IFPRI Discussion Paper 01960

August 2020

Impact of Laser Land Levelling on Food Production and Farmers' Income

Evidence from Drought Prone Semi-Arid Tropics in India

Barun Deb Pal

Shreya Kapoor

Sunil Saroj

M.L. Jat

Yogesh Kumar

K.H. Anantha

South Asia Regional Office

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

The International Food Policy Research Institute (IFPRI), a CGIAR Research Center established in 1975, provides research-based policy solutions to sustainably reduce poverty and end hunger and malnutrition. IFPRI's strategic research aims to foster a climate-resilient and sustainable food supply; promote healthy diets and nutrition for all; build inclusive and efficient markets, trade systems, and food industries; transform agricultural and rural economies; and strengthen institutions and governance. Gender is integrated in all the Institute's work. Partnerships, communications, capacity strengthening, and data and knowledge management are essential components to translate IFPRI's research from action to impact. The Institute's regional and country programs play a critical role in responding to demand for food policy research and in delivering holistic support for country-led development. IFPRI collaborates with partners around the world.

AUTHORS

Barun Deb Pal (b.debpal@cgiar.org) is a program manager in the South Asia Regional Office of the International Food Policy Research Institute (IFPRI), New Delhi, India.

Shreya Kapoor (s.kapoor@cgiar.org) is a research analyst in IFPRI's South Asia Regional Office, New Delhi, India.

Sunil Saroj (s.saroj@cgiar.org) is a senior research analyst in IFPRI's South Asia Regional Office, New Delhi, India.

M.L. Jat (m.jat@cgiar.org) is a principal scientist/systems agronomist and sustainable intensification strategy lead at the International Maize and Wheat Improvement Centre (CIMMYT), India.

Yogesh Kumar (yogeshkumar.singh@yahoo.co.in) is an assistant research scientist at CIMMYT, India.

K.H. Anantha (k.anantha@cgiar.org) is a senior scientist (Natural Resource Management) at the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), India.

Notices

[1] IFPRI Discussion Papers contain preliminary material and research results and are circulated in order to stimulate discussion and critical comment. They have not been subject to a formal external review via IFPRI's Publications Review Committee. Any opinions stated herein are those of the author(s) and are not necessarily representative of or endorsed by IFPRI.

[2] The boundaries and names shown and the designations used on the map(s) herein do not imply official endorsement or acceptance by the International Food Policy Research Institute (IFPRI) or its partners and contributors.

Contents

List of Tables

List of Figures

Abstract

Climate change has brought large instabilities in agricultural systems, in terms of both crop yield and net farm income. Climate smart agriculture is one of the innovative methods that tries to build resilience in agricultural systems. A study is conducted in Raichur district of Karnataka state in India to assess the impact of adoption of laser land levelling (LLL), a climate smart agriculture technology, on crop yield and farmers' income. A primary survey was conducted in 2018 among 604 paddy growing farmers in Raichur district. The study provides results based on both qualitative and quantitative analysis of the data. The study examines farmers' perceptions about climate change and effectiveness of LLL. Statistically, the results are evaluated using econometric methods like propensity score matching, coarsened exact matching, and endogenous switching regression. Advanced econometric methods are adopted to check for the problem of unobserved endogeneity. Adoption of laser land levelers increased crop yield by 0.5 tonnes/hectare and net farm income by Rs. 5000 per annum. Further, farmers observed drought as the most extreme climatic event which resulted in heavy crop loss to them. Lastly, farmers revealed that adoption of LLL reduced cost of cultivation and limits crop loss due to climate variability.

Keywords: Climate Change Adaptation, Climate smart agriculture, Impact assessment, Sustainable development, Econometric Modeling, Agricultural Technology, livelihoods

Acknowledgments

This study has been conducted with the financial support from both Department of Agriculture, Government of Karnataka (through ICRISAT, Hyderabad) and CGIAR's research programme on climate change agriculture and food security (CCAFS), which is carried out with the support from CGIAR Trust Fund and through bilateral funding agreements. Authors are deeply grateful to all the donors for adequate financial support for successful implementation of the primary survey and subsequent analysis. While conducting primary survey in Raichur district, the research team received extensive support from the scientists and faculties from the university of Agriculture Science, Raichur as well as from different agricultural line departments. Last but not the least, we are thankful to all farmers and research staff of CGIAR institutions based in the study area for their co-operation and help.

List of Acronyms

ATT	Average Treatment Effect on Treated
CEM	Coarsened Exact Matching
CGIAR	Consultative Group for International Agricultural Research
CIMMYT	International Center for Wheat and Maize Improvement Center
CSA	Climate Smart Agriculture
ESR	Endogenous Switching Regression
ICAR	Indian Council for Agricultural Research
ICRISAT	International Crops Research Institute for the Semi-Arid Tropics
GoK	Government of Karnataka
KSNDMC	Karnataka State Natural Disaster Monitoring Center
LLL	Laser Land Levelling
MIB	Monotonic Imbalance Bounding
PSM	Propensity Score Matching
RSK	Raita Samparka Kendra

1. Introduction

Semi-arid regions around the world are hotspots of poverty, malnutrition, and degradation of environmental resources. Crop productivity in these regions is only one fifth to a half of the potential yield (Wani, et al., 2012). Extremes of heat and cold, droughts and floods, and various other forms of extreme climatic events are additional challenges to agricultural productivity, farm incomes and food security in this region (Battisti & Naylor, 2009). There are various studies that suggest that agricultural production is significantly affected due to abrupt increase in temperature (Lobell, et. al., 2012; Aggarwal, et al., 2009), changes in monsoon patterns (Prasanna, 2014; Mall, et. al. 2006), and variations in frequency and intensity of extreme climatic events like floods and droughts (Brida et.al., 2013; Singh, et. al., 2013). Therefore, it has become imperative to identify and evaluate options for adapting to climate change. According to Wani et al. (2012), the potential of dryland farms can be unlocked by employing improved technologies in a sustainable manner. Ghimire, et al., (2015) stress that the adoption of new techniques should occur through an integrated approach in order to increase agricultural productivity. According to these researchers, innovative and new agricultural technology helps improve the welfare of poor people directly by increasing their incomes and indirectly by raising the employment and wage rates of landless laborers, and by minimizing price fluctuations. Climate-smart agriculture (CSA) is an approach to adapting and mitigating the effects of climate change (Lipper, et al., 2014). CSA employs agricultural technologies that increase crop productivity, enhance farmers' net income, reduce risk due to weather variability, and reduce the water, energy and emissions footprints of agriculture. Conclusively, CSA aims to expand productivity and income, boost resilience, and decrease greenhouse gas emissions from agricultural activities (FAO, 2012; Lipper et.al., 2018). Climate-smart agriculture can thus address many of the challenges faced by dryland agriculture.

Laser land levelling (LLL) is an innovative method that helps to reduce water, nutrient, and energy inputs in dryland agriculture and enhance income of farmers by increasing crop productivity (Shahani, et al., 2016). Unevenness of the soil surface has a major impact on nutrient and water management and hence on germination and crop yield (Shahani, et al., 2016). Laser land levelling thus facilitates good agronomic, soil, and crop management practices. However, the effectiveness of LLL varies across agroclimatic conditions and few, if any studies have been conducted in the semi-arid zone. Furthermore, there have been few studies of the effectiveness of LLL on farmers' livelihoods. Therefore, this study is conducted to investigate what impact LLL might have on crop yield and income of the farmers located in semi-arid region and whether adoption of LLL technique could minimize losses resulting from long dry spells or drought faced by farmers.

Following this introductory section, rest of this paper is organized as follows. The section 2 provides brief description about the study area and section 3 describes sample size and its distribution across sample unit. The sample selection method is also described in this section. The conceptual and econometric framework used in the study is described in section 4 and section 5 describes results from this study. Finally, section 6 concludes this paper with key policy implications.

