Adoption of climate-smart agriculture technology in drought-prone area of India – implications on farmers' livelihoods

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Abstract

Purpose – Laser land leveling (LLL) is a climate-smart technology that improves water use efficiency and reduces risk in crop cultivation due to weather variability. Hence, this technology is useful for cultivating water-intensive crops in a sustainable way. Given this background, the state government of Karnataka initiated to promote LLL in drought-prone districts and selected Raichur district for implementation. Moreover, farmers in this district had observed drought situation during monsoon paddy growing season in 2018. Therefore, this study attempts to investigate the importance of LLL technology for paddy cultivation under drought conditions.

Design/methodology/approach – A primary survey with 604 farmer households had been conducted in Raichur in 2018. Among them, 50% are adopters of LLL who have been selected purposively and rest 50% are non-adopters who have grown paddy in the adjacent or nearest plot of the laser-leveled plot. The adoption and causal impact of LLL has been estimated using propensity score matching, coarsened exact matching and endogenous switching regression methods.

Findings – The result reveals a positive and significant impact of LLL on paddy yield and net returns to the farmers. The results indicate an increment of 12 and 16% in rice yield and net income, respectively, for LLL adopters in comparison to the non-adopters of LLL.

Research limitations/implications – The major limitation of the study is that it does not adopt the method of experimental study due to certain limitations; hence, the authors employed a quasi-experimental method to look at the possible impact of adoption of LL.

Originality/value – There have been various agronomic studies focusing on the *ex-ante* assessment of the LLL. This study is an *ex-post* assessment of the technology on the crop yield and farmers' income in a dry semi-arid region of India, which, according to the authors, is the first in this approach.

Keywords Climate-smart agriculture, Laser land leveling, Paddy yield, Net farm income, Karnataka

Paper type Research paper

1. Introduction

Semi-arid regions around the world are hotspots of poverty, malnutrition and degradation of environmental resources. It covers 35% of agricultural land in India spread across the states of Karnataka, Telangana, Maharashtra, Tamil Nadu, Madhya Pradesh, Gujarat, Rajasthan,

JEL Classification — C5, Q1, Q16, Q24, Q25, Q56

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Punjab and Haryana (Ramarao *et al.*, 2019). 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 and Naylor, 2009). There are various studies that suggest agricultural production is significantly affected due to abrupt increase in temperature (Lobell *et al.*, 2012; Aggarwal, 2008), changes in monsoon patterns (Prasanna, 2014; Mall *et al.*, 2006) and variations in the frequency and intensity of extreme climatic events like floods and droughts (Brida and Owiyo, 2013; Singh *et al.*, 2013). A study by the Acevedo *et al.* (2018) reveals that for emerging market economies, a 1°C increase in temperature would reduce agricultural growth by 1.7%, while a 100 mm reduction in rain would reduce growth by 0.35%. Current coping strategies are not efficient to cope up with the future climate changes due to the variability in biotic and abiotic conditions, which is expected to rise in future (Berger and Troost, 2014).

According to Wani *et al.* (2012), the potential of dryland farms can be unlocked by employing improved technologies in a sustainable manner. Research has stated that adoption of agricultural technology and innovations is essential for ensuring farming system transformations, improvement in agricultural productivity and food security, accelerating rural economic growth and eradicating rural poverty and vulnerabilities (Kumar *et al.*, 2020, 2021; Mottaleb, 2018). Ghimire *et al.* (2015) stressed that the adoption of new techniques should occur through an integrated approach 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 that calls for adoption of 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 (Lipper and Zilberman, 2018; Sousa *et al.*, 2018; Arslan *et al.*, 2015; Lipper *et al.*, 2014; FAO, 2012).

Laser land leveling (LLL) is one of the climate-smart technologies that helps in improving crop establishment and crop maturity, raises cultivable land area by 3–5 %, increases water application efficiency potential up to 50%, increases cropping intensity up to 40%, increases crop yield (wheat – 15%, sugarcane – 42%, rice – 61% and cotton – 66%), controls emergence of salt patches in the soil, saves irrigation water by approximately 35–40%, minimizes weed problems and improves weed control efficiency (Kanannavar *et al.*, 2020; Aggarwal *et al.*, 2010; Jat *et al.*, 2006; Rajput *et al.*, 2004).

Premised on this wisdom, the state government of Karnataka in India had implemented "Bhoosamrudhi programme" in the year 2013 to promote improved and innovative technologies for agricultural activities in the state Karnataka. Initially four districts – Chikkamagaluru, Raichur, Vijayapura and Tumkur, were selected for the pilot program, and LLL was one of the priority technologies first demonstrated in paddy-based cropping system in the Raichur district and then gradually spread across other parts of the state. Providing subsidy to the customs hiring center for purchasing LLL machines and subsidy to the farmers on application of this machine were major interventions made by the government of Karnataka in collaboration with state agriculture universities and consultative group of international agricultural research (CGIAR) centers (Wani *et al.*, 2015). Although, the demonstration of LLL technology in agriculture fields of Karnataka was started with procurement of laser-guided land leveler from Spectra Precision Pvt., Ltd, New Delhi, in the year 2008–2009 by University of Agriculture Science, Raichur, but the Bhoosamrudhi program was the first ever program backed by the state government in Karnataka to demonstrate improved technologies, including LLL (Kanannavar *et al.*, 2020). However, the Bhoosamrudhi program in the above-mentioned four districts was ended in the year 2016, but many questions unfolded. First, are the farmers in these districts still adopting the LLL technology beyond the demonstrations plot? Secondly, the state Karnataka is a drought-prone state, so whether this LLL technologies are helping farmers to cope with the variability in weather like long dry spell or seasonal drought?

