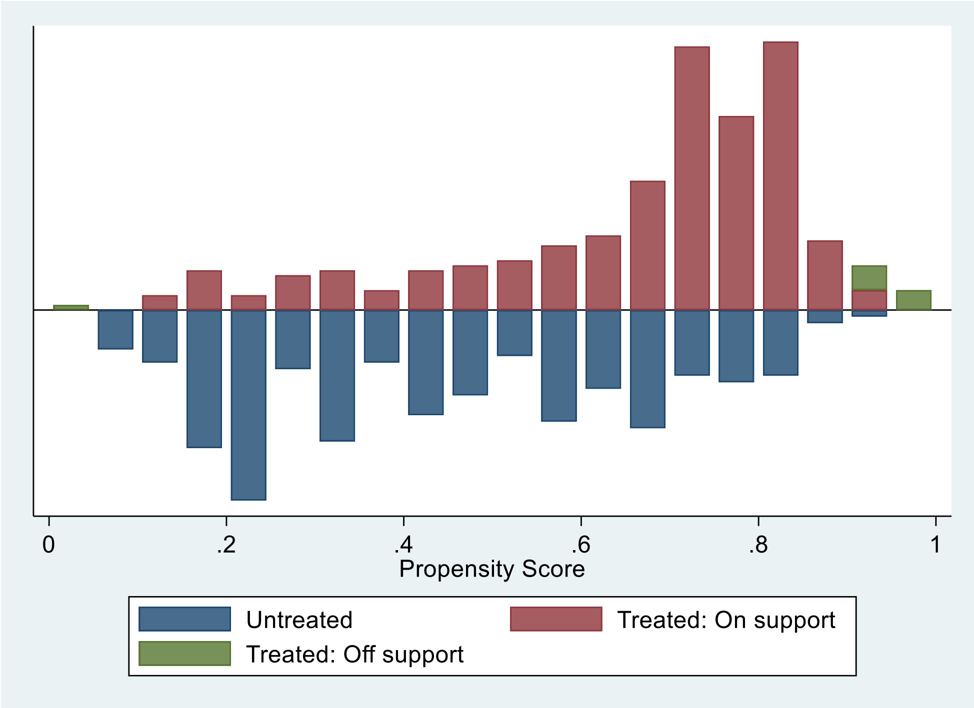

Figure A3. Common support for high vs improved.