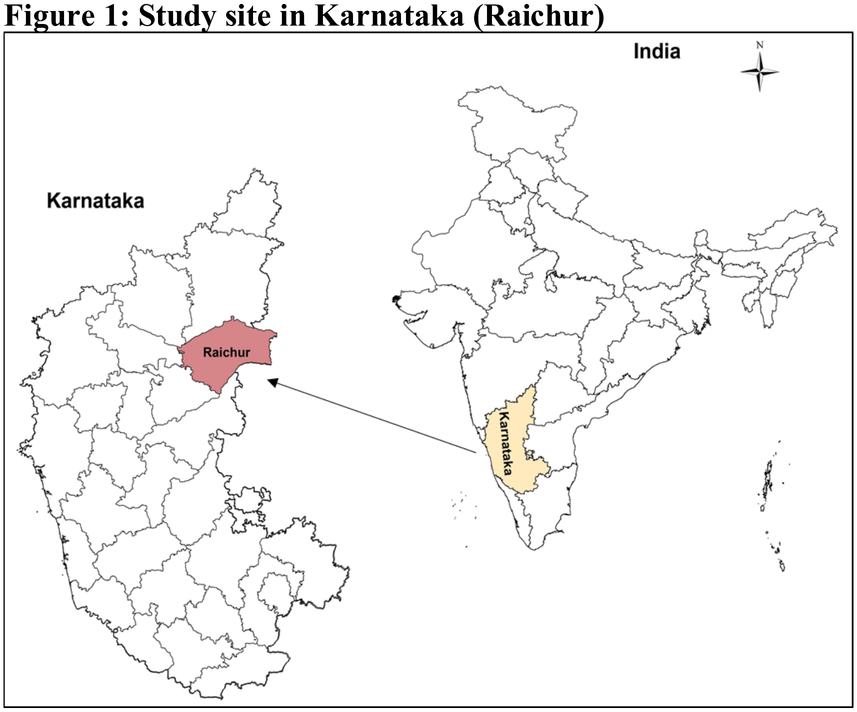
2. Data and Sampling

2.1 Study Area

The state of Karnataka in India is selected for this study. As per Census 2011, agriculture supports 13.74 million workers, comprising 23.61% as cultivators and 25.67% as agricultural workers, altogether agriculture employs more than 60% of the Karnataka's workforce (Bhende, 2013). Karnataka has the largest rainfed area in the country after Rajasthan, and small and marginal farmers with landholdings less than 2 hectares produce almost half of the food grown in the state (GoK, 2011). The state has large portions of agricultural land exposed to vagaries of monsoon with extreme agro-climatic and resource constraints (Bhende, 2013). However, poor soil, water, and crop management practices are depleting soil nutrients and degrading the land, which is resulting in low crop productivity (Bhattacharya, et al., 2015).

In 2013, the Government of Karnataka initiated the *Bhoosamrudhi* programme to promote innovative technologies in the agriculture sector, with the objective of increasing crop production by 20%, enhancing farmers income by 25% and reducing vulnerability due to climate variability (Wani, et al., 2015). A consortium of CGIAR institutions led by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), agriculture universities and Indian Council of Agricultural Research (ICAR) institutions was formed to conduct pilot tests of the technologies across selected districts. Several improved and innovative technologies have been tested in the pilot areas and several trainings have been conducted to motivate farmers to adopt those technologies. Laser land levelling was one among these improved technologies tested among the paddy-growing farmers in Raichur district of Karnataka. The location of the study site is presented in Figure 1.

Figure 1: Study site in Karnataka (Raichur)



Source: Created by authors

Raichur district is in the north eastern dry zone of the Karnataka state. Raichur has about 4,75,000 hectares of net sown area and 5,66,000 hectares of gross cropped area with a cropping intensity of 111.9%. Paddy occupies almost 25% of the gross cropped area. Seventy per cent of the gross cropped area is rainfed. Canals are the most widely used source of irrigation water (almost 72% of the total irrigated area) followed by open wells (8.22%) and bore wells (7.57%) (Directorate of Economics and Statistics, 2019).

Climate change is expected to increase the length and severity of drought. The district has been witnessing erratic and declining rainfall since 2014 and the Karnataka State Natural Disaster Monitoring Centre (KSNDMC) declared that Raichur was affected by severe drought in 2018. Previous studies have indicated that laser land levelling is suitable for all crops and helps conserve water and increase crop productivity (Ali, et. al., 2018; Kumari, et al., 2017; Aryal, et. al., 2015). Adoption of LLL has the potential to increase paddy yield and agriculture production in Raichur district, increase and stabilize farmers' income and build resilience against climate change impacts on paddy production.

2.2 Sampling

A primary survey of farmer households was conducted in Raichur district of Karnataka, a semi-arid region in India, between November 2018 and March 2019, immediately after paddy harvest. Responses were received from 604 paddy farmers, of whom 275 were non-adopters of LLL and 329 were adopter farmers. The LLL technology adopters were selected purposively in consultation with experts from the State Agriculture University, Raichur, scientists from the International Maize and Wheat Improvement Center (CIMMYT) and ICRISAT. Adopter farmers included those who owned an LLL machine and those who rented an LLL machine to level their land. Non-adopters were selected based on being neighboring farmers with land near the laser-levelled plot and who cultivated paddy in the same season. Data was collected on general and geographical characteristics of the respondents, whether they owned or rented LLL machines, the area under crop cultivation, crop yield, farm income, cost of cultivation, asset holdings, household sources of income, household characteristics, and major constraints that farmers face in adopting LLL.
The details of sample size and their distribution with respect to adopters and non-adopters are presented in Table 1.

Table 1: Sample selected for the study, by administrative blocks

	Adopters		**Non-adopters**		**Total**	
Administrative district	**Number**	**%**	**Number**	**%**	**Number**	**%**
Raichur	88	55.0	72	45.0	160	26.5
Devdurga	138	82.1	30	17.9	168	27.8
Manvi	39	20.9	148	79.1	187	30.9
Sindhanur	64	71.9	25	28.1	89	14.7
Total	329	54.5	275	45.5	604	100

3. Analytical Framework

The decision to adopt LLL may be determined by several characteristics of farmers, like landholding size, socioeconomic characteristics and their perception of the inherent features of the practices. Farmers' education, machinery ownership, irrigation water supply, capacity-enhancement activities and profit-oriented behavior are the key determinants in enhancing adoption of certified seed technology (Mariano et al. 2012). To assess the impact of a new technology, a researcher should be able to assess the situation in counterfactual and non-counterfactual scenario and inferences can be drawn and implemented as policy (Mendola 2007). To address this methodological gap, Mendola (2007) used cross-sectional household survey data of rural Bangladesh and isolated the causal effect of adopting high-yielding varieties of rice on poverty alleviation by using the PSM method.

The study examined the impact of the LLL technology on crop productivity[1] and net income[2] earned by farmers. We have employed the following econometric tools to construct our empirical model of the impact of LLL on crop yield and income of the farmers.

3.1 Propensity score matching

In propensity score matching (PSM), households are ranked according to their own behaviour towards technology adoption to ensure that technology effects are evaluated among groups of farmers possessing similar characteristics (Mendola, 2007). The objective is to identify farmers who did not adopt the technology (control group) who are like the farmers who adopted the technology (treatment group) in all relevant observable features, i.e. the only difference between the control and treatment group is the adoption of LLL. PSM also helps to generate the average treatment effect for the treatment group (ATT).

There are several methods that can be used to match the propensity scores of the treatment and control groups, namely nearest neighborhood, kernel, radius matching, and bootstrapping. In general, these methods should yield the same results but in practice there are trade-offs in terms of bias and efficiency with each method (Caliendo & Kopeining, 2008). This study used the nearest neighborhood matching technique to find the 'neighbors' value (propensity score) of control plots that was closest to the values of treated plots. The purpose here is to balance the observed distribution of covariates across the treatment groups and control groups. The balancing test helps to ascertain whether the differences in covariates in the two groups of the matched sample have been eliminated or not. If the differences between the two groups are eliminated, then the matched comparison group can be considered a plausible counterfactual (Akhter & Awudu, 2010). The most frequently used measure of whether balancing has been successful is the standardized mean difference (bias); this should be minimal between treatment and control groups. In principle, after matching, there should be no systematic differences in the distribution of covariates between the groups (Rosenbaum

[1] Crop productivity is total production divided by the total area cultivated

[2] Net income is calculated as the difference between the total revenue earned and total cost incurred by the farmers. Total revenue is the product of the total quantity of commodity sold and price at which it is sold. Total cost is the sum of different costs incurred by the farmer during crop cultivation. The major costs considered in this study included canal water charges, electricity for irrigation, fertilizer, seed, labour, rental machines for ploughing and levelling, and fuel.

& Rubin, 1985). PSM estimators do not account for selection on unobservable factors. Hence, it is accepted that such selection bias has little impact on the results.

ATT is calculated as follows. Let ‘Di’ be an indicator of whether a farmer is adopter or a non-adopter of the technology. The potential productivity outcome of being an adopter, represented by i, for each farmer is defined as (Di). The ATT is computed as:

$$\Delta_{ATT} = E(\Delta|D_i = 1) = E[(\tau\,(1)|D_i = 1] - E[(\tau\,(0)|D_i = 1] \tag{1}$$

where Δ_{ATT} is the average treatment effect on the treated plot; $E[(\tau\,(1)|D_i = 1]$ is the expected outcome variable of a beneficiary farmer; and $E[(\tau\,(0)|D_i = 1]$ is the expected outcome variable of an adopter farmer if they are not the user of LLL machine. The PSM technique involves imposition of conditional independence and common support assumptions for identification. If the above two assumptions are fulfilled, then the PSM estimator for ATT is given as follows:

$$\Delta\frac{PSM}{ATT} = E_{p(X)|D_i=1}\{E[(\tau\,(1)|D_i = 1, p(X)] - E[(\tau\,(0)|D_i = 1, p(X)]\} \tag{2}$$

3.2 Coarsened exact matching

Coarsened exact matching (CEM) is an alternative technique to PSM, belonging to the Monotonic Imbalance Bounding (MIB) group developed by (Iacus, et al., 2011) CEM works in sample distributions and requires no assumption about the data generation process except for the usual ignorability assumptions. This method assures that the imbalance between the matched and unmatched groups will not be greater than the ex-ante choice stated by the user. (Iacus, et al., 2011) have shown that CEM is better than other commonly used matching methods at reducing imbalance, model dependence, estimation error bias, variance, and mean square error. The mechanism behind CEM is to coarsen each variable by recoding so that largely identical values are grouped and assigned the same value; this is followed by application of the exact matching principle to identify matches and to remove unmatched units. Finally, the coarsened data are withdrawn, and original values of the matched data are retained.
After coarsening, CEM creates a set of strata, say, s € S, each with few coarsened values of X. Consider a sample of size n ($n \leq N$) which contains units drawn from population N. Let T_i denote an indicator variable for unit i which takes value 1 if the i^{th} unit belongs to the treatment group and takes value 0 if the i^{th} unit belongs to the control group. The observed outcome variable $Y_i = T_i Y_i (1) + (1-T_i)$ Yi (0) where $Y_i(0)$ is the outcome for the non-adopters of LLL and $Y_i(1)$ is the outcome for the adopters of LLL. In order to estimate the impact of the technology intervention on a selected group of households, the standard ignorability assumption is that, conditional on X, the treatment variable is independent of the potential outcomes and that every treated unit receives the same treatment. A fixed causal effect is a function of potential outcome defined as $Y_i(1) - Y_i(0)$.
The estimates for the causal effects on outcome variables can be defined as:

$$SATT = \frac{1}{n_T} \sum_{i\varepsilon\tau} TE_i \tag{3}$$

where $TE_i = Y_i(1) - Y_i(0) \mid X_i$ and n_T = total number of treated units in the original sample. This estimate is valid only when all treated units are matched. However, when all the units do not match, as is the case of the current study, SATT changes to LSATT or local sample average treatment for all treated plots, which is estimated by:

$$LSATT = \frac{1}{m_T} \sum_{i \varepsilon T^m} TE_i \qquad (4)$$

where m_T = number of matched treated units and T^m = subset of matched treated units.

3.3 Endogenous switching regression

In some cases, the standard econometric model of using pooled sample of treatment and control groups may be inappropriate since it assumes that the set of covariates has the same impact on both the groups. To counter this issue, this study employed endogenous switching regression (ESR) to check for robustness and account for selection bias present in the former model. ESR addresses the endogeneity problem by estimating selection and outcome equations simultaneously using the full information maximum likelihood method (Lokshin & Sajaia, 2004; Wossen, et al., 2017; Ma & Abdulai, 2016; Kumar, et al., 2018).
The selection equation for the beneficiary household can be stated as:

$$Z_i^* = X_i\alpha + \delta_i \; with \; M_i = \begin{cases} 1 \; if \; Z_i^* > 0 \\ 0 \; ; otherwise \end{cases} \qquad (5)$$

where X_i is the vector of explanatory variables comprising sociodemographic details of the households. The variables included in the vector are size of agricultural landholding, household size, crop insurance, educational qualifications, visits made to and from Raita Samparka Kendra (RSK), number of adult male members engaged in farming activity, constraints faced by farmers in adopting LLL (machine supply, training, rent of machine, and irrigation facility), and asset ownership (livestock, tractor, and pump sets). The relationship between the vector of independent variables X and outcome variable Y can be represented as Y = f(X). The household will adopt LLL ($Z_i = 1$) when Y>0, where Y stands for the outcome generated from the adopters of LLL *vis-à-vis* non-adopters of LLL.
Now, the outcome equation conditional on treatment can be stated as:

$$Regime\ 1: Y_{1i} = X_{1i} + \mu_{1i} \; if \; Z_i = 1 \qquad (6)$$

$$Regime\ 2: Y_{2i} = X_{2i} + \mu_{2i} \; if \; Z_i = 0 \qquad (7)$$

where Y_i is the resultant variable (output from LLL adopters) and the error terms (μ_{1i} and μ_{2i}) are assumed to have a tri-variate normal distribution with zero mean and covariance. If the estimated covariance between δ and μ's (ρ_1 and ρ_2, respectively) are statistically significant, then adopter households and income are positively correlated. Using this approach, we find signs of endogenous switching and rejected the null hypothesis that sample selection bias was absent. Maddala & Nelson (1975) defined this model as the switching regression model with endogenous switching which can be used to estimate ATT and ATU (average treatment effects on control households).

The ESR model involves application of an instrumental variable that directly affects the endogenous variable without having a direct impact on the outcome variable. In this study, this instrumental variable used is the number of farmers having access to canal irrigation.
In addition to the above ESR model, we also calculated the household's conditional expectation for income in four different cases:

$$E\,(Y_{1i} | Z_i = 1) = [\textstyle\sum_{Zi=1}(X_{1i}\beta_1 + \sigma_{1n}\gamma_{1i})]/N_1 \quad (8)$$

$$E\,(Y_{2i} | Z_i = 0) = [\textstyle\sum_{Zi=0}(X_{2i}\beta_2 + \sigma_{2n}\gamma_{2i})]/N_0 \quad (9)$$

$$E\,(Y_{1i} | Z_i = 1) = [\textstyle\sum_{Zi=1}(X_{1i}\beta_2 + \sigma_{2n}\gamma_{1i})]/N_1 \quad (10)$$

$$E\,(Y_{1i} | Z_i = 0) = [\textstyle\sum_{Zi=0}(X_{2i}\beta_1 + \sigma_{1n}\gamma_{2i})]/N_0 \quad (11)$$

where N_1 and N_0 are the number of observations with Z_i = 1 and Z_i = 0, respectively. The above equations are illustrated in Table 2. Cases (a) and (b) depict the actual expectation observed from the sample, while cases (c) and (d) represent counterfactual expected results. However, following the approach of Heckman, et al., (2001), in calculating the effect of treatment 'laser land leveler' on adopter households (TT), the study used the difference between case (a) and case (c) to calculate the impact of use of LLL on the outcome variable. Likewise, the difference between case (b) and case (d) indicates the impact of LLL on households that did not adopt LLL (TU).