There are only few studies available on Karnataka that reveal the impact of LLL technology on crop yield, input use and farmers' income (Kanannavar *et al.*, 2020; Chilur *et al.*, 2016; Wani *et al.*, 2015). Moreover, the available studies have followed either an engineering approach or an agronomist approach to assess impact of LLL based on the demonstrated plot. Apart from these studies, there are studies that have analyzed the effectiveness of the LLL technology through the lenses of climate change adaptation and resource use efficiency in agriculture (Khatri-Chettri *et al.*, 2016; Aryal *et al.*, 2015; Sapkota *et al.*, 2015; Taneja *et al.*, 2014). Although these studies have selected a large number of sample farmers to assess farmers' perception and experience in adoption of the LLL technology, the study area was limited within the Indo-Gangetic Plains in India. Again, the effectiveness of LLL varies across the agro-climatic conditions prevailing in different regions (Jat *et al.*, 2006). Therefore, the purpose of this study is to conduct a systematic investigation on the trend in adoption of LLL in the study area, factors influencing adoption of LLL and assess its effectiveness in farmers' well-being. Moreover, this study was conducted in the year 2018–2019 when farmers in the study area were affected due to drought. Hence, understanding the effectiveness of LLL to cope with the drought situation for crop cultivation in the study area is also an important aspect of this study. Unlike existing studies that use traditional "before and after approach" for impact assessment, this study has followed advanced econometric methods (quasi-experiment) like propensity score matching (PSM), coarsened exact matching (CEM) and endogenous switching regression (ESR) to investigate impact of LLL on crop yield and net return of the farmers. Thus, this study will add to knowledge on impact of LLL on farmers' well-being by providing evidence beyond the experimental plots in the study area. This study also generates evidence on effectiveness of LLL in the semi-arid region in India, which can motivate policy makers of other states in India that belongs to the semi-arid region to initiate pilot projects on upscaling of LLL in those states. Global research and donor community to scale up research and development in the semi-arid region to develop an effective business model for upscaling of climate-smart technologies like LLL to adapt with the progressive climate change impact on Indian agriculture.

Following this introductory section, the rest of this paper is organized as follows. Section 2 illustrates the study area and sampling approach adopted for the study. Section 3 emphasizes on the conceptual and econometric framework implemented in the study. Section 4 provides detailed results from the study, followed by discussions in Section 5. 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 the recent Periodic Labor Force Survey, 2018–2019, agriculture employs 41% (8.4 million workers) of the Karnataka's workforce, comprising 62.1% as cultivators and 37.6% as agricultural workers. This state has largest rainfed area in the country after Rajasthan, and small and marginal farmers with landholdings less than 2 ha 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 (Bhattacharyya *et al.*, 2015). In 2013, the government of Karnataka initiated the *Bhoosamrudhi* program to promote innovative technologies in the agriculture sector, with the objective of increasing the 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. LLL was one among these improved technologies tested among the paddy-growing farmers in the Raichur district of Karnataka. The location of the study site is presented in Figure 1.

The Raichur district is in the northeastern dry zone of the Karnataka state. Raichur has about 4,75,000 ha of net sown area, and 5,66,000 ha of gross cropped area with a cropping intensity of 111.9%. Paddy occupies almost 25% of the gross cropped area. About 70% 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). The district has been witnessing erratic and declining rainfall since 2014, and the Karnataka State Natural Disaster Monitoring Center (KSNDMC) declared that Raichur was affected by severe drought in 2018. Moreover, the annual average rainfall in this district was an average 60% lower than the normal rainfall between the year 2011 and 2018 (Figure 2). Therefore, agriculture in the study area is highly vulnerable due to weather variability, and if no interventions take place, progressive changes in temperature and precipitation will threaten the agricultural production and farmers' livelihood in the long run.

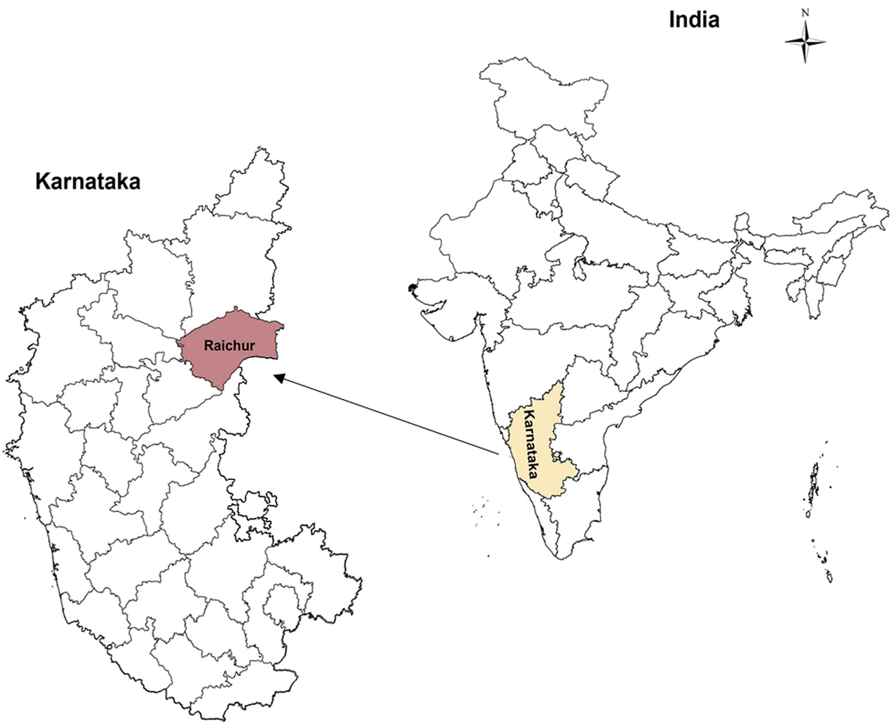
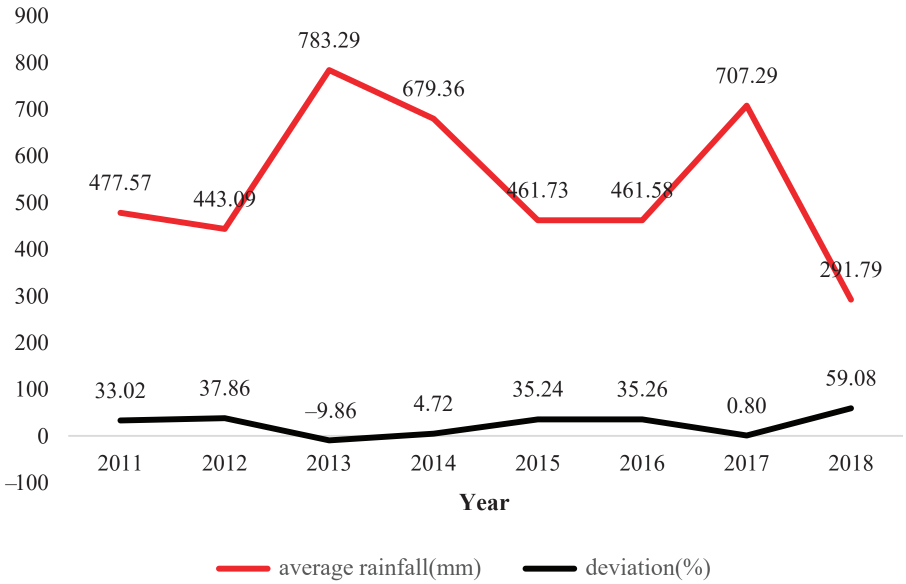


