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Factors determining the adoption of laser land leveling in the irrigated rice–wheat system in Haryana, India

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ABSTRACT

Laser land leveling has been increasingly adopted in the irrigated rice (*Oryza sativa* L.)–wheat (*Triticum aestivum* L.) cropping system in the state of Haryana (India), located in the north-western Indo-Gangetic Plains. Still, many farmers have applied it to only a fraction of their land. In this study, we used data collected from 621 farm households in Haryana and applied a double-hurdle model for assessing the factors that determine the adoption and intensity of laser-leveling technology. The results show that large land holders are more likely to laser level their farm land; however, we found a negative association between land holdings and the proportion of laser-leveled land. Information about technology through farmer-to-farmer communication and through private traders, participation in agricultural training and membership in local agricultural institutions increased both the likelihood and the intensity of adoption. Our findings call for a closer collaboration among the various stakeholders, specifically to promote farmer-to-farmer communication through increased participation in local institutions and increase the rate of adoption of laser leveling technology.

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Adoption intensity; double-hurdle model; farmer-to-farmer communication; Indo-Gangetic Plains; technology adoption

Introduction

The Green Revolution transformed India's north-western Indo-Gangetic Plains (IGP) into a staple-food basket. However, sustainability of agricultural growth in the irrigated intensive rice–wheat system is increasingly challenged by factors such as declining groundwater tables, soil degradation, ever-increasing land scarcity and energy use, and climate change. Uneven field topography can significantly reduce both water and land productivity under the prevailing flood-irrigated system (Gill 2014). Further, 10–25% of irrigation water is often lost because of poor management and uneven fields (Jat et al. 2006). Laser land leveling is an improved precision land-leveling

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technology, which boosts water and land productivity (Jat et al. 2015; Naresh et al. 2014).

Agriculture accounts for 18% of total national greenhouse gas (GHG) emissions in India (INCCA 2010). Reducing GHG emissions from the agriculture sector will help India achieve the target set in the United Nations Framework Convention on Climate Change (UNFCCC). Laser land leveling reduces GHG emissions from irrigated agricultural systems by: (i) reducing pumping time for irrigation; (ii) reducing (tractor) cultivation time; and (iii) improving N-fertilizer-use efficiency (Gill 2014; Jat et al. 2015; Naresh et al. 2014). Laser land leveling is estimated to reduce GHG emissions in Haryana by 0.15 metric tons (MT) of CO_2 eq per year per ha (Gill 2014). A laser-leveled field requires much less energy (saving almost 765 kWh per ha in the rice–wheat cropping system) for pumping irrigation water compared with a traditional land leveling techniques (Aryal et al. 2015a). A large-scale uptake of a climate-smart technology like laser land leveling that reduces GHG emissions could make a substantial contribution toward achieving mitigation targets.

Importantly, for farmer acceptance, laser land leveling benefits extend beyond the environmental and mitigation spheres. A shift from traditional land leveling to laser land leveling can increase the yields of rice and wheat by 342 kg/ha and 323 kg/ha, respectively (Aryal et al. 2015a). The average laser land leveling cost is about US$50 per ha as a service charge; however, farmers can increase their net return by about US$130 in the rice–wheat system (Khatri-Chhetri et al. 2016). It is a promising climate-smart technology, as it reduces the amounts of energy and water used for irrigation, enhances fertilizer-use efficiency and increases crop yields (Aryal et al. 2015a; Jat et al. 2015).

The laser land leveling was introduced in India in 2001 in the western IGP by the Rice-Wheat Consortium (RWC), a collaborative eco-regional initiative by the CGIAR centers and the Indian Council of Agricultural Research (ICAR), which has been variously supported since then (Jat et al. 2006; Lybbert et al. 2013b). Across time, several farmers purchased laser land levelers and started custom hiring services. Increased awareness and potential benefits, trained human resources and government support through subsidy led to an increased number of farmers owning laser land levelers. Still, increased availability of custom-hire services is one of the main drivers that facilitated the expansion of laser land leveling technology, including its adoption by resource-poor farmers (Aryal et al. 2015a). The market price of a laser land leveler (i.e., the capital equipment) is around US$5,920,[1] but it is variously subsidized. For instance, the Haryana government, at present, provides US$830 as a subsidy to individual farmers and almost US$2,500 if a group of farmers buys the equipment under the National Food Security Mission (NFSM) (http://nfsm.gov.in/Circulars_Notifications/2015-16/CDP%20revised%20AAP_2015-16_Haryana.pdf). The laser land leveling makes an important contribution to the energy-irrigation nexus in Indian agriculture. Given that electricity use for agriculture is highly subsidized in several Indian states, including Haryana, its cost to the government is massive. Reducing or withdrawing the subsidy remains politically challenging, so a second best alternative is to promote technologies that save energy used for irrigation.

During the decade following its introduction, laser land leveling spread rapidly among farmers in India's NW IGP – Haryana, Punjab and western Uttar Pradesh, and covered an estimated 200,000 ha in the late 2000s (Lybbert et al. 2013a); and more than 25,000 laser land levelers were estimated to be in operation in India's IGP (Jat et al. 2015). In Haryana, laser land leveling was introduced in 2004. In 2007–08, the number of new subsidized laser land leveling units in Haryana was only 22, increasing to 806 per year in 2012–13; across the 6-year period, a cumulative total of >1,500 subsidized units were in operation (Gill 2014). On average, each unit levels 212 ha annually according to key informants, with estimates of laser-leveled areas being 544,000–650,000 ha in Haryana alone, saving an estimated 1 billion cubic meter of water per annum (Gill 2014). In Haryana, there were 2.5 M ha under wheat and 1.2 M ha under rice cultivation in 2013.

Still, there is lack of empirical validation of estimates of the extent of adoption and knowledge about the determinants of adoption is quite limited. Improved understanding of these issues should help scale up the promising laser land leveling technology, which supports all three pillars of climate-smart agriculture, including food security, and adaptation to and mitigation of climate change (CIMMYT 2015; Dinesh et al. 2015; Gill 2014). Therefore, this study was designed to examine the factors determining laser land leveling adoption and adoption intensity by using representative primary data collected from Haryana, India.

Materials and methods

Study area

The study focuses on Karnal District of Haryana state, India (Figure 1). This district lies within the temperate zone, which annually receives around 760 mm of rainfall, primarily during the monsoon season. The rice–wheat rotation is the dominant cropping system of the study area. Wheat is grown in the cool winter season (November to April) and rice in the monsoon season (June to October). The average yields of rice and wheat are 3.3 Mg ha^{-1} and 4.4 Mg ha^{-1}, respectively (Government of Haryana 2013). The soil is primarily alluvial, calcareous, low in organic carbon, and weakly structured, with a light-to-medium texture (Aryal et al. 2015b). Although Karnal District has well-developed canal irrigation facilities, groundwater has increasingly become the major source of irrigation (Erenstein 2009).

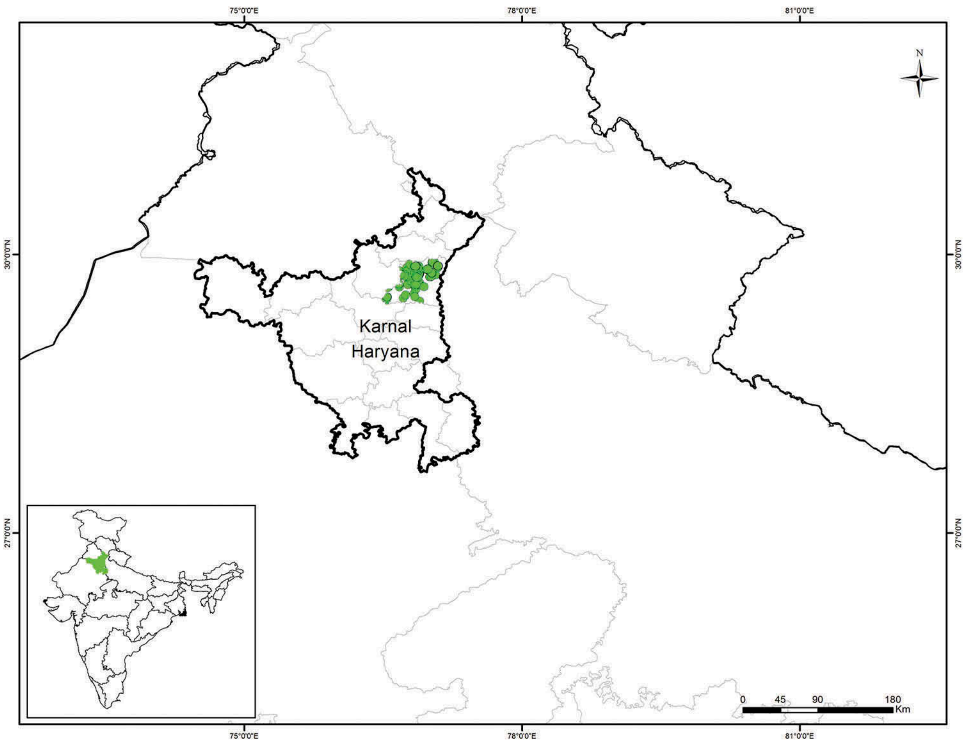

Figure 1. Survey locations in Karnal district, Haryana State, India.

Electric pump sets are commonly used for irrigating the fields (Aryal et al. 2015a). The rice–wheat system is highly mechanized, input-intensive and commercial. Farmers in this area use other climate-smart agricultural practices, such as zero tillage and, to a limited extent, direct-seeded rice. Informal focus group discussions revealed that only a few farmers in the study villages owned laser land levelers and provided services to farmers on a hire basis, charging US$9–12 per hour.

The data for this study were collected, in the second half of 2013, from 626 farm households in 13 villages of Karnal district; however, data from only 621 farm households could be used in the analyses. The survey households were randomly selected from each village. We collected information on household characteristics, farm-plot characteristics, access to credit, extension services, market characteristics, training received, inputs used and crop yield. To assess adoption behavior, information from both adopters and non-adopters of laser land leveling was analyzed.

Empirical framework

The extent of laser land leveling adoption was expected to contain both zeros and positive values. For such a data structure, a standard, censored

Tobit model or a double-hurdle model is usually applied to assess the determinants of adoption and intensity of adoption of a technology (Wooldridge 2002). The major difference between the two models is that the former assumes that the same mechanism determines both the adoption and its intensity, whereas the latter assumes that two separate stochastic processes determine first the decision to adopt and then the intensity of adoption (Cameron and Trivedi 2009; Wooldridge 2002). Although there is the possibility that the same mechanisms could determine both the adoption and intensity of adoption, there is no reason to expect this a priori. Thus, we estimated both models and compared them based on model selection criteria. Of the variants of the double-hurdle model, we used the Cragg model (Cragg 1971) and the Wooldridge model (Wooldridge 2002, pp. 536–538). In these double-hurdle models, the first part corresponds to household's choice of whether to adopt or not to adopt (a probit model) and the second part corresponds to the intensity of adoption (i.e., how much area of land is laser-leveled, given that adoption decision has been made, using a truncated regression in the Cragg model and a log-normal regression in the Wooldridge model). To compare the Cragg model with the Wooldridge model, we used the Vuong test for model selection, as these two models are non-nested to each other (Vuong 1989).

Specification of variables in the analysis and estimation issues

In the econometric analysis, the explanatory variables were chosen on the basis of a review of existing literature on determinants of technology adoption and data availability. The set of explanatory variables included household characteristics, economic variables, access to market and extension services, institutional factors, access to technology information and training, farm land characteristics and social capital. Table 1 contains a description of the variables used in the analysis.

Household characteristics included education, age, caste, gender and main occupation of the household head. Often, there is a positive association between the education level and technology adoption (Feder and Umali 1993). As educated farmers have better access to information on improved technologies than uneducated farmers, we hypothesized that a household headed by a literate person would be more likely to adopt laser land leveling. In South Asian countries, caste is also one of the important variables affecting technology adoption (Aryal and Holden 2012; Pender and Kerr 1998; Yamano, Rajendran, and Malabayabas 2015). Despite legal abolition of the caste system, it still prevails in Indian society and this either facilitates or restricts the access to information, markets and resources (Aryal and Holden 2013). Male-headed households are generally more likely to adopt new

Table 1. Description of variables used in the study

Variables	Mean	SD	Variable description†
Dependent variables			
Use of laser land leveling (dummy)	0.546	0.498	D: 1 if part or all of land is laser leveled and 0 otherwise
Proportion of laser leveled land	0.361	0.403	C: proportion of laser leveled land out of total land
Household characteristics			
Male headed household (HH) (dummy)	0.969	0.172	D: 1 if male and 0 otherwise
General caste (dummy)	0.761	0.426	D: 1 if general caste and 0 if backward/scheduled caste
Age (years)	49.5	12.9	C: Age of household head
Literate HH head (dummy)	0.678	0.468	D: 1 if literate and 0 otherwise
Farming main occupation of HH head (dummy)	0.905	0.293	D: 1 if farming and 0 otherwise
Household size (#)	6.042	2.477	C: number of members in HH.
Farm land characteristics			
Fertile soil (dummy)	0.945	0.227	D: 1 if reportedly good soil by farmer and 0 otherwise
Deep soil (dummy)	0.372	0.189	D: 1 if reportedly deep soil profile by farmer and 0 otherwise
Flat field topography (dummy)	0.911	0.284	D: 1 if reportedly no to gentle slope and 0 otherwise
Plot distance (km)	1.366	0.942	C: distance from homestead to plot (in km)
Owner-operated land (dummy)	0.89	0.313	D: 1 if owner-operated and 0 if rented
Economic and social capital			
Farm size (ha)	4.032	5.374	C: farm land (in ha)
Livestock (TLU)	3.811	5.708	C: livestock owned in tropical livestock unit (TLU)
Asset index	0.879	0.505	C: Household asset index
Credit Access (dummy)	0.398	0.489	D: 1 if farmer has access to credit and 0 otherwise
Institutional membership (dummy)	0.349	0.476	D: 1 if membership in local institutions and 0 otherwise
Access to markets, agricultural extension service and training			
Local market (km)	2.023	1.641	C: distance to local market (in km)
Agriculture extension (km)	5.116	2.841	C: distance to nearest extension service (in km)
Training (dummy)	0.221	0.415	D: 1 if had agricultural training and 0 otherwise
Main source of information			
Farmer to farmer (dummy)	0.168	0.372	D: 1 if information received from other farmers and farm cooperatives, and 0 otherwise
Extension service (dummy)	0.048	0.215	D: 1 if information received from government extension service and 0 otherwise
Mass and electronic media (dummy)	0.010	0.098	D: 1 if information received from radio, newspaper, TV, mobile and 0 otherwise
Private traders (dummy)	0.193	0.138	D: 1 if information received from private traders including rental service providers and 0 otherwise

†C and D refers to continuous and dummy variables, respectively.

technologies (Asfaw and Admassie 2004), although a recent study in India by Aryal et al. (2014) found that female-headed households were more likely to adopt climate-smart agricultural practices, including new technologies. The authors related this to the increased labor scarcity in female-headed households. The age of the household head is related to two major issues: experience in farming and resistance to change. In addition, a farm household being located in a project intervention village is expected to favor laser land leveling adoption having been more directly exposed to the technology and associated knowledge.

Economic characteristics, such as the number of livestock owned, farm size and household asset index, are associated with the wealth status of the household. We constructed a household asset index using the principal component analysis. This helped us reduce the number of variables in the analysis and the possibility of multicollinearity among the explanatory variables. In addition, we tested multicollinearity using a variance influence factor. Wealthier households are better able to bear risks associated with the adoption of new technology than poorer ones (Kassie et al. 2013). For instance, adoption of zero tillage was closely related to the wealth of the household in its initial diffusion stage (Erenstein and Farooq 2009). Hence, wealthier households are more likely to adopt laser land leveling and laser level a larger proportion of their land.

Land characteristics, such as soil depth, soil fertility and slope, are likely to variously influence adoption decisions. For instance, farmers are more likely to adopt soil and water conservation technology on fertile lands (Abdulai and Huffman 2014). Land tenure status is also one of the key variables affecting farmers' investment in land and new technology adoption (Abdulai, Owusu, and Goetz 2011). We hypothesized that owner-operated land would be more likely to be laser-leveled compared with rented land. In many cases, tenants need the landlord's permission to laser level and tenants are less assured of reaping the longer-term benefits of laser land leveling.

Social indicators (e.g., membership or association in groups, such as farmers' cooperatives, savings and credit groups, youth associations, local administration, seed producer and marketing groups) may increase the likelihood of adoption through information sharing, relaxing of liquidity constraints and mitigation of risks (Kassie et al. 2013; Teklewold, Kassie, and Shiferaw 2013). Similarly, distance to market and distance from homestead to farm plot and extension services affect availability and use of inputs and information and, thereby, adoption decisions. Transaction costs associated with input and the opportunity costs of labor have been directly linked to adoption decisions (Teklewold, Kassie, and Shiferaw 2013) and farm homesteads being further away from markets and the farm plot have been reported to reduce their probability of adoption (Kassie et al. 2013). We expect the distance to market to be an important variable, as the majority of farmers use private custom hiring services for laser land leveling. Extension centers are major information disseminators to farmers, and provide training on different practices, such as soil-water management, seeds of new varieties, adaptation to climate change, and minimum tillage. Access to these institutions and participation in training on agricultural technologies can increase the likelihood of adoption (Di Falco, Veronesi, and Yesuf 2011). A source of information is an important determinant of technology adoption and, in India, caste may also affect access to information. Farmers at the bottom of the social hierarchy (based on caste) have access to fewer information sources, and mostly depend on informal social networks and local input dealers (Birthal et al. 2015).

Results and discussion

Of the 621 sample farm households used in the analysis, 339 (54.6%) were found to have adopted laser land leveling. Among the adopters, only 103 (30.4%) households had laser-leveled all of their operated land, whereas the remainder 236 (69.6%) households had done it on part of their land.

Descriptive statistics

In Table 2, adopting versus non-adopting sample households are contrasted; significant differences were found in several aspects. Farm households

Table 2. Characteristics of sample households by laser land leveling adoption

Variables	Adopters	Non-adopters	*t*-Test
Household (HH) characteristics			
Male headed HH (%)	96.4	97.5	0.76
General caste (%)	82.3	68.8	3.98**
Age (in years)	48.6	50.6	1.88!
Literate HH head (%)	74.0	60.3	3.69**
Farming main occupation of HH head (%)	92.3	88.3	1.71!
HH size (#)	6.26	5.78	2.44*
Farm land characteristics			
Fertile soil (%)	93.8	95.4	0.87
Deep soil (%)	2.65	5.67	1.97*
Flat field topography (%)	93.2	86.7	1.99*
Plot distance (km)	1.39	1.33	0.93
Owner-operated land (%)	0.92	0.85	2.36*
Economic variables and social capital			
Farm size (ha)	5.56	2.19	6.49**
Livestock (TLU)	4.45	3.05	3.07**
Asset index	1.02	0.93	7.79**
Credit Access (%)	48.4	29.1	4.99**
Institutional membership (%)	41.6	27.0	3.85**
Access to markets, extension service and training			
Local market (km)	2.83	2.90	0.65
Agriculture extension (km)	5.17	5.27	0.14
Training (%)	27.43	15.60	3.57**
Major Source of information			
Farmer to farmer (%)	19.8	12.8	2.34*
Extension service (%)	6.41	3.24	3.40**
Mass and electronic media (%)	1.88	1.76	0.29
Private traders (%)	23.3	7.32	4.41**
Total number of observation	**339**	**282**	

!,*, and ** refer to significant at the $p < 0.10$, $p < 0.05$ and $p < 0.01$ level, respectively.

adopting laser land leveling more commonly belonged to the prevailing general caste group, had more literate and older household heads, had larger households and had farming as the main occupation. Farm plots with reportedly deep soil profiles were more common among non-adopters, whereas adopters had flatter fields.

The average operated farm size was significantly bigger among the adopters (5.56 ha) as compared to non-adopters (2.19 ha). Similarly, the adopters had more livestock, better access to credit, membership in groups, and asset ownership as represented by the asset index. However, there was no significant difference in market access measured as the average distance to local markets and agricultural extension service centers (Table 2).

Adopters tended to have better access to information from various sources, including farmer-to-farmer communication (i.e., relatives, neighbors and members of local farm cooperatives), government extension services and private traders. Participation in training to acquire knowledge about new agricultural technologies was significantly higher among adopters than non-adopters.

Analysis of the determinants of adoption and intensity of adoption of laser land leveling

We estimated a censored Tobit model and two versions of double-hurdle model (i.e., Cragg model and Wooldridge model) to examine the determinants of adoption and intensity of adoption of laser land leveling. We compared these models using model selection tests; the Cragg model was preferred to both the Tobit and Wooldridge models (Table 3).

The decisions to adopt laser land leveling and the intensity of its adoption (when adopted) are variously determined by two sets of determinants (Table 4). It means variables that significantly affect the likelihood to adopt might or might not impact the intensity of adoption of laser land leveling technology.

Table 3. Results of model selection tests

Compared models	Tests used	Test values	Results
Cragg vs. Tobit	Likelihood Ratio (LR) test	LR chi-square = 285.68; Prob > Chi-square = 0.000	Cragg model is preferred to Tobit model
Wooldridge versus Tobit	Vuong test	|V| = 147.69 Critical value (c) = 2.58	Wooldridge model is preferred to Tobit model
Cragg versus Wooldridge	Vuong test	|V| = 73.89 Critical value (c) = 2.58	Cragg model is preferred to Wooldridge model

Table 4. Determinants of laser land leveling adoption and its intensity (Cragg double-hurdle model)

	Probit		Truncated regression	
	Coefficient	S.E.	Coefficient	S.E
Household (HH) characteristics				
Male headed HH (dummy)	0.093*	0.032	0.076	0.087
General caste (dummy)	0.182**	0.041	0.015	0.045
Age of HH head (in years)	−0.008	0.005	0.004**	0.001
Literate HH head (dummy)	0.266*	0.106	0.019	0.042
Farming as main occupation of HH head	0.338**	0.110	0.126*	0.061
HH size (dummy)	0.021	0.031	−0.017*	0.008
Farm land characteristics				
Fertile soil (dummy)	0.213**	0.073	0.196*	0.075
Deep soil (dummy)	−0.543!	0.308	0.025	0.102
Flat field topography (dummy)	0.258	0.208	−0.082	0.069
Distance from homestead to farm (km)	−0.116!	0.066	0.044**	0.016
Owner-operated land (dummy)	0.109**	0.052	0.051	0.049
Economic and social capital				
Farm size operated (ha)	0.174**	0.016	−0.025**	0.003
Livestock owned (TLU)	0.017	0.016	0.001	0.002
Asset index	0.246*	0.047	0.015	0.036
Credit access (dummy)	0.302*	0.129	0.008	0.035
Institutional membership (dummy)	0.162*	0.080	0.149**	0.050
Access to market				
Distance to local market (km)	−0.105**	0.023	0.022**	0.007
Distance to agricultural extension service (km)	−0.067*	0.032	−0.012	0.010
Agricultural training (dummy)	0.129**	0.041	0.113**	0.034
Major source of information				
Farmer to farmer (dummy)	0.501*	0.203	0.115*	0.047
Government institution (dummy)	0.105*	0.051	−0.061	0.079
Mass and electronic media (dummy)	−0.070	0.747	0.157	0.182
Private traders (dummy)	0.154*	0.071	0.256**	0.087
Constant	−0.464	0.794	0.8027**	0.154
Sigma constant			0.263**	0.010
Number of observation	621		339	
Wald Chi-square	117.12**		155.35**	

!,*, and ** refer to significant at the $p < 0.10$, $p < 0.05$ and $p < 0.01$ level, respectively.

Several household characteristics were found to have significant impact on either the adoption decision, adoption intensity or both. For instance, male-headed households and general caste households were positively associated with the likelihood of adoption of laser land leveling. On the other hand, the age of the household head was only positively associated with the intensity of adoption, when technology was adopted. Compared to illiterate household heads, literate ones were more likely to adopt, similar to other adoption studies (Abdulai and Huffman 2014; Arslan et al. 2014) and were likely associated with access to information (Asfaw and Admassie 2004). Households with farming as main occupation were found to have both a higher likelihood of adopting the technology and a higher intensity of adoption.

Farmers with fertile soil were more likely to laser level and had a higher intensity of adoption than those with poor soils. However, farmers with reportedly deep soil profiles had a reduced likelihood of adoption. Fields that were far from the homestead were less likely to be laser-leveled, but if done, the intensity of adoption was higher, likely reflecting the prevailing reliance of sample households on laser land leveling service providers.

Farm size had a differential impact on the probability of adoption and intensity of adoption of laser land leveling. Farm size positively increased the likelihood of adoption of laser land leveling, but decreased the adoption intensity. Quick follow up field work in the study area reiterated that large farms were indeed more likely to laser-level their rice–wheat fields.

Institutional aspects, such as access to market and extension services, were found to be other determinants of adoption. Households that were far from the agricultural extension service providers were less likely to adopt laser land leveling, likely reflecting that increased distance hampered getting access to information and added transaction costs. Similarly, farmers far from the main market were found to have significantly less probability of adopting laser land leveling. However, if these relatively remote farmers did adopt, their adoption intensity was higher, similar to the remoteness from the homestead and again likely associated with the reliance on custom hiring services. Training in agriculture was found to increase both the likelihood of adopting laser land leveling and the adoption intensity. Therefore, increasing technology demonstration at farmers' fields and provision of training on agricultural technologies that are suitable to local conditions can increase the uptake of laser land leveling by the farmers.

Among the information sources used by farmers, farmer-to-farmer communication and private traders were found to be most effective. Farmer-to-farmer communication in our sample included discussion with neighboring farmers, relatives in the local area, members of local farm cooperatives and lead farmers in the area. Farmer-to-farmer communication was found to positively affect both the probability of adoption and intensity of adoption. We found similar positive associations between the information provided by the private traders and the adoption and adoption intensity. Governmental institutions were also a major source of information for farmers, which increased the probability of adoption.

Our findings showed that government extension services and information systems, and information from private seed/input companies had contributed positively to the likelihood of adopting laser land leveling. This reinforces the need to work in collaboration to further increase the uptake of promising technologies, such as laser land leveling.

Conclusions

This paper contributes to the literature on agricultural technology adoption, especially on the adoption of laser land leveling, a promising climate-smart technology. Using empirical data from 2013, our results showed that 55% of the sample households had adopted laser land leveling, although only 30% of the adopters had laser-leveled all of their operational farm land. We found significant differences between the adopters and non-adopters relative to household characteristics, economic and social capital, and information sources. A persistent finding was that the adopters tended to be wealthier across the portfolio of indicators. Further promoting local service providers to cover larger areas and larger numbers of smaller landholdings might be an option to enhance the equitable uptake of such technologies.

This study showed that trainings related to agricultural technologies enhanced the probability of adoption of laser land leveling. Another important finding was that farmer-to-farmer communication was the most effective method of transferring technological knowledge. Therefore, correct initial application and adoption of new technologies, such as laser land leveling, and their good subsequent performance are critical. Networking with lead farmers in the village and providing training to them can further boost the technology uptake. Haryana's government institutions have supported the promotion of climate-smart technologies, particualrly facilitating the diffusion of laser land leveling. Our study suggests that a favorable, enabling environment, with diverse stakeholders working collaboratively with each other, with a common interest, is the key to the promotion of climate-smart agriculture. Another key ingredient is having viable, robust, economically attractive innovations, and the rapid uptake of laser land leveling in Haryana is a case in point.

Note

1. US$ = equivalent to 60 Indian Rupees in 2013.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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