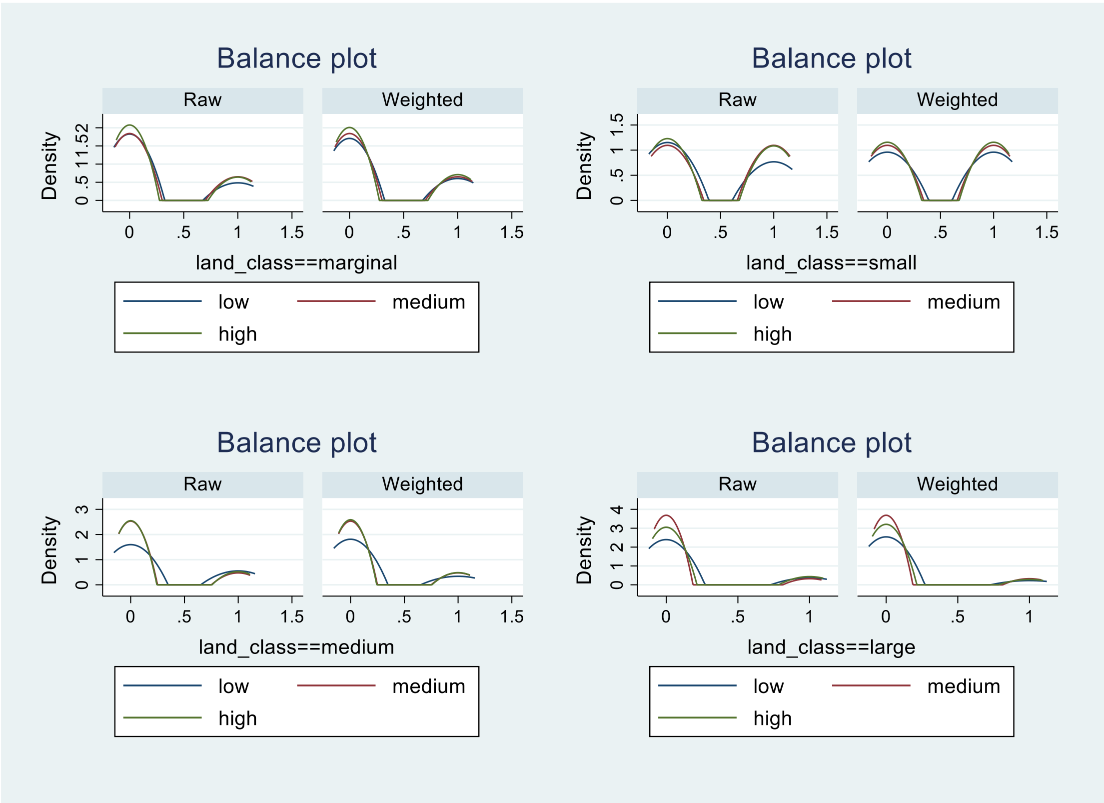

Figure A4. Balance plot for land ownership.

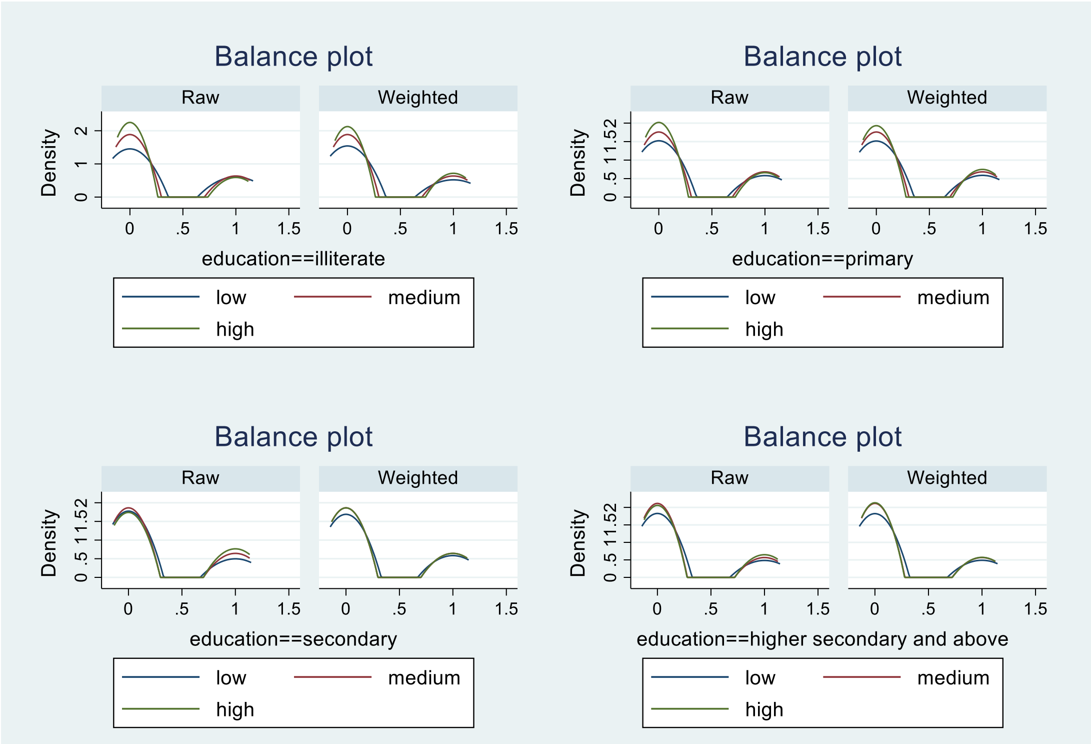

Figure A5. Balance plots for education levels.