Figure 1.
Study site in Karnataka (Raichur)



Source(s): Based on data obtained from Karnataka State Natural Disaster Monitoring Centre

Figure 2.
Rainfall pattern in the Raichur district

2.2 Data sampling

A primary survey of farmer households was conducted in the Raichur district of Karnataka, 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. Adopter farmers included those who owned an LLL machine and those who rented an LLL machine to level their land. The LLL technology adopters were selected through the snowball sampling method. In this process, we have first identified the owners of the LLL machine in the districts in consultation with experts from the State Agriculture University, Raichur, and scientists from the International Maize and Wheat Improvement Center (CIMMYT) and ICRISAT. After identifying the owners of the LLL machines, we had traced the users of LLL technology in the selected districts, and thus, we had selected adopter farmers for this study. Non-adopters were selected based on being neighboring farmers with land near the laser-leveled plot and who cultivated paddy in the same season. Data were 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.

2.3 Year-wise adoption of laser land leveling

Figure 3 shows the year-wise adoption of LLL among the surveyed farmers. The Bhoosamrudhi project was initiated in the district as a pilot program between 2013 and 2016, but its efficacy is still prevalent. We see a spike in the number of adopters between 2016 and 2018. We observe that maximum adoption of LLL technology was reported in the year 2018 (survey year). Therefore, this indicates that LLL technology has proved to be a boon to the farmers in a semi-arid drought-prone region because of its potential yield and income benefits.

3. Empirical framework

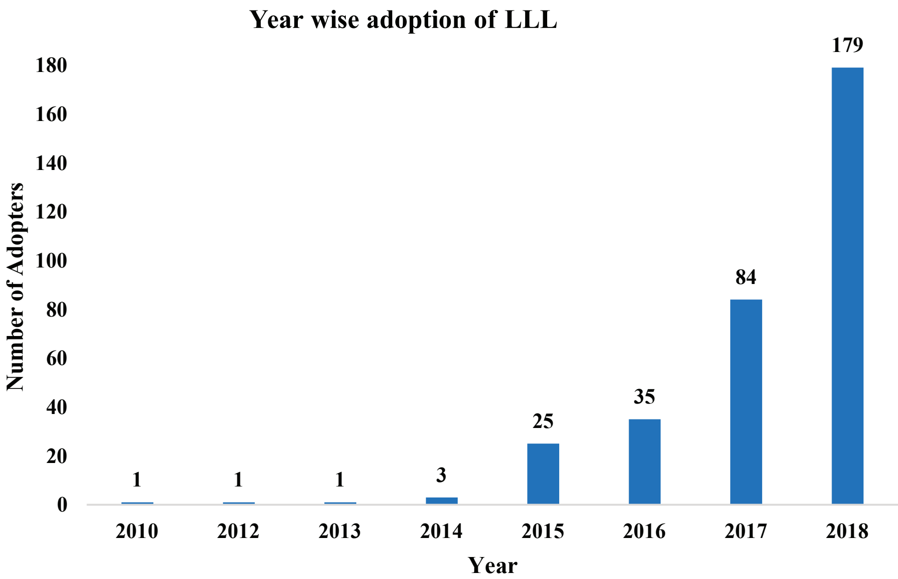
In this study, we have estimated the impact of the LLL technology on crop productivity [1] and net income [2] of the farmers in the study area. Unlike existing studies that use traditional "before and after approach" for impact assessment, this study has followed advanced econometric methods (quasi-experiment) like PSM, CEM and ESR to investigate impact of LLL on crop yield and net return of the farmers. Details about these methods are described below.

3.1 Propensity score matching

Under the PSM method, households are ranked according to their own behavior toward technology adoption to ensure that technology effects are evaluated among groups of farmers possessing similar characteristics (Mendola, 2007). The main purpose of using this method is to find a group of farmers who did not adopt the technology (control) like the farmers who adopted the technology (treatment) in all relevant observable characteristics such as land size, household size, education, assets, constraints, and adult male member engaged in farming. PSM also helps to generate the average treatment effect for the treatment group (ATT).

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

Administrative block	Adopters Number	Adopters %	Non-adopters Number	Non-adopters %	Total Number	Total %
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 (Raichur district)	329	54.5	275	45.5	604	100



Source(s): Authors' creation from IFPRI – GoK survey, 2018-19

Figure 3.
Year-wise adoption of laser land levelers

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 and 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 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 and 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 and 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 "D_i" be an indicator of whether a farmer is an 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 (D_i). 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

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, $s \in S$, 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 ith unit belongs to the treatment group and takes value 0 if the ith unit belongs to the control group. The observed outcome variable $Y_i = T_i\, Y_i\,(1) + (1\text{-}T_i)\, Y_i\,(0)$ 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. 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 $\mathrm{TE}_i = Y_i\,(1) - Y_i\,(0) \mid X_i$ 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:

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

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 ESR to check for robustness and account for selection bias present in the former model. In the ESR model, we have considered only those observations that were under common support region in the PSM method and dropped "off-support" sample from our analysis for robust estimation in the ESR model. ESR addresses the endogeneity problem by estimating selection and outcome equations simultaneously using the full information maximum likelihood method (Kumar *et al.*, 2018; Wossen *et al.*, 2017; Ma and Abdulai, 2016; Lokshin and Sajaia, 2004). The ESR model has two main parts, a probit model to identify the determinants of adoption of technology and two functions of outcome variable, one for adopter and second for non-adopter. The selection equation for the beneficiary household can be stated as:

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

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:

$$\textit{Regime } 1: \; Y_{1i} = X_{1i} + \mu_{1i} \text{ if } Z_i = 1 \tag{6}$$

$$\textit{Regime } 2: \; Y_{2i} = X_{2i} + \mu_{2i} \text{ if } Z_i = 0 \tag{7}$$

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 values (ρ_1 and ρ_2, respectively) are statistically significant, then adopter households and income are positively correlated. Using this approach, we found signs of endogenous switching and rejected the null hypothesis that sample selection bias was absent. Maddala and 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 (IV) that directly affects the endogenous variable without having a direct impact on the outcome variable.

In addition to the above ESR model, we also calculated the household's conditional expectation for income in four different cases:

$$E(Y_{1i}|Z_i = 1) = \left[\sum\nolimits_{Zi=1}(X_{1i}\beta_1 + \sigma_{1n}\gamma_{1i})\right] \Big/ N_1 \quad (8)$$

$$E(Y_{2i}|Z_i = 0) = \left[\sum\nolimits_{Zi=0}(X_{2i}\beta_2 + \sigma_{2n}\gamma_{2i})\right] \Big/ N_0 \quad (9)$$

$$E(Y_{1i}|Z_i = 1) = \left[\sum\nolimits_{Zi=1}(X_{1i}\beta_2 + \sigma_{2n}\gamma_{1i})\right] \Big/ N_1 \quad (10)$$

$$E(Y_{1i}|Z_i = 0) = \left[\sum\nolimits_{Zi=0}(X_{2i}\beta_1 + \sigma_{1n}\gamma_{2i})\right] \Big/ N_0 \quad (11)$$

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 Cases (*a*) and (*c*) to calculate the impact of use of LLL on the outcome variable. Likewise, the difference between Cases (*b*) and (*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 Cases (*a*) and (*d*), and for the group of households that did not adopt LLL as the difference between Cases (*c*) and (*b*) (Cater and 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.

3.3.1 Instrument variable selection. IVs are used for controlling the confounding and measurement error in observational studies. Just like propensity scores, IVs can be used to adjust for both observed and unobserved confounding effects. There are two main principles for selecting an IV, first, it causes variation in the treatment variable and secondly, it does not directly affect the dependent variable but only indirectly through the explanatory variable. There are two main issues that may arise in the application of IVs, first, we may choose a bad

	Decision stage		
TH	Treatment	Control	Treatment effects
Treatment	$E(Y_{1i}\|Z_i = 1)$	$E(Y_{2i}\|Z_i = 1)$	TT
Control	$E(Y_{1i}\|Z_i = 0)$	$E(Y_{2i}\|Z_i = 0)$	TU
Heterogeneity effects	BH^1	BH^2	TH

Source(s): Cater and Milon (2005)

Table 2. Decision stage treatment and heterogeneity effects

instrument which might result from the IV being correlated with the omitted variables or second, bias may arise if the instruments are weakly correlated with the explanatory variables (Angrist and Krueger, 2001). In this study, farmers having access to canal irrigation have been taken as the IV because canal irrigation is the main source of irrigation for all the farmers in the district. Canal irrigation accessibility has an indirect impact for LLL users because it is assumed to be a water-saving technique, and we can see the negative coefficient of Rho values in Table A3. This variable affects our outcome variables, yield and net farm income, indirectly through the explanatory variables. Further, we have done the validation test of selection instrument. The details are provided in Table A5 in Appendix. A variable is a valid selection instrument if it affects the LLL users but does not have a significant association with the outcome variables of the non-LLL users.

4. Results

4.1 Descriptive statistics

Table 3 provides the summary statistics of the sample farmers for the key variables used in the empirical analysis. Adopters had significantly larger landholdings than non-adopters,

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 (INR)	58,117.23	51,661.7	6,455.53***	55,178.04
Total cost (INR)	22,466.83	21,060.35	1,406.48	21,826.46
Net income (INR)	38,612.36	32,812.12	5,800.24***	35,971.52
Yield (tons/ha)	4.81	4.29	0.51***	4.57

Source(s): Authors' calculation from IFPRI-GoK survey, 2018–2019; ***p < 0.01, **p < 0.05, *p < 0.1

Table 3.
Descriptive statistics of important variables

10.53 ha compared to 5.44 ha 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 tons/ha compared with 4.29 tons/ha). Adopters also reported significantly higher net income than non-adopters (INR38,612.4/ha, compared with INR32,812.12/ha).

Although the adopters of LLL technology have paddy yield 10% higher than that of non-adopters, the non-adopters still achieved an average yield of around 3 tons/ha even in the drought year. This gives rise to two research questions, first, does it make sense to invest an additional INR1,400 per ha (Table 3) to adopt LLL to increase average yield by only 0.5 tons/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 a detailed analysis of the farmers' household data and their 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 the 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 observed by the farmers in the study area is drought. Almost 90% of the 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 the past 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

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 past 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***

Note(s): % values are shown in the parenthesis. *** $p < 0.01$
Source(s): Authors' calculation from IFPRI-GoK survey, 2018–2019

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

it is useful to reduce cost of cultivation, and 95% identified its usefulness in reducing crop loss due to climate change (Figures 4 and 5).

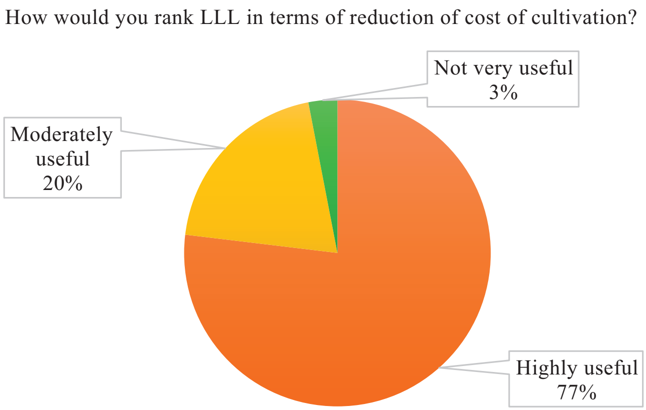
Therefore, based on the above assessment from the farmers, we can argue that Raichur is highly vulnerable to drought, and sample farmers (both adopters and non-adopters) believe that LLL is an effective technology to adapt during frequent climate extreme events. To validate farmers' perception, we use a statistical tool to understand the deviation between the yield reported by the sample farmers from the average district yield of past three years (2015, 2016 and 2017). Kernel density function is used to portray the difference and is presented in Figure 6. We can see that a graph for non-adopters is inclined more leftward from the mean line than the graph of adopters of LLL. This clearly suggests that LLL adopters have a 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.