The study also calculated the effect of base heterogeneity for the group of households that adopted LLL as the difference between case (a) and case (d), and for the group of households that did not adopt LLL as the difference between case (c) and case (b) (Cater & Milon, 2005). Lastly, the study also computed the transitional heterogeneity (TH), which highlights whether the effect of adoption of laser land levelers on the outcome variable is larger or smaller for households who adopted LLL in comparison to those households that did not adopt LLL, i.e., difference between TT and TU.

Table 2: Decision stage treatment and heterogeneity effect

Transitional heterogeneity	**Decision stage**		**Treatment effects**
	Treatment	**Control**	
Treatment	(a) $E(Y_{1i}\|Z_i = 1)$	(c) $E(Y_{2i}\|Z_i = 1)$	TT
Control	(d) $E(Y_{1i}\|Z_i = 0)$	(b) $E(Y_{2i}\|Z_i = 0)$	TU
Heterogeneity effects	BH^1	BH^2	TH

Source: Carter & Milon, 2005

4. Results and Discussion

4.1 Descriptive Statistics

Table 3 provides summary statistics of the sample farmer households for the key variables used in the empirical analysis. Adopters had significantly larger landholdings than non-adopters,10.53 hectares compared to 5.44 hectares per farmer household. Adopter farmers had slightly fewer adult male members working in agriculture (1.76) than did non-adopters (1.92). Adopters had significantly more interactions with RSKs than non-adopters. Significantly fewer adopters were illiterate and significantly more had at least a primary-school level education than the case for non-adopters, although there is no difference in the proportions with higher levels of education.

Adopters were significantly more likely to own assets such as livestock, pumps and tractors than were non-adopters. A significantly greater proportion of adopters identified constraints to adoption of LLL, including rent of the machine, training, machine supply, and availability of irrigation. Adopters had significantly higher average yields than non-adopters (4.8 tonnes/hectare compared with 4.29 tonnes/hectare). Adopters also reported significantly higher net income than non-adopters (Rs.35,650.4/ha, compared with Rs.30601.35/ha.

Table 3: Descriptive statistics of important variables

Variable	Adopter (N = 329)	Non-adopter (N = 275)	Difference in means (t-test)	Total (N= 604)
Sociodemographic characteristics				
Agriculture land owned (ha)	10.53	5.44	5.09**	8.21
Household size (no.)	6.04	6.38	-0.34	6.2
Adult males in farming (no.)	1.76	1.92	-0.15*	1.84
Crop loan	0.66	0.69	-0.03	0.67
Visits made to and from RSK	0.26	0.16	0.09***	0.21
Education				
Illiterate	0.23	0.37	-0.15***	0.29
Primary	0.38	0.25	0.13***	0.33
Secondary	0.22	0.21	0.02	0.22
Higher secondary and above	0.16	0.16	-0.002	0.16
Asset ownership				
Livestock	0.65	0.55	0.11***	0.61
Pump sets	0.57	0.37	0.20***	0.48
Tractors	0.54	0.40	0.14***	0.48
Constraints in adopting LLL				
Training	0.83	0.47	0.36***	0.66
Machine supply	0.72	0.43	0.29***	0.59
Irrigation facility	0.48	0.29	0.18***	0.39
Rent of machine	0.91	0.55	0.37***	0.75
Weeding problem	0.09	0.07	0.03	0.08
Other details				
Total revenue (Rupees)	58,117.23	51,661.7	6,455.53***	55178.04

Variable	Adopter (N = 329)	Non-adopter (N = 275)	Difference in means (t-test)	Total (N= 604)
Total cost (Rupees)	22,466.83	21,060.35	1,406.48	21826.46
Net income (Rupees)	35,650.4	30,601.35	5,049.05***	35968.21
Yield (tonnes/hectare)	4.8	4.29	0.51***	4.57
Administrative district				
Raichur	0.27	0.26	0.005	0.26
Devdurga	0.42	0.11	0.31***	0.28
Manvi	0.12	0.54	-0.42***	0.31
Sindhanur	0.19	0.09	0.10***	0.15

Source: Authors' calculation based on IFPRI-GoK survey, 2018-19; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Although the adopters of LLL technology have paddy yield 10% higher than that of non-adopters, but the non-adopters still achieved an average yield of around 4 tonnes/hectare even in the drought year. This gives rise to two research questions, first, does it make sense to invest an additional Rs.1,400 per ha (Table 3) to adopt LLL to increase average yield by only 0.5 tonnes/ha?, and second, although LLL has limited impact on absolute yield advantage, does it have a significant impact on the distribution of yield between adopters and non-adopters. To answer the above two questions, one must conduct detailed analysis of the farmers' household data and its impact on distribution. The study focusses on two sets of assessment, first, we have analyzed farmers perception of the climate extreme events and effectiveness of LLL to adapt with that event, and secondly, we have plotted distribution of yield for both adopters and non-adopters to understand impact of LLL on yield distribution.

Table 4 presents perceptions about climate change and its harmful impact from the adopters and non-adopters of LLL and adopted farmers' views on the benefits of adoption of LLL. As observed from this table, the most extreme climatic event most commonly observed by the farmers in the study area is drought. Almost 90% of sample farmers reported drought as a severe climatic event in the study area. Approximately 90% of both adopters and non-adopters reported crop loss in last five years. Further questioning of LLL adopters on cost of cultivation and crop loss due to climate change found that 92% observed reduction in cost of cultivation of paddy and 64% thought that LLL had reduced crop loss due to climate variability. When adopters were asked to rate LLL in terms of its usefulness, 97% stated that it is useful to reduce cost of cultivation and 95% identified its usefulness in reducing crop loss due to climate change.

Table 4: Farmers' observations on climate change and LLL adoption

Questions	Adopters of LLL (329)	Non-adopters of LLL (275)	Total (604)	Difference in means
Extreme climatic event witnessed by the respondent (Drought)	96.05	89.82	93.21	6.23***
Did you observe crop loss in the last five years? (Yes)	89.67	89.45	89.57	0.21
Only adopters will answer the following questions:				
	Yes	**No**	**Total**	**Difference in mean**
Did you observe that adoption of LLL reduces cost of cultivation?	92.71	0.36	50.66	92.34***
Do you think adoption of LLL reduces crop loss due to climatic variability?	64.44	0.36	35.26	64.07***

Source: Source: Authors' calculation from IFPRI-GoK survey, 2018–19;
Note: % values are shown in the parenthesis.

Figure 2: Ranking LLL in terms of reduction in cost of cultivation by adopters

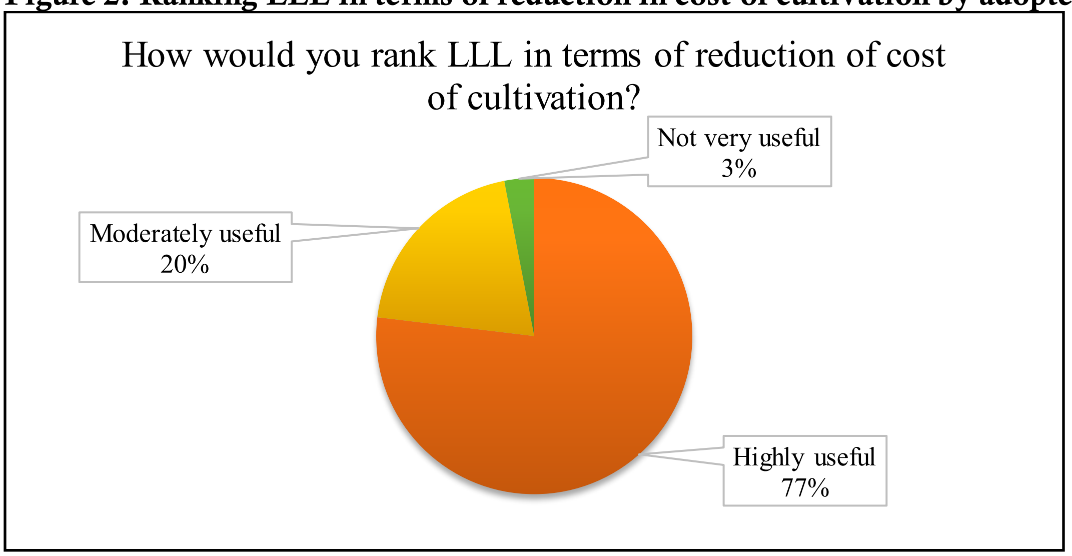
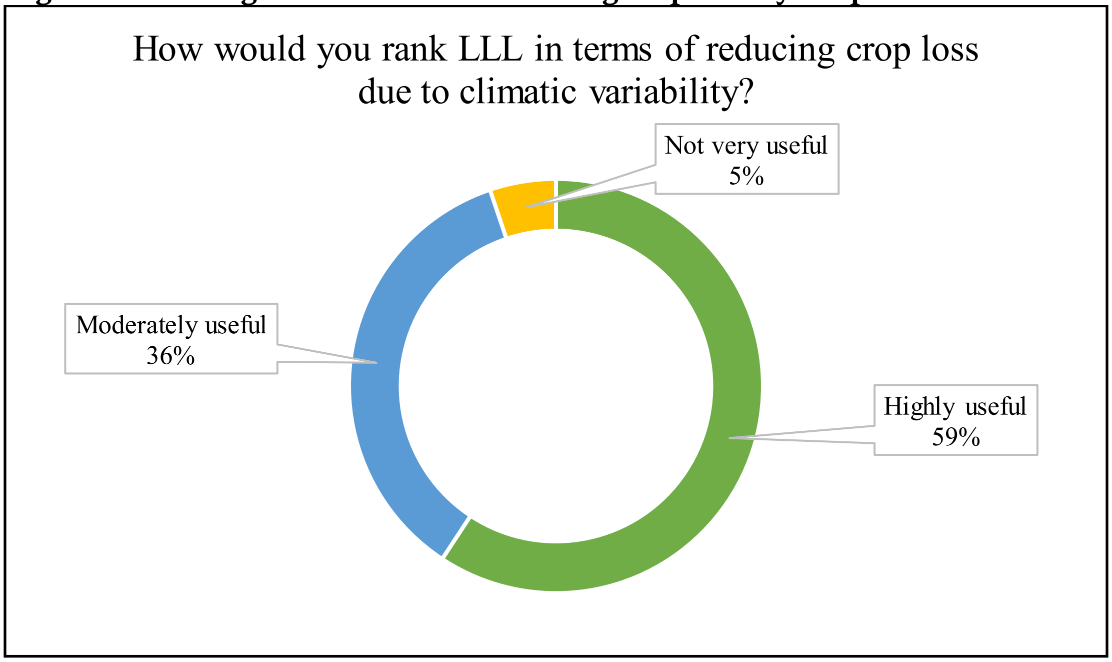


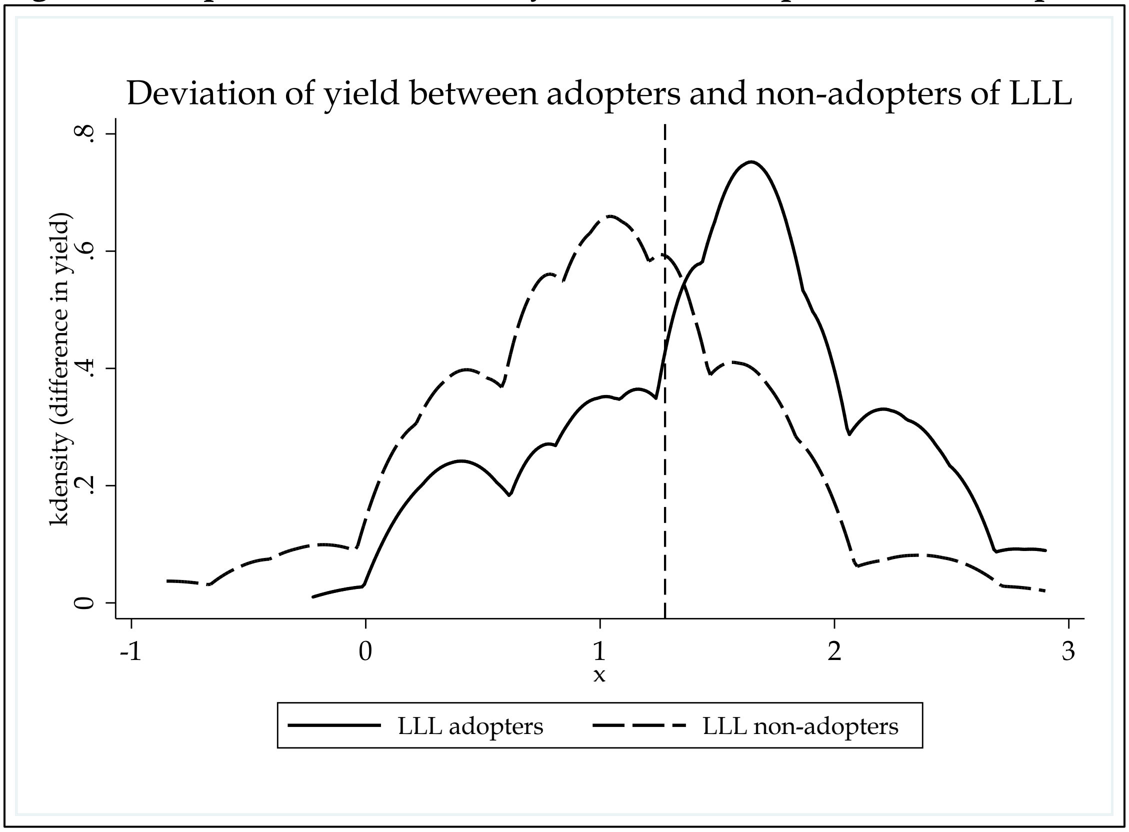
Figure 3: Ranking LLL in terms of reducing crop loss by adopters



Therefore, based on the above assessment from the farmers, we can argue that the Raichur is highly vulnerable to drought and sample farmers (both adopters and non-adopters) believe that LLL is an effective technology to adapt during frequent climate extreme events.

In order to validate farmers' perception, we use a statistical tool to understand the deviation between the yield reported by the sample farmers from the average district yield of last three years (2015, 2016, and 2017). The average district yield for three years is calculated from the district wise yield data taken from Directorate of Economics and Statistics, Department of Agriculture, Cooperation and Farmers Welfare, Ministry of Agriculture and Farmers Welfare, Government of India. Kernel density function is used to portray the difference and is presented in Figure 4 below. We can see that graph for non-adopters is inclined more leftwards from the mean line than the graph of adopters of LLL. This clearly suggests that LLL adopters have higher difference in yield than non-adopters, indicating a gainful endeavor for the adopters. The skewness coefficient for adopters' computes to be -0.12 while for non-adopters, it turns out to be -0.17, suggesting more negative skewness for non-adopters than adopters of LLL. Therefore, the yield gap is less for adopters of LLL than for non-adopters, indicating that LLL helps reduce yield declines of paddy caused by drought.

Figure 4: Comparison of deviation in yield between adopters and non-adopters of LLL



To delve further into the unobservable factors affecting the treatment and control groups, we build counterfactuals to minimize the effect of such factors on the crop yield and net income of the farmers by applying matching techniques to control for selection bias and unforeseen factors between the adopters and non-adopters of LLL.

4.2 Estimates from matching algorithms

Table 5 shows the results obtained from propensity score matching (PSM) and coarsened exact matching (CEM) for two outcome variables: yield (tonnes/hectare) and net income (rupees). PSM estimates shows that net income of the farmers who adopt LLL increases by Rs.5238 as compared to those farmers who did not adopt LLL. On the other hand, CEM results show an increase of Rs. 4834 in net income of LLL adopters in comparison to non-LLL adopters. Similarly, for crop yield PSM and CEM results exhibit an increase of 0.43 tonnes/ha and 0.68 tonnes/ha, respectively for LLL adopters in comparison to non-LLL adopters. Both the algorithms mention that adopters had higher net income and yield than non-adopters. The detailed results for PSM and CEM are attached in the Appendix.

Table 5: Estimates from propensity score matching (PSM) and coarsened exact matching (CEM) for yield (tonnes/hectare) and net income (rupees)

Outcome variable	PSM	CEM
Net income (rupees)	5,238.29**	4,834.57***
	(1,266.56)	(2,495.64)
Yield (tonnes/hectare)	0.43**	0.685***
	(0.74)	(1.30)

Source: Authors' estimation based on IFPRI-GoK Survey, 2018–19; Robust standard errors are given in parentheses; *** p<0.01, ** p<0.05, * p<0.1

4.3 Estimates from endogenous switching regression

Endogenous switching regression (ESR) is undertaken to account for selection bias and to check for robustness. Table 6 presents the treatment and heterogeneity effect results obtained from ESR model. We can observe that yield of LLL adopted farmers computes to be 4.76 tonnes/hectare while for the non-LLL adopted farmers, yield turns out to be only 4.05 tonnes/hectare. Therefore, treatment effect on treated (TT) is equal to 0.71 tonnes/hectare, signifying an advantage to LLL adopted farmers. However, more interesting results are for non-LLL adopted farmers who have an average yield of 4.24 tonnes/hectare but would have had an average yield of 5.84 tonnes/hectare if they would have adopted laser land leveler. The difference of 1.59 tonnes/hectare in yield between the two situations for the non-adopted farmers define the treatment effect on untreated (TU). Heterogeneity effect (TH) comes out to be 0.88 tonnes/hectare implying that non-LLL farmers will gain if they adopt the LLL technology.

Similarly, LLL adopted farmers have an average net income of Rs.37813 while the average net income would have reduced to Rs.26879 if they were non adopters of LLL technology. Hence, the treatment effect on treated (TT) calculates to be Rs.10933. This signify that farmers adopting LLL are more benefitted as compared to those who are non-adopters of LLL. Non-adopters of LLL technology have an average net income of Rs.30622 but would eventually rise to Rs.53439 if they adopt LLL technology. Here, treatment effect on untreated (TU) is equal to Rs.22816 and heterogeneity effect computes to be Rs.11883 implying a positive outcome for non-LLL farmers. All the results for crop yield and net income are statistically significant at 99% level of confidence interval. The results thus obtained in this study are in line with the results reported by Aryal et. al., (2015) for Punjab and Haryana, and Ali, et al., (2018) for Pakistan Punjab. Regime wise equations are presented in tabel A3 and A4 in the appendix.

Table 6: Treatment and heterogeneity effect from the endogenous switching regression

	Treatment	Control	Treatment effects
Yield (tonnes/hectare)			
Treatment	4.76	4.05	TT = 0.71***
Control	5.84	4.24	TU = 1.59***
Heterogeneity effect	BH_1 = -1.08	BH_2 = -0.19	TH = -0.88***
Net income (rupees)			
Treatment	37,813.66	26,879.88	TT= 10,933.78***
Control	53,439.69	30,622.74	TU= 22,816.95***
Heterogeneity effect	BH_1 = -15,626.03	BH_2 = -3,742.86	TH= -11,883.17***

Source: Authors' estimation based on IFPRI-GoK Survey, 2018–19; *** p<0.01, ** p<0.05, * p<0.1

5. Conclusion

Drought is most frequently observed climate extreme event in semi-arid region that causes loss in crop yield and net income of the farmers. As argued by various agricultural scientists, adoption of climate smart technology to reduce crop and income loss of the farmers is an essential step. Laser Land Levelling is one such climate smart technology that is potential to adapt with the climate variability due to efficient use of water, reduce cost of cultivation and minimize risk of crop yield and income loss to the farmers. However, limited evidences are available to argue the effectiveness of LLL technology in reducing crop loss due to drought event in semi-arid region. Therefore, this study fills this knowledge gap by providing empirical evidence on effectiveness of LLL under drought situation in the selected study region within semi-arid region of the state Karnataka in India. Results from this study clearly demonstrate that crop yield in laser land leveled plot is higher than the non-LLL plot even in the drought year. Moreover, LLL reduces yield gap across the farmers who has adopted LLL.

On the other hand, LLL reduces costs incurred by farmers and increase yield and net income. A laser land levelled plot has a life span of three years which reduces the cost of levelling the farmlands for three consecutive years. A cost–benefit ratio between the adopters and non-adopters of LLL are estimated as 2.59 and 2.45, respectively, indicating a higher level of benefit for the adopters as compared to the non-adopters. This clearly hints at a larger profit margin to LLL farmers for the next two years when they would be saving a higher portion on land levelling as compared to non-LLL farmers.

Finally, this study has identified several constraints limiting uptake of LLL, including inadequate training facilities, shortage of machine supply and lack of operating skill for the machine, inadequate irrigation sources, lack of improved seeds, and problem with weeding. Therefore, strengthening agricultural extension services to increase awareness about the LLL among the farmers along with accessibility of machines would be given priority by the government to upscale LLL technology in the region. Further, operating skill of LLL machine is a crucial factor to derive full benefit of the technology. Therefore, skill development training would be essential to increase accessibility of the machine by the farmers. Finally, further research and development are needed to enhance the crop productivity and income of the farmers using LLL. The public sector can collaborate with private institutions in increasing availability of LLL machinery and improved seeds. Emphasis should be placed on strengthening financing options for farmers, promoting green agriculture, disseminating technology, and decentralizing institutions for efficient implementation and execution of the programs.

6. References

Aggarwal, P. K., Singh, A. K., Samra, J. S., Singh, G., Gogoi, A. K., Rao, G. S., & Ramkrishna, Y. S. (2009). Introduction. In *Global Climate Change and Indian Agriculture.* New Delhi, India: Indian Council of Agricultural Research.

Akhter, A., & Awudu, A. (2010). The adoption of genetically modified cotton and poverty reduction in Pakistan. *Journal of Agriculture Economics, 61*(1), 175-192.

Ali, A., Hussain, I., Rahut, D. B., & Erenstein, O. (2018). Lase-land levelling adoption and its impact on water use, crop yields and household income: Empirical evidence from the rice-wheat system of Pakistan Punjab. *Food Policy, 77*, 19-32.

Aryal, J. P., Mehrotra, M. B., Jat, M. L., & Sidhu, H. S. (2015). Impacts of laser land levelling in rice-wheat systems of the north-western indo-gangetic plains of India. *Food Security, 7*, 725-738.

Battisti, D. S., & Naylor, R. L. (2009). Historical warnings of future food insecurity with unprecedented seasonal heat. *Science, 323*(5911), 240-244.

Bhattacharya, R., Ghosh, B. N., Mishra, P. K., Mandal, B., Rao, C. S., Sarkar, D., & Das, K. (2015). Soil Degradation in India:Challenges and Potential Solutions. *Sustainability, 7*(4), 3528-3570.

Bhende, M. J. (2013). Agriculture Profile of Karnataka State. Bangalore: Agriculture Development and Rural Transformation Centre, Institute for Social and Economic Change.

Brida, A. B., & Owiyo, T. (2013). Loss and damage from the double blow of flood and drought in Mozambique. *International Journal of Global Warming, 5*(4), 514-531.

Caliendo, M., & Kopeining, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys, 22*, 31-72.

Carter, D. W., & Milon, J. (2005). Price knowledge in household demand for utility services. *Land Economics, 81*(2), 265-283.

Directorate of Economics and Statistics. (2019). *District wise land use statistics*. Retrieved December 2019, from Ministry of Agriculture and Farmers Welfare, Government of India: http://eands.dacnet.nic.in/.

FAO. (2012). The state of Food and Agriculture. Rome: Food and Agriculture Organization of the United Nations.

Ghimire, R., Huang, W.-C., & Shreshta, R. B. (2015). Factors affecting adoption of improved rice varieities among rural farm households in central Nepal. *Rice Science, 22*(1), 35-43.

GoK. (2011). Karnataka Agriculture Budget, 2011-12. Bangalore: Government of Karnataka.

Heckman, J., Tobias, J. L., & Vytlacil, E. (2001). Four parameters of interest in the evaluation of social programs. *Southern Economic Journal, 68*(2), 210-223.

Iacus, S. M., King, G., & Porro, G. (2011). Causal inference without balance checking : Coarsened Exact Matching.

Kumar, S., Bhatt, B. P., Dey, A., Shivani, & Kumar, U. (2018). Integrated farming system in Inida: Current status, scope & future prospects in changing agricultural scenario. *Indian journal of agricultural sciences, 88*(11), 1661-1675.

Kumari, R., Sharma , B., & Kumari, P. (2017). Laser land levelling for enhancing agricultural input use efficiency. *Indian Farmer, 4*(8), 659-662.

Lipper, L., & Zilberman, D. (2018). Climate Smart Agriculture. In L. Lipper, N. McCarthy, D. Zilberman, S. Asfaw, & G. Branca, *A short history of the evolution of the climate smart agriculture approach and its link to climate change and sustainable agriculture debates* (pp. 13-30). Springer.

Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., & Bwalya, M. (2014). Climate Smart Agriculture for food security. *Nature & Climate Chnage, 4*, 1068-1072.

Lobell, D., Sibley, A., & Ortriz-Monasterio, J. I. (2012). Extreme heat effects on wheat senescence in India. *Nature Climate Change, 2*, 186-189.

Lokshin, M., & Sajaia, Z. (2004). Maximum likelihood estimation of endogenous switching regression. *Stata Journal, 4*(3), 282-289.

Ma, W., & Abdulai, A. (2016). Does cooperative membership improve household welfare? Evidence from apple farmers in China. *Food Policy, 58*, 94-102.

Maddala, G. S., & Nelson, F. D. (1975). Specification errors in limited dependent variable models. *NBER Working Paper Series - Working Paper No. 96*, N.A.

Mall, R. K., Gupta, A., Singh, R. S., & Rathore, L. S. (2006). Water resource and climate change: an Indian perspective. *Current Science, 90*(12), 1610-1626.

Mariano, M. J., Villano, R. A., & Fleming, E. (2012). Factors influencing farmer's adoption of mordern rice technologies and good management practices in Philippines. *Agricultural Systems, 110*, 41-53.

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

Prasanna, V. (2014). Impact of monsoon rainfall on the total foodgrain yield over India. *Journal of Earth System Science, 123*(5), 1129-1145.

Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician, 29*(1), 33-38.

Shahani, W. A., Kaiwen, F., & Memon, A. (2016). Impact of laser land levelling on water use efficiency and crop productivity in cotton-wheat cropping system in Sindh. *International Journal of Research - Granthalaya, 4*(2), 220-231.

Singh, G., Mishra, D., Singh, K., & Parmar, R. (2013). Effect of rainwater harvesting on plant growth, soil water dynamics and herbaceous biomass during rehabilitation of degraded hills in Rajasthan, India. *Indian Journal of Ecological Management, 310*, 612-622.

Wani, S. P., Anantha, K. H., Dharamrajan, B. K., & Krishnappa, K. (2015). Bhoo-Samruddhi: A compendium of success stories . *Research Report-IDC 2*, 48. Patenchuru, Telangana, India: International Crops Research Institute for the Semi-Arid Tropics (ICRISAT).

Wani, S. P., Sarvesh, K. V., Krishnappa, K., Dharamrajan, B. K., & Deepaja, S. M. (2012). Bhoochetana: Mission to boost productivity of rainfed agriculture through science-led interventions in Karnataka. Patancheru: International Crops Research Institute for the Semi-Arid Tropics (ICRISAT).

Wossen, T., Abdoulaye, T., Alene, A., & Haile, M. G. (2017). Impacts of extension access and cooperative membership on technology adoption and household welfare. *Journal of Rural Studies, 54*, 223-233.

Appendix

Figure A1: Common support

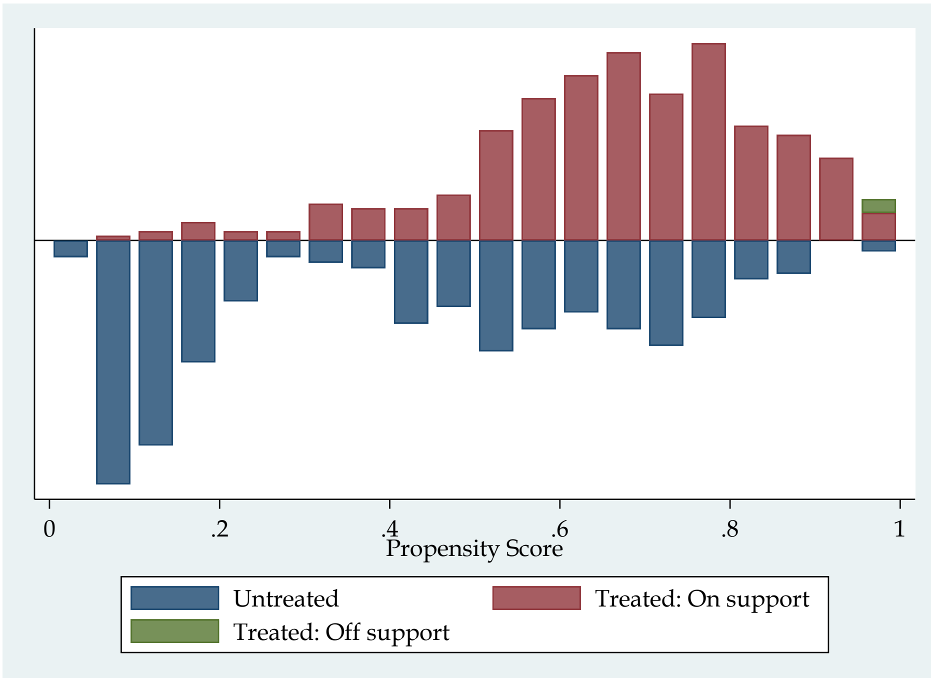


Table A1: T-test for quality of means of each variable before and after match

Variable	Matched	Treated	Control	% bias	% reduction in bias	T	p>t
Agriculture land owned (hectare)	U	10.54	5.39	46.8	88.9	5.51	0.01
	M	9.68	9.11	5.2		0.70	0.48
Household size (number)	U	6.04	6.41	-10.6	70.8	-1.29	0.19
	M	5.98	5.87	3.1		0.42	0.67
Visit made to and from RSK	U	0.26	0.16	24.7	46.8	2.97	0.O1
	M	0.25	0.31	-13.1		-1.49	0.14
Adult male member in farming	U	1.76	1.92	-14.8	80.7	-1.81	0.07
	M	1.75	1.73	2.9		0.38	0.70
Education (Base: Illiterate)							
Primary	U	0.38	0.26	27.7	64.4	3.34	0.01
	M	0.38	0.34	9.8		1.20	0.23
Secondary	U	0.22	0.22	3.1	83.7	0.37	0.71
	M	0.23	0.23	-0.5		-0.06	0.95
Higher secondary and above	U	0.16	0.16	1.9	-78.9	0.23	0.82
	M	0.16	0.17	-3.4		-0.42	0.67
Assets							
Crop loan (Yes = 1, No = 0)	U	0.66	0.69	-6.2	-45	-0.76	0.45
	M	0.66	0.70	-9.0		-1.16	0.25
Own livestock (Yes = 1, No = 0)	U	0.66	0.55	23.0	34.4	2.80	0.01
	M	0.66	0.58	15.1		1.92	0.05
Own pump set (Yes = 1, No = 0)	U	0.57	0.37	40.3	85.8	4.88	0.01
	M	0.57	0.54	5.7		0.71	0.47
Own tractor (Yes = 1, No = 0)	U	0.55	0.41	28.0	76.8	3.40	0.01
	M	0.54	0.57	-6.5		-0.82	0.41
Constraints in adopting LLL							
Machine supply	U	0.73	0.44	61.7	82.2	7.52	0.01
	M	0.73	0.78	-11		-1.52	0.13
Training	U	0.83	0.47	81.1	92.5	9.98	0.01
	M	0.84	0.86	-6.1		-0.95	0.34
Rent of machine	U	0.91	0.55	89.6	91.2	11.15	0.01
	M	0.91	0.95	-7.9		-1.59	0.11
Irrigation facility	U	0.48	0.29	38.1	67.7	4.60	0.01
	M	0.48	0.54	-12.3		-1.50	0.14

Source: Authors' estimation based on IFPRI-GoK Survey, 2018–19; *** p<0.01, ** p<0.05, * p<0.1
Note: U stands for unmatched and M stands for matched.

Table A2: Estimates from coarsened exact matching model

Variables	**Net income (rupees)**	**Yield (tonnes/hectare)**
LLL user (Yes = 1, No = 0)	4,834.571**	0.685***
	(2,149.541)	(0.119)
Agriculture land owned (hectare)	-168.022	-0.004
	(131.442)	(0.006)
Household size (number)	-359.696	0.024
	(514.448)	(0.033)
Visit made to and from RSK	-12,379.588***	-0.231
	(3,380.612)	(0.204)
Adult male members in farming	1,574.156	0.120
	(2,146.442)	(0.104)
Education (Base: Illiterate)		
Primary	5,076.552	0.335**
	(3,559.385)	(0.166)
Secondary	2,191.317	0.347
	(5,077.789)	(0.319)
Higher secondary and above	-7,332.530	-0.166
	(6,941.623)	(0.300)
Assets		
Crop loan (Yes = 1, No = 0)	3,217.311	0.270*
	(3,351.579)	(0.141)
Own livestock (Yes = 1, No = 0)	-485.833	-0.073
	(2,383.756)	(0.120)
Own pump set (Yes = 1, No = 0)	3,779.156	0.109
	(3,295.495)	(0.170)
Own tractor (Yes = 1, No = 0)	-341.022	0.123
	(3,405.071)	(0.185)
Constraints to adopting LLL		
Machine supply	6,454.129*	0.168
	(3,628.132)	(0.217)
Training	420.241	-0.321
	(4,862.904)	(0.416)
Irrigation facility	-5,330.024	-0.085
	(3,289.905)	(0.178)
Constant	27,445.165***	3.685***
	(5,137.276)	(0.459)
Observations	94	94
R-squared	0.317	0.420

Source: Authors' estimation based on IFPRI-GoK Survey, 2018–19; *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Drivers of yield (tonnes/hectare), endogenous switching regression model

Variables	Treatment = 1 (farmers in treatment group)	Control = 0 (farmers in control group)	Treatment = 1, Other = 0	Ordinary least squares
LLL user (Yes = 1, No = 0)	-	-	-	0.097** (0.289)
Log agriculture land owned (hectare)	-0.005 (0.011)	0.004 (0.015)	0.332*** (0.071)	0.015 (0.009)
Log household size (number)	-0.004 (0.022)	-0.019 (0.029)	-0.187 (0.151)	-0.015 (0.024)
Adult male member in farming	0.012 (0.011)	0.016 (0.012)	-0.108 (0.071)	0.008 (0.004)
Visit made to and from RSK	-0.003 (0.020)	-0.006 (0.029)	0.205 (0.141)	-0.001 (0.012)
Education (Base: Illiterate)				
Primary	-0.002 (0.024)	0.006 (0.026)	0.263 (0.153)	0.016 (0.017)
Secondary	0.016 (0.026)	0.059** (0.029)	0.017** (0.169)	0.041 (0.024)
Higher secondary and above	0.024 (0.029)	-0.015 (0.028)	-0.021 (0.188)	0.007 (0.019)
Assets				
Crop loan (Yes = 1, No = 0)	0.033* (0.019)	-0.005 (0.023)	-0.191 (0.128)	0.005 (0.018)
Own livestock (Yes = 1, No = 0)	-0.012 (0.018)	0.007 (0.021)	0.234* (0.123)	0.005 (0.013)
Own pump set (Yes = 1, No = 0)	-0.035* (0.019)	0.008 (0.023)	0.249** (0.122)	0.003 (0.025)
Own tractor (Yes = 1, No = 0)	0.007 (0.021)	0.039 (0.024)	-0.029 (0.139)	0.022 (0.011)
Constraints to adopting LLL				
Machine supply	0.029 (0.019)	-0.005 (0.033)	0.057 (0.141)	0.027 (0.021)
Training	-0.034 (0.025)	-0.029 (0.041)	0.478*** (0.168)	-0.008 (0.035)
Rent of machine	-0.062* (0.034)	0.015 (0.043)	0.856*** (0.192)	0.008 (0.036)
Irrigation facility	-0.026 (0.018)	-0.010 (0.027)	-0.016 (0.130)	-0.021 (0.019)
Constant	6.305*** (0.065)	6.001*** (0.045)	-0.434 (0.349)	6.005*** (0.045)
Observations	594	594	594	594

Source: Authors' estimation based on IFPRI-GoK Survey, 2018–19; *** p<0.01, ** p<0.05, * p<0.1

Table A4: Drivers of net income (rupees), endogenous switching regression model

Variables	Treatment = 1 (farmers in treatment group)	Control= 0 (farmers in control group)	Treatment =1, Other = 0	Ordinary least squares
LLL user (Yes = 1, No = 0)	-	-	-	0.191** (0.052)
Log agriculture land owned (hectare)	-0.169 (0.017)	0.038 (0.036)	0.307*** (0.073)	0.027*** (0.004)
Log household size (number)	0.002 (0.035)	-0.133* (0.074)	-0.241 (0.151)	-0.073 (0.075)
Adult male member in farming	0.017 (0.017)	0.045 (0.032)	-0.087 (0.073)	0.022 (0.016)
Visit made to and from RSK	-0.055* (0.031)	-0.183** (0.074)	0.205 (0.141)	-0.080* (0.033)
Education (Base: Illiterate)				
Primary	0.038 (0.036)	-0.018 (0.069)	0.361** (0.156)	0.035 (0.053)
Secondary	0.058 (0.041)	-0.033 (0.075)	0.064 (0.171)	0.025 (0.085)
Higher secondary and above	0.084 (0.045)	-0.058 (0.078)	0.010 (0.188)	0.023 (0.041)
Assets				
Crop loan (Yes = 1, No = 0)	0.074** (0.029)	0.055 (0.058)	-0.214 (0.131)	0.033 (0.049)
Own livestock (Yes = 1, No = 0)	-0.063** (0.029)	-0.106* (0.055)	0.267** (0.123)	-0.074 (0.034)
Own pump set (Yes = 1, No = 0)	-0.037 (0.029)	-0.132** (0.057)	0.196 (0.123)	-0.047 (0.019)
Own tractor (Yes = 1, No = 0)	0.030 (0.033)	0.086 (0.061)	0.015 (0.134)	0.049 (0.027)
Constraints to adopting LLL				
Machine supply	-0.012 (0.031)	-0.041 (0.086)	0.109 (0.142)	-0.002 (0.008)
Training	-0.064 (0.040)	-0.055 (0.103)	0.443 (0.170)	-0.005 (0.007)
Rent of machine	-0.092* (0.052)	0.184 (0.109)	0.870*** (0.196)	0.101** (0.013)
Irrigation facility	-0.040 (0.028)	-0.096 (0.071)	-0.001 (0.130)	-0.054 (0.029)
Constant	10.782*** (0.093)	10.408*** (0.116)	-0.306 (0.351)	10.345*** (0.119)
Observations	594	594	594	594

Source: Authors' estimation based on IFPRI-GoK Survey, 2018–19; *** p<0.01, ** p<0.05, * p<0.1.

ALL IFPRI DISCUSSION PAPERS

All discussion papers are available **here**

They can be downloaded free of charge

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
www.ifpri.org

IFPRI HEADQUARTERS
1201 Eye Street, NW
Washington, DC 20005 USA
Tel.: +1-202-862-5600
Fax: +1-202-862-5606
Email: ifpri@cgiar.org

SOUTH ASIA REGIONAL OFFICE
Block C, NASC Complex, DPS Marg
Opposite Todapur, Pusa
New Delhi 110012, India
Phone: +91-11-66166565
Fax: +91-11-66781699
Email: ifpri-newdelhi@cgiar.org
http://southasia.ifpri.info/