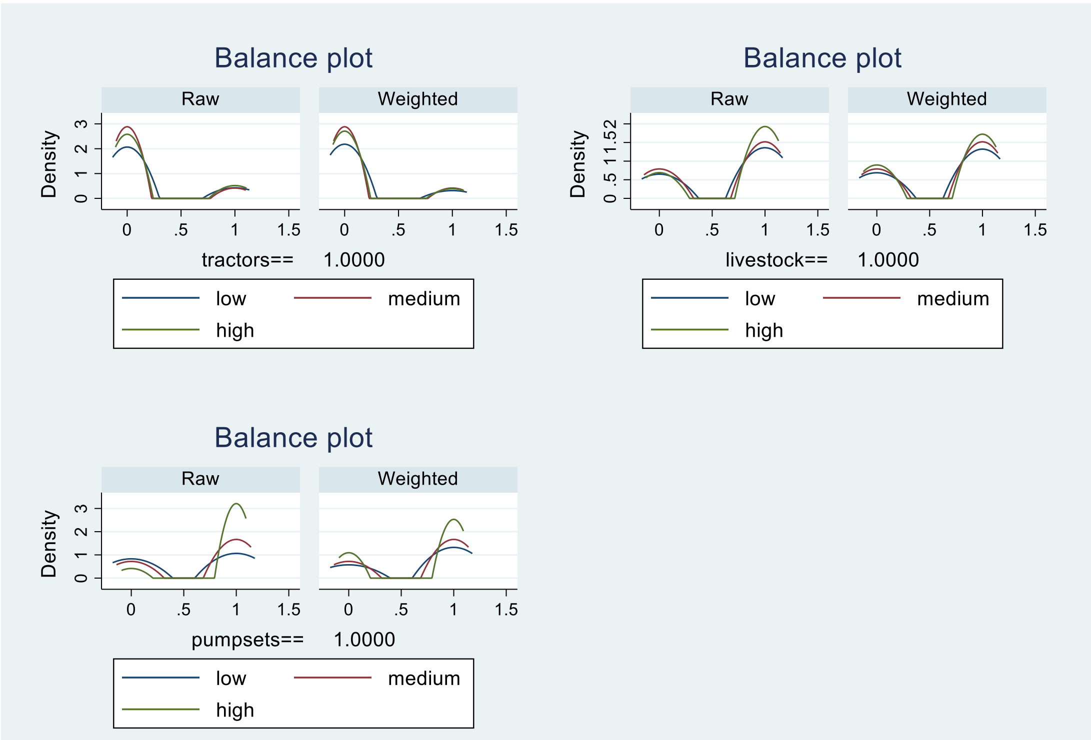

Figure A6. Balance plot for asset ownership (livestock, pumpset and tractor).

Table A1. T-test quality of means before and after matching for low vs improved.

Variable	Unmatched/ Matched	Mean Treatment	Mean Control	% bias	% reduction in bias	t-test T	t-test p>|t|
Land class (Base: Marginal)							
Small	U	0.4	0.436	-7.2	-94.1	-0.61	0.544
	M	0.437	0.368	14.0		0.98	0.329
Medium	U	0.257	0.092	44.5	95.8	4.04	0.001
	M	0.187	0.181	1.9		0.12	0.902
Large	U	0.133	0.064	23.2	90.0	2.08	0.039
	M	0.146	0.153	-2.3		-0.13	0.893
Education (Base: Illiterate)							
Primary	U	0.276	0.266	2.3	-276.8	0.19	0.848
	M	0.271	0.232	8.6		0.61	0.545
Secondary	U	0.219	0.243	-5.7	-145.2	-0.48	0.634
	M	0.239	0.298	-14.0		-0.92	0.359
Higher-secondary and above	U	0.209	0.197	3.0	-324.3	0.26	0.797
	M	0.219	0.167	12.9		0.91	0.363
Asset ownership (Yes = 1, No = 0)							
Livestock	U	0.677	0.541	27.8	71.7	2.32	0.021
	M	0.646	0.607	7.9		0.54	0.587
Pumpset	U	0.562	0.537	5.0	-698.9	0.42	0.671
	M	0.542	0.743	-40.3		-2.96	0.003
Tractor	U	0.171	0.050	39.1	100.0	3.62	0.001
	M	0.156	0.156	0.01		-0.01	1.000

Source: Authors' calculations based on IFPRI-GoK survey, 2018-19.

Table A2. T-test quality of means before and after matching for medium vs improved.

Variable	Unmatched/ Matched	Mean		% bias	% reduction in bias	t-test	
		Treatment	Control			t	p>|t|
Land class (Base: Marginal)							
Small	U	0.5	0.435	12.9	92.4	1.35	0.178
	M	0.515	0.519	-1.0		-0.10	0.921
Medium	U	0.158	0.091	20.0	80.2	2.10	0.037
	M	0.117	0.131	-4.0		-0.40	0.690
Large	U	0.081	0.064	6.5	41.9	0.68	0.497
	M	0.083	0.074	3.8		0.37	0.713
Education (Base: Illiterate)							
Primary	U	0.279	0.266	3.0	50.6	0.31	0.756
	M	0.279	0.273	1.5		0.15	0.883
Secondary	U	0.256	0.243	3.1	28.1	0.33	0.742
	M	0.25	0.240	2.3		0.23	0.818
Higher-secondary and above	U	0.212	0.197	3.6	20.9	0.38	0.708
	M	0.201	0.189	2.8		0.29	0.771
Asset ownership (Yes = 1, No = 0)							
Livestock	U	0.657	0.541	23.9	97.2	2.50	0.013
	M	0.642	0.645	-0.7		-0.07	0.945
Pumpset	U	0.698	0.536	33.6	77.7	3.53	0.001
	M	0.672	0.707	-7.5		-0.78	0.434
Tractor	U	0.126	0.050	26.8	89.2	2.81	0.005
	M	0.078	0.070	2.9		0.31	0.754

Source: Authors' calculations based on IFPRI-GoK survey, 2018-19.

Table A3. T-test quality of means before and after matching for high vs improved.

Variable	Unmatched/ Matched	Mean Treatment	Control	% bias	% reduction in bias	t-test t	p>|t|
Land class (Base: Marginal)							
Small	U	0.468	0.435	6.6	23.6	0.74	0.462
	M	0.467	0.492	-5.1		-0.59	0.553
Medium	U	0.170	0.092	23.4	61.8	2.56	0.011
	M	0.176	0.146	8.9		0.96	0.337
Large	U	0.125	0.064	20.8	-16.4	2.28	0.023
	M	0.115	0.185	-24.3		-2.34	0.020
Education (Base: Illiterate)							
Primary	U	0.246	0.266	-4.5	-108.8	-0.50	0.619
	M	0.255	0.296	-9.3		-1.07	0.283
Secondary	U	0.305	0.243	14.0	88.5	1.55	0.121
	M	0.298	0.306	-1.6		-0.18	0.854
Higher-secondary and above	U	0.239	0.197	10.2	-84.1	1.14	0.257
	M	0.234	0.156	18.9		2.33	0.020
Asset ownership (Yes = 1, No = 0)							
Livestock	U	0.736	0.541	41.3	90.2	4.64	0.001
	M	0.730	0.711	4.1		0.50	0.615
Pumpset	U	0.885	0.537	83.2	98.3	9.55	0.001
	M	0.884	0.878	1.4		0.22	0.827
Tractor	U	0.167	0.050	38.0	62.9	4.09	0.001
	M	0.141	0.183	-14.1		-1.38	0.168

Source: Authors' calculations based on IFPRI-GoK survey, 2018-19.