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 Impact results

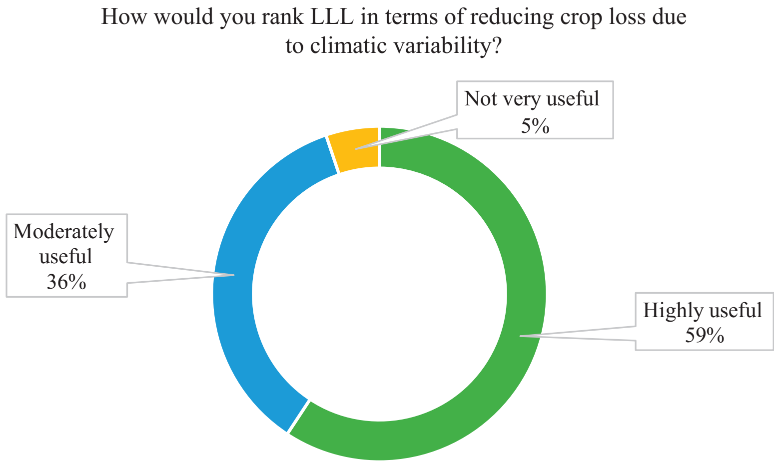
PSM and CEM results are displayed in Table 5 to witness the impact of adoption of LLL on crop yield and net farm income of the adopters over non-adopters. Estimates from PSM show that the net income of the farmers who adopt LLL increases by INR3,725 as compared to the non-adopters of LLL. Further, CEM results show a rise of INR4,834 in net income of LLL adopters in comparison to non-LLL adopters. Similarly, for crop yield, PSM and CEM results exhibit an increase of 0.33 and 0.68 tons/ha, respectively, for LLL adopters in comparison to non-LLL adopters. These results align with the results obtained by Kumar *et al.* (2020, 2021) for India. The detailed results for PSM and CEM are attached in the Appendix (Tables A1 and A2).

The ESR method is undertaken to account for selection bias and to check for robustness. Table 6 presents the treatment and heterogeneity effect results obtained from the ESR model.



Source(s): Authors' creation from IFPRI – GoK survey, 2018-19

Figure 4.
Ranking LLL in terms of reduction in cost of cultivation by adopters



Source(s): Authors' creation from IFPRI – GoK survey, 2018-19

Figure 5.
Ranking LLL in terms of reducing crop loss by adopters

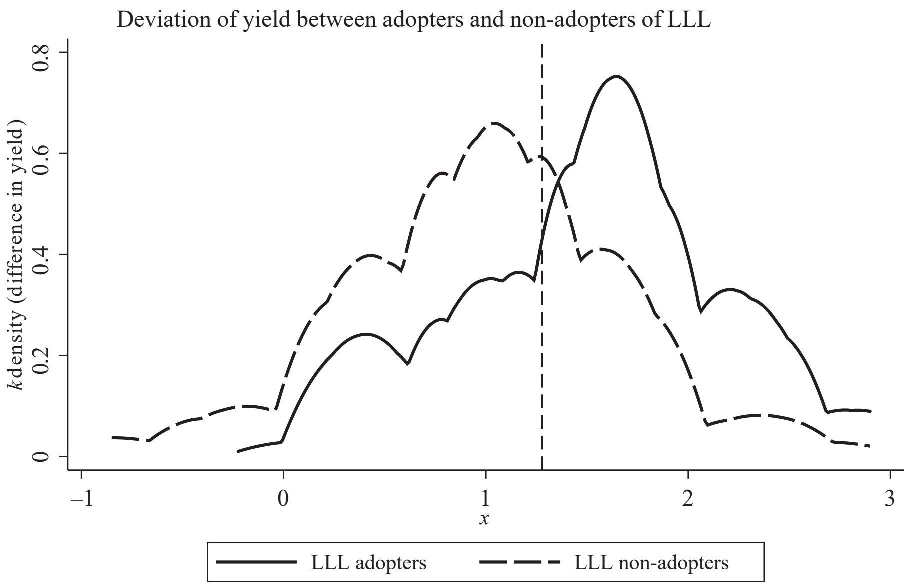


Figure 6.
Comparison of deviation in yield between adopters and non-adopters of LLL

Table 5.
Estimates from PSM and CEM for yield (tons/ha) and net income (INR)

Outcome variable	PSM	CEM
Net income (INR)	3,725.35*** (1,519.91)	4,834.57*** (2,149.54)
Yield (tons/h)	0.33** (0.09)	0.685*** (0.12)

Source(s): Authors' estimation based on IFPRI-GoK Survey, 2018–2019; robust standard errors are given in parentheses; ***p < 0.01, **p < 0.05

We can observe that the yield of LLL-adopted farmers computes to be 4.76 tons/ha, while for the non-LLL adopted farmers, the yield turns out to be only 4.07 tons/ha. Therefore, treatment effect on treated (TT) is equal to 0.69 tons/ha, 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 tons/ha but would have had an average yield of 5.85 tons/ha if they would have adopted laser land leveler. The difference of 1.60 tons/ha in the yield between the two situations for the non-adopted farmers define the treatment effect on untreated (TU). Heterogeneity effect (TH) comes out to be 0.91 tons/ha, implying that non-LLL farmers will gain if they adopt the LLL technology.

Similarly, LLL adopted farmers have an average net income of INR37,753 while the average net income would have reduced to INR26,375 if they were non-adopters of the LLL technology. Hence, TT calculates to be INR11,377. This signifies 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 INR30,685 but would eventually rise to INR53,450 if they adopt LLL technology. Here, TU is equal to INR22,764, and the heterogeneity effect computes to be INR11,386, 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 for both outcome variables are presented in Tables A3 and A4 in the Appendix.

5. Discussion

LLL is a climate-smart agricultural technology that helps in cost minimization by improving resource efficiency. It also helps in building resilience to the agricultural systems that are vulnerable to different climatic vagaries. LLL technology was demonstrated at a few selected farmer fields as a part of the pilot project introduced in the study area between 2013 and 2016. In addition to that, several trainings were organized, and a subsidy of INR100,000 on the purchase of LLL machine was given to the farmers. From our primary survey, we have found that the number of adopters increased tremendously after 2016, maximum being in 2018, highlighting the utility of the technology. During our survey, we also observed that the adoption of LLL is greater among the farmers living in downstream areas of the canal command area as compared to those living in upstream areas. The uncertainty in rainfall causes disruption in canal water supply for irrigation, and farmers cultivating paddy in the downstream of canal command area face severe water scarcity due to the interrupted supply of water. Therefore, the water scarcity led farmers to adopt LLL; as a result, we observe low variability in the yield across the sample farmers (Figure 5). Moreover, farmers in the study area have observed saving water without losing the yield. All this led to a rise in adopters of

Table 6. Treatment and heterogeneity effect from the ESR

	Treatment	Control	Treatment effects
Yield (tons/ha)			
Treatment	4.76	4.07	TT = 0.69***
Control	5.85	4.24	TU = 1.60***
Heterogeneity effect	$BH_1 = -1.08$	$BH_2 = -0.17$	TH = −0.91***
Net income (INR)			
Treatment	37,753.36	26,375.8	TT = 11,377.56***
Control	53,449.77	30,685.75	TU = 22,764.02***
Heterogeneity effect	$BH_1 = -15{,}696.41$	$BH_2 = -4{,}309.96$	TH = −11,386.46***

Source(s): Authors' estimation based on IFPRI-GoK Survey, 2018–2019; ***$p < 0.01$

LLL in the study area. LLL has also demonstrated to be a potential risk minimizer. The average yield of adopters was reported to be higher than that of non-adopters. This is also visible from Figure 6, which depicts higher negative deviation for non-adopters as compared to the adopters. The skewness coefficient is reported to be higher for non-adopters as compared to adopters. Therefore, it can be said that paddy cultivation under LLL technology has become less risky in drought-prone regions of India.

The results based on our study substantiate that LLL has been helpful in improving the productivity of paddy and increasing the monetary welfare of the farmers. Land possessed by the farmers indicate a positive variation between the adopter and non-adopter farmers. The average size of landholdings by the technology adopted farmers is 10.53 ha and for non-adopted farmers is 5.44 ha. This implies large farmers are the early adopters of LLL in the study area, and extension institutions need to be strengthened to sensitize relatively small farmers to adopt LLL technology. Farmer's education has played an important role in the adoption of LLL technology in the study area. Moreover, a special technical skill is required to operate an LLL machine to level the land. Therefore, educated farmers need to be encouraged to come forward to adopt LLL machine and the practice.

PSM and CEM techniques have been used to match adopters and non-adopters to find out the impact of technology intervention on farmers' income and crop yield. Here, we have observed that technology adoption has a positive and significant impact on both the outcome variables. The PSM results are generated using the logit regression and nearest neighborhood algorithm. Under logit regression, the main factors affecting the adoption turn out to be land size, primary level of education, rent of machine and training for the machine. The likelihood of a farmer being an adopter increases by 2% if there is a unit increase in the agricultural landholding size. This further suggests that higher the landholding size, higher is the probability of adoption of the technology. Primary level of education increases the probability of being an adopter by 45%. This means that the primary level of literacy is an important factor that aids in determining the adoption of the LLL technology. Lastly, inappropriate training for LLL and higher rent of the LLL machine act as an obstacle in the adoption.

The PSM results satisfy the balancing property since there is a considerable overlap between the treated and untreated observations. Further, we also observe that there is a substantial reduction in mean bias and median bias after matching (Table A1). Figure A1 depicting common support is attached in the Appendix. Therefore, the PSM results suggest that adopters of LLL gain by INR3,725 and 0.33 tons/ha in comparison to the non-adopters of LLL. Further, the CEM results show an increase of INR4,834 in the net income of LLL adopters in comparison to non-LLL adopters. Similarly, for crop yield, the PSM and CEM results exhibit an increase of 0.33 and 0.68 tons/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. PSM undertakes the presence endogeneity in the form of observable factors, while the unobservable factors are not noticed such as information asymmetries, skill levels, etc., which justifies the application of the ESR method to account for unobserved endogeneity present in the data. The ESR results indicate a net rise of 0.91 tons/ha rise in crop productivity and INR11,386 in the income of the farmers. In case of yield, agricultural land, primary level of education, livestock and pump set ownership, and training and rent of LLL machine have a significant and positive impact for the adopters. Similarly, for net income, agricultural landholding, primary education, livestock and pump set possession, and training and rent of machine have a positive and significant impact for the adopters.

It is observed from the expert consultation during the survey that the plot size of at least 0.5 acre is necessary to operate LLL machines effectively, and hence, this can be technically feasible for the small farmer's land as well, provided they are aware about benefits of this technology and are also willing to adopt that technology in their land. In the above discussion, we have also explained that the probability of LLL adoption increases more if farmers receive training than the size of land they hold. Apart from this technical feasibility, economic feasibility to the small farmers is also important for upscaling this technology. In this context, rent of the machine is instrumental; higher rent cannot be afforded by the small and marginal farmers. On the other hand, increase in demand for leveling will increase the economic viability for the farmers or the custom hiring centers to make investment on the LLL machines. Therefore, policy and institutional arrangement is essential to increase the demand for leveling, which in turn enables the customs hiring business in the Karnataka state. Hence, subsidized rates should be fixed to increase its accessibility.

6. Conclusion and policy implications

Drought is a most frequently observed climate extreme event in the semi-arid region, which causes loss in the 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. LLL is one such climate-smart technology that has potential to adapt with the climate variability because of the efficient use of water, reduce cost of cultivation and minimize risk of crop yield and income loss to the farmers. However, limited evidence are available to argue the effectiveness of LLL technology in reducing crop loss due to drought event in the semi-arid region. Therefore, this study fills this knowledge gap by providing empirical evidence on the effectiveness of LLL under drought situation in the selected study region within the semi-arid region of the state of Karnataka in India.

The 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 the yield gap across the farmers who have adopted LLL. On the other hand, LLL reduces costs incurred by farmers and increases the yield and net income. The cost of owning an LLL machine (excluding a tractor) is around INR1.5 lakhs, which imposes financial burden on small and marginal landowners, but the life span of laser-leveled plot is three years, which reduces the cost of leveling the farmlands for three consecutive years. A cost–benefit ratio between the adopters and non-adopters of LLL is estimated as 1.72 and 1.56, respectively, for paddy cultivation in the study area. This implies an INR100 investment in agriculture, including LLL technology, will yield the net revenue of INR172 as compared to return of INR156 when the same amount of money has been invested without LLL technology. Therefore, adopters of the LLL technology will gain 16% more return than non-adopters even in the year when the study area observed long dry spell during the paddy growing season.

Despite higher return from the adoption of the LLL technology, the existing constraints are limiting adoption of this technology to a greater scale in the study area. 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 are few important constraints that were reported by the farmers during the survey. Therefore, strengthening agricultural extension services to increase awareness about the LLL among the farmers along with accessibility of machines should be given priority by the government to upscale the LLL technology in the region. Further, the operating skill of the 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. Moreover, further research and development is needed to enhance the crop productivity and income of the farmers using LLL. The public sector can collaborate with private institutions in increasing the 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. Finally, demonstrations can be given by the scientists to the farmers on their fields to make the farmers tech-friendly and promote adoption.

Notes

1. Crop productivity is the total production divided by the total area cultivated.
2. Net income is calculated as the difference between the total revenue earned minus 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 of machines for ploughing and leveling, and fuel.

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Appendix

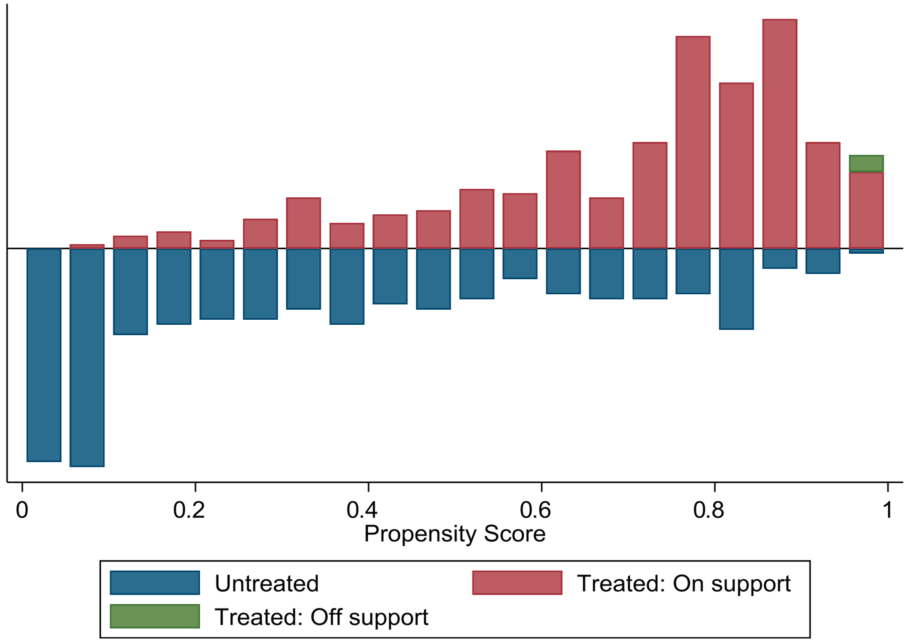

Figure A1.
Common support

Variable	Matched	Treated	Control	% bias	% reduction in bias	*t*	*p* > *t*
Agriculture land owned (ha)	*U*	10.53	5.43	46.5	93.9	5.54	0.01
	M	9.49	9.80	−2.8		−0.38	0.71
Household size (number)	*U*	6.04	6.38	−9.6	92.5	−1.19	0.24
	M	5.99	5.97	0.7		0.10	0.92
Visit made to and from RSK	*U*	0.26	0.16	23.6	78.5	2.87	0.01
	M	0.25	0.23	5.1		0.61	0.54
Adult male member in farming	*U*	1.77	1.92	−15.1	96.8	−1.85	0.06
	M	1.76	1.75	0.5		0.07	0.95
Education (base: illiterate)							
Primary	*U*	0.38	0.25	28.4	73.5	3.46	0.01
	M	0.38	0.42	−7.5		−0.91	0.36
Secondary	*U*	0.22	0.21	4.3	−10.4	0.52	0.60
	M	0.22	0.24	−4.7		−0.59	0.56
Higher secondary and above	*U*	0.16	0.16	−0.7	−343.8	−0.08	0.93
	M	0.16	0.15	3.1		0.39	0.69
Assets (Yes = 1, No = 0)							
Crop loan	*U*	0.66	0.69	−7.5	50.1	−0.91	0.36
	M	0.66	0.64	3.7		0.47	0.64
Own livestock	*U*	0.66	0.55	22.8	93.5	2.80	0.01
	M	0.65	0.64	1.5		0.19	0.85
Own pump set	*U*	0.57	0.37	40.9	88.7	5.01	0.01
	M	0.57	0.59	−4.6		−0.58	0.56
Own tractor	*U*	0.55	0.41	28.2	45.0	3.45	0.01
	M	0.54	0.62	−15.5		−1.99	0.05
Constraints in adopting LLL							
Machine supply	*U*	0.72	0.43	61.5	75.7	7.56	0.01
	M	0.72	0.79	−15.0		−2.11	0.04
Training	*U*	0.83	0.47	81.5	79.8	10.10	0.01
	M	0.83	0.76	16.5		2.30	0.02
Rent of machine	*U*	0.91	0.55	90.3	91.0	11.31	0.01
	M	0.91	0.95	−8.1		−1.68	0.09
Irrigation facility	*U*	0.48	0.29	38.6	92.8	4.70	0.01
	M	0.49	0.47	2.8		0.34	0.73

Note(s): *U* stands for unmatched and *M* stands for matched
Source(s): Authors' estimation based on IFPRI-GoK Survey, 2018–2019

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

Variables	L1 values	Net income (INR)	Yield (tons/ha)
LLL user (Yes = 1, No = 0)	–	4,834.571**	0.685***
		(2,149.541)	(0.119)
Agriculture land owned (ha)	0.211	−168.022	−0.004
		(131.442)	(0.006)
Household size (number)	0.099	−359.696	0.024
		(514.448)	(0.033)
Visit made to and from RSK	0.001	−12,379.588***	−0.231
		(3,380.612)	(0.204)
Adult male members in farming	0.001	1,574.156	0.120
		(2,146.442)	(0.104)
Education (base: illiterate)			
Primary	0.001	5,076.552	0.335**
		(3,559.385)	(0.166)
Secondary	0.001	2,191.317	0.347
		(5,077.789)	(0.319)
Higher secondary and above	0.001	−7,332.530	−0.166
		(6,941.623)	(0.300)
Assets			
Crop loan (Yes = 1, No = 0)	0.001	3,217.311	0.270*
		(3,351.579)	(0.141)
Own livestock (Yes = 1, No = 0)	0.001	−485.833	−0.073
		(2,383.756)	(0.120)
Own pump set (Yes = 1, No = 0)	0.001	3,779.156	0.109
		(3,295.495)	(0.170)
Own tractor (Yes = 1, No = 0)	0.001	−341.022	0.123
		(3,405.071)	(0.185)
Constraints to adopting LLL			
Machine supply	0.001	6,454.129*	0.168
		(3,628.132)	(0.217)
Training	0.001	420.241	−0.321
		(4,862.904)	(0.416)
Irrigation facility	0.001	−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(s): Authors' estimation based on IFPRI-GoK Survey, 2018–2019; robust standard errors in the parenthesis; ***p < 0.01, **p < 0.05, *p < 0.1

Table A2. Estimates from CEM model

	Treatment = 1 (farmers in treatment group)	Control = 0 (farmers in control group)	Treatment = 1, other = 0	Ordinary least squares
Constant	1.709*** (0.070)	1.393*** (0.045)	−0.721*** (0.351)	7.383*** (0.053)
LLL user (Yes = 1, No = 0)	–	–	–	0.082** (0.030)
Log agriculture land owned (ha)	−0.006 (0.011)	0.003 (0.014)	0.318*** (0.069)	0.013 (0.009)
Log household size (number)	−0.005 (0.022)	−0.019 (0.028)	−0.163 (0.150)	−0.017 (0.024)
Adult male member in farming	0.012 (0.011)	0.017 (0.012)	−0.115 (0.071)	0.009* (0.004)
Visit made to and from RSK	−0.004 (0.020)	−0.002 (0.029)	0.185 (0.140)	−0.003 (0.010)
Education (base: illiterate)				
Primary	−0.004 (0.024)	0.008 (0.026)	0.258* (0.153)	0.015 (0.017)
Secondary	0.018 (0.026)	0.061** (0.029)	0.013 (0.168)	0.041 (0.022)
Higher secondary and above	0.028 (0.029)	−0.012 (0.030)	−0.072 (0.187)	0.008 (0.019)
Assets				
Crop loan (Yes = 1, No = 0)	0.036* (0.019)	−0.007 (0.022)	−0.212* (0.128)	0.008 (0.021)
Own livestock (Yes = 1, No = 0)	−0.011 (0.026)	0.004 (0.021)	0.234* (0.122)	−0.003 (0.015)
Own pump set (Yes = 1, No = 0)	−0.035* (0.019)	0.011 (0.022)	0.257** (0.121)	−0.001 (0.024)
Own tractor (Yes = 1, No = 0)	0.007 (0.021)	0.042* (0.023)	−0.018 (0.138)	0.023 (0.012)
Constraints to adopting LLL				
Machine supply	0.032 (0.020)	−0.007 (0.033)	0.046 (0.140)	0.027 (0.018)
Training	−0.034 (0.025)	−0.031 (0.039)	0.465*** (0.166)	−0.017 (0.032)
Rent of machine	−0.066* (0.036)	0.019 (0.042)	0.891*** (0.193)	0.009 (0.035)
Irrigation facility	−0.028 (0.018)	−0.008 (0.027)	−0.016 (0.130)	−0.015 (0.017)
IV	–	–	−0.758*** (0.352)	–
$Ln\sigma_1$	−1.801*** (0.076)			
ρ_1	−1.109*** (0.282)			
$Ln\sigma_2$		−1.841*** (0.058)		
ρ_2		−0.245 (0.324)		
Observations	600	600	600	600

Source(s): Authors' estimation based on IFPRI-GoK Survey, 2018–2019; robust standard error in the parenthesis; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table A3. Drivers of yield (tons/ha), ESR model

	Treatment = 1 (farmers in treatment group)	Control = 0 (farmers in control group)	Treatment = 1, other = 0	Ordinary least squares
Constant	10.810*** (0.100)	10.420*** (0.114)	−0.613* (0.341)	10.389*** (0.112)
LLL user (Yes = 1, No = 0)	–	–	–	0.169** (0.048)
Log agriculture land owned	−0.020 (0.017)	0.016 (0.033)	0.303*** (0.070)	0.023** (0.008)
Log household size	0.004 (0.035)	−0.136* (0.072)	−0.228 (0.148)	−0.065 (0.071)
Adult male member in farming	0.016 (0.018)	0.057* (0.031)	−0.095 (0.073)	0.022 (0.017)
Visit made to and from RSK	−0.057* (0.031)	−0.189*** (0.072)	0.181 (0.140)	−0.085* (0.035)
Education (base: illiterate)				
Primary	0.031 (0.036)	−0.016 (0.066)	0.305** (0.152)	0.029 (0.051)
Secondary	0.055 (0.040)	−0.024 (0.073)	0.041 (0.170)	0.022 (0.082)
Higher secondary and above	0.085* (0.045)	−0.042 (0.076)	−0.061 (0.187)	0.029 (0.038)
Assets (Yes = 1, No = 0)				
Crop loan	0.076** (0.029)	0.036 (0.056)	−0.210 (0.128)	0.037 (0.054)
Own livestock	−0.065** (0.029)	−0.105** (0.053)	0.243** (0.121)	−0.077 (0.034)
Own pump set	−0.039 (0.030)	−0.125** (0.056)	0.251** (0.121)	−0.059** (0.012)
Own tractor	0.030 (0.033)	0.078 (0.059)	0.024 (0.135)	0.053 (0.028)
Constraints to adopting LLL				
Machine supply	−0.003 (0.031)	−0.023 (0.084)	0.091 (0.140)	0.008 (0.005)
Training	−0.072* (0.040)	−0.062 (0.097)	0.392** (0.167)	−0.024*** (0.007)
Rent of machine	−0.087 (0.053)	0.163 (0.102)	0.971*** (0.194)	0.092*** (0.012)
Irrigation facility	−0.042 (0.029)	−0.098 (0.069)	0.006 (0.129)	−0.058 (0.030)
IV	–	–	−0.825*** (0.236)	–
$\mathrm{Ln}\sigma_1$	−1.351*** (0.070)			
ρ_1	−1.165*** (0.252)			
$\mathrm{Ln}\sigma_2$		−0.906*** (0.053)		
ρ_2		−0.267 (0.234)		
Observations	600	600	600	600

Source: Authors' estimation based on IFPRI-GoK Survey, 2018–2019; robust standard error in the parenthesis; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A4.
Drivers of net income (INR), ESR model

Parameter estimates	Model 1 LLL adopter (Yes = 1, No = 0)	Model 2 Rice yield for non-LLL adopters	Model 3 Net income for non-LLL adopters
Access to canal irrigation	−1.075***	0.006	−0.272
Constant	1.100***	1.424***	10.642***
Wald test on IV	Chi (2) = 50.05	F-stat = 3.75	F-stat = 2.92
Observations	604	275	275

Note(s): *** $p < 0.01$

Table A5. Parameter estimates – validity test of the selected instrument

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