ZEF-Discussion Papers on Development Policy No. 346

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Private service provision contributes to widespread innovation adoption among smallholder farmers: Laser land levelling technology in northwestern India

Bonn, May 2024

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Subash Surendran-Padmaja, Martin C. Parlasca, Matin Qaim, and Vijesh V. Krishna, Private service provision contributes to widespread innovation adoption among smallholder farmers: Laser land levelling technology in northwestern India, ZEF – Discussion Papers on Development Policy No. 346, Center for Development Research, Bonn, May 2024, pp. 31.

ISSN: 1436-9931

Published by:
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Acknowledgements

We acknowledge funding by the Academy for International Agricultural Research (ACINAR). ACINAR, commissioned by the German Federal Ministry for Economic Cooperation and Development (BMZ), is being carried out by ATSAF (Council for Tropical and Subtropical Agricultural Research) e.V. on behalf of the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH. We also acknowledge the funding support from the CGIAR-Standing Panel on Impact Assessment (SPIA) and the Indian Council of Agricultural Research (ICAR) for data collection. We are grateful to the farmers who trusted us and provided us with their valuable time and knowledge despite the ongoing 'Farmer's protest' in 2021. Also, we acknowledge the Survey Jena team and their team of enumerators who supported us for the survey.

Abstract

This study investigates key institutional factors promoting the adoption of laser land levelling (LLL), a technology that has gained wide popularity among farmers in northwestern India despite being indivisible. The main objective is to evaluate the role of service providers, offering LLL on a rental basis to farmers, for technology dissemination among smallholders with fragmented plots. Plot-level data from 1,661 households across 84 villages in Punjab and western Uttar Pradesh in India were collected and used to analyse farmers' LLL technology perceptions and adoption decisions. Regression models were developed to estimate the role of local service provision for LLL adoption while controlling for farm, household, and other contextual variables. The analysis pays particular attention to the heterogeneous effects of service provision on farmers with different farm and plot sizes. The data and estimates reveal that local access to a larger number of service providers is associated with higher rates of LLL adoption among farmers. The effect of service providers on adoption varies by farm and plot size: it is larger on smaller farms/plots. The findings suggest that a conducive institutional environment that accommodates the specific needs of different farm sizes can speed up innovation adoption. This finding makes a case for re-evaluating traditional agricultural technology scaling models to include individual service provision for broader and more inclusive adoption.

Keywords: Adoption, Smallholder farmers, Agricultural machinery, Indivisible agricultural technology

JEL Codes: O13, Q15, Q16, Q18

1. Introduction

Agricultural technologies are critical for efficient and sustainable farming. Yet, the adoption of new technologies is sometimes slow and limited, especially among smallholder farmers. Technologies involving agricultural machinery are often particularly challenging for smallholders to adopt (Ruzzante and Bilton, 2021). One key reason is that machinery is not easily divisible, which differentiates it from many other agricultural technologies, such as new seeds and fertilisers. Indivisible technologies are often costly and cannot be tested in small quantities for gaining more experience before fully adopting them (Lu et al., 2016). Hence, adoption rates of many indivisible technologies remain low in the small farm sector. One exception is laser land levelling (LLL) technology, more formally also known as laser-assisted precision land levelling, which is widely adopted in northwestern India (Aryal et al., 2020; Villalba et al., 2024).

Adoption of indivisible technologies can be facilitated through service providers that rent out machinery (Lu et al., 2016). Different types of institutions can act as service providers, including farmer co-operatives, custom hiring centres, or private enterprises (Daum et al., 2021; Villalba et al., 2024). Previous research shows that farmers are willing to pay for land levelling operations (Lybbert et al. 2018, Paudel et al. 2023), suggesting that service providers can play an important role in the adoption of LLL technology. However, linkages between private service provision and actual adoption decisions of farmers are so far poorly understood (Gulati et al., 2017; Schut et al., 2020; Van Loon et al., 2020).

The availability of rental services for LLL makes the technology accessible to farmers who cannot or do not want to own the equipment themselves. In this study, we, therefore, first ask the question of how the availability of private service providers in the local context influences farmers' use of LLL technology. We hypothesise that a larger number of service providers locally available leads to higher adoption rates of LLL. However, private service providers may not make LLL technology equally accessible to all types of farmers. In particular, service providers may prefer offering their services to larger farms and larger plots to exploit economies of scale. In addition, farmers with small land holdings may be liquidity-constrained and risk-averse, making them less attractive business partners for private service providers (Hu et al., 2022). Hence, we are also interested in analysing whether the availability of service provision has differential effects on LLL adoption among smaller and larger farms and plots.

To address our research questions, we use plot-level data from 1,661 farm households across 84 villages in the states of Punjab and western Uttar Pradesh, located in northwestern India. We add to the literature in several ways. First, while a few studies on LLL adoption exist, all primarily focus on demand-side drivers of adoption, such as farm and farmer characteristics (e.g. farm size, soil fertility, cropping system, age, education, gender) or household characteristics (e.g. household size, off-farm income, access to credit) (Ali et al., 2018; Aryal et al., 2018; Aryal et al., 2020; Pal et al., 2021; Sheikh et al., 2022). We are particularly interested in the role of private service providers as a potential supply-side driver of adoption. Second, much of the existing technology adoption literature looks at farmers' adoption decision as a one-time choice. However, often adoption is a process that starts before the actual decision to use a technology for the first time and also continues afterwards. Such dynamics need to be understood in order to be able to address possible adoption constraints effectively (Ishtiaque et al., 2024). We explore some of the relevant dynamics by analysing the timing of LLL adoption, farmers' perceptions of technology effects, as well as the frequency of technology use, given that land preparation and levelling decisions have to be made repeatedly.

The remainder of this article is structured as follows. In section 2, we provide some more background on the LLL technology and how it was introduced in the Indian context. In section 3, we discuss the theoretical framework of the technology adoption analysis, whereas in section 4 we introduce the empirical approach. The empirical results are presented and discussed in section 5, while section 6 concludes.

2. Laser land levelling technology and service providers

Laser land levelling technology was developed in the USA in the 1970s, and subsequently manufactured and disseminated in other countries including Italy, Russia, Egypt, India, Pakistan, China, Iran, Vietnam, Cambodia, Nepal, and Tajikistan, among others (Chen et al., 2024). In India, the technology was introduced in 2001 by the International Maize and Wheat Improvement Center (CIMMYT) and the International Rice Research Institute (IRRI) along with national partners (Indian Council of Agricultural Research and State Agricultural Universities), with the primary objective to solve the issue of rapidly declining groundwater levels (Aryal et al., 2018). In the northern parts of India, rice was introduced as a major crop during the Green Revolution in the 1960s and is typically grown under submerged conditions, needing substantial amounts of irrigation water (Evenson and Gollin, 2003). The over-extraction of groundwater for agriculture in northwestern India has resulted in the region having the world's largest 'groundwater footprint', with potentially serious consequences for future agricultural production potentials (Jain et al., 2021).

Land levelling is an operation undertaken by farmers before growing a crop. It facilitates a more uniform distribution of water and fertilisers, which is essential for efficient input use and high yields (Jat et al., 2006; Chen et al., 2024). Proper land levelling is particularly important in rice-wheat systems in which flood irrigation is used and where a certain water depth must be maintained for rice cultivation (Jat et al., 2006; Nguyen-Van-Hung et al., 2022). Unlike the traditional approach of land levelling, namely to use wooden or iron planks, LLL technology is more precise: with its precision-guided system, LLL can achieve a smoother surface (± 2cm) (Jat et al., 2006). LLL technology consists of a tractor-mounted bucket scrapper with a receiver, a control box in the tractor, and an independent transmitter on a tripod (Figure A1 in the Appendix).

Purchasing LLL technology is costly, which is seen as an important adoption hurdle for smallholder farmers (Larson et al., 2016). One often-used policy strategy to address accessibility issues is to establish a system of renting out the technology through co-operatives. However, in northwestern India, LLL technology is mainly accessed through private service providers who are oftentimes farmers themselves (Aryal et al., 2018; Gulati et al., 2017). In Punjab and western Uttar Pradesh, the government under the Sub-Mission on Agricultural Mechanization, offers subsidies of about 80% and 50% to both co-operatives and individual farmers for purchasing LLL technology. These subsidies facilitated a rapid increase in the number of LLL machinery in Punjab and western Uttar Pradesh, from less than 1,000 in 2003 to more than 90,000 in 2015 (Sidhu et al., 2008; Jat et al., 2006; GoI, 2023). The strong demand for this technology has led to the designing, assembling, and local manufacturing of LLL machinery in the region (Paudel et al., 2023).

3. Theoretical background

The earliest literature explaining the adoption of indivisible technologies is the threshold model by David (1966). The threshold model assumes that farmers can adopt a technology only through own purchase; in this model, farmers will only adopt when they exceed a certain critical level of land holding. However, Feder et al. (1985) observed that the adoption of indivisible technologies by smallholders can also happen through rental services. Sunding and Zilberman (2001) proposed the generalised threshold model, addressing limitations of the traditional threshold model. The generalised threshold model considers that farmers are heterogeneous and that the adoption process is dynamic. It further assumes that technology adoption through renting can be a risk-reducing strategy. Building on the generalised threshold model, Lu et al. (2016) developed a framework accounting for heterogeneity in land size and conditions in which renting of technology by service providers emerges.

In their framework, Lu et al. (2016) hypothesise that farm size and land quality influence the threshold at which the decision to own or rent a technology becomes profitable for farmers. That is, farmers with small land holdings can access the technology by renting instead of purchasing it. In our study, we test this hypothesis empirically by exploring the relationship between the availability of rental services for the technology and farmers' LLL adoption. We expand the literature on the effect of rental services on technology adoption and – in this connection – also explore the role of land size.

4. Materials and methods

4.1 Study area, sampling, and data

We collected data from farmers in the regions of Punjab and western Uttar Pradesh in northwestern India. Both regions are known for their rapid depletion of groundwater resources (CGWB, 2021). The study sites encompass eight districts, including Ludhiana, Fatehgarh Sahib, Sangrur, and Patiala in Punjab, and Saharanpur, Baghpat, Shamli, and Muzaffarnagar in western Uttar Pradesh (Figure 1). We selected these districts purposively to reflect different conditions and cropping patterns. Punjab is known for its rice-wheat cropping system, whereas most farmers in western Uttar Pradesh practice a more diversified system, including sugarcane, rice, and wheat. Most previous work on LLL adoption and impacts focuses on the rice-wheat system alone (Aryal et al., 2015; Ali et al., 2018; Gulati et al., 2017; Larson et al., 2016; Lybbert et al 2018; Paudel et al., 2023).

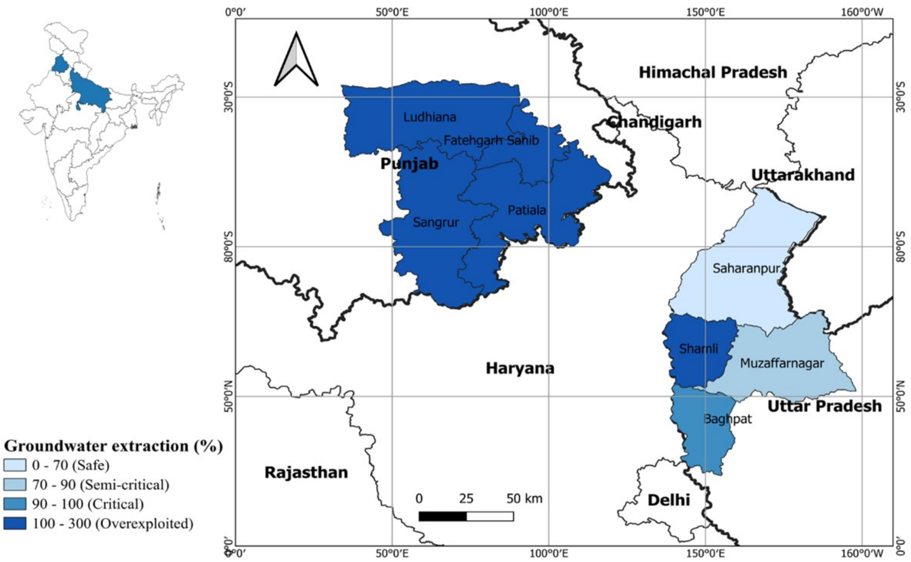


Figure 1: Map of study area showing groundwater extraction rates at the district level.

Source: Developed by authors based on data on groundwater extraction from the Central Ground Water Board (CGWB), Hyderabad, India.

The study districts in Punjab and western Uttar Pradesh share similar socioeconomic attributes, fall in the same climate zone (semi-arid temperate), and have similar soil characteristics. However, they differ in terms of irrigation policies and groundwater extraction levels. The Punjab Preservation of Subsoil Water Act of 2009 mandates delayed rice sowing in Punjab to conserve water (Tripathi et al., 2016). Such a policy is not in place in western Uttar Pradesh. Additionally, irrigation electricity tariffs vary between the two states; Punjab offers free irrigation electricity in eight-hour blocks, whereas western Uttar Pradesh applies a fixed rate based on pump horsepower (Sidhu et al., 2020). The study districts have different groundwater extraction rates. In Punjab, all four districts are classified as “overexploited”, whereas in western Uttar Pradesh, one is classified as “overexploited”, one as “critical”, one as “semi-critical”, and one as “safe” (Figure 1).

For the study, we conducted a survey of 1,661 farm households in the eight districts. In Punjab, the survey was implemented from June to August 2021, and in western Uttar Pradesh from October to December 2021. In the two states and eight districts, villages and farm households were selected randomly. In Punjab, we cover 52 villages and 1,021 farm households. In western Uttar Pradesh, we cover 32 villages and 640 farm households.

In each household, we carried out structured personal interview to collect detailed data on farm and household characteristics, the adoption of LLL technology at the plot level, perceived impacts of LLL, and the availability of service providers in the village or nearby. Detailed biophysical attributes of each plot and crop cultivation data for the two most recent seasons prior to the survey were also compiled. In addition, detailed input and output data were collected from all plots under cultivation by the sample households (a total of 3,369 plots).

4.2 Empirical framework

We use the farm household survey data to analyse LLL diffusion among farmers in Punjab and western Uttar Pradesh over time, as well as farmers’ perceptions about the impacts of this technology on crop yields, the use of water and other inputs, and crop profits. These analyses use simple descriptive statistics.

In addition, we use regression models to examine determinants of LLL adoption with a particular focus on the role of private service providers. For this, we estimate a probit model as follows:

$$P(Y_i = 1) = \Phi\ (\beta_0 +\ \beta_1 Service\ provider_i +\ \theta \boldsymbol{X}_{ik} +\ \mu_i) \qquad \text{(Eq.1)}$$

where $P(Y_i = 1)$ is the probability of LLL adoption on plot i. This binary outcome variable takes the value of one if the farmer used LLL on plot i in the season prior to the survey (2020/21), and zero otherwise. Note that we also run an alternative adoption model in which LLL was used in any of the three previous seasons, given that most farmers do not use LLL every year. The key explanatory variable is $Service\ provider_i$, which is the self-reported number of LLL service providers available within the village of the farmer cultivating plot i, or sufficiently nearby such that the LLL service could be used. The main coefficient of interest is β_1. A positive β_1 would support our first hypothesis (H1) that a larger number of service providers locally available leads to higher adoption of LLL. $\boldsymbol{X}_{ik}$, a vector of k control variables at the plot, household, and village level that may also influence LLL adoption (see details below). $\Phi(.)$ in Eq. (1) is the probability distribution function of the standard normal distribution.

Next, we are interested in understanding whether the availability of service providers has differential technology adoption effects for smaller and larger plots and farms. Specifically, we test the hypothesis (H2) that an increasing number of service providers locally available reduces possible differences in adoption between smaller and larger farms and plots. To test this hypothesis, we use the following two probit models with additional interaction terms:

$$P(Y_i = 1) = \Phi\,(\gamma_0 + \gamma_1 Plot\ size_i + \gamma_2 Service\ provider_i + \gamma_3\, Service\ provider_i \times Plot\ size_i + \Gamma \boldsymbol{X}_{ik} + \varepsilon_i) \quad \text{(Eq. 2)}$$

$$P(Y_i = 1) = \Phi\,(\delta_0 + \delta_1 Farm\ size_i + \delta_2 Service\ provider_i + \delta_3 Farm\ size \times Service\ provider_i + \Delta \boldsymbol{X}_{ik} + \varepsilon_i) \quad \text{(Eq. 3)}$$

In Eq. (2), we introduce $Plot\ size_i$ and an interaction term between $Plot\ size_i$ and $Service\ provider_i$. A positive (negative) coefficient γ_1 would indicate that LLL adoption is more (less) likely on larger plots. A positive (negative) interaction coefficient γ_3 would indicate that the effect of a larger number of LLL service providers is bigger (smaller) on large than on small plots. Eq. (3) follow the same structure but looks at farm size instead of plot size. Plot size and farm size are not the same, as most farms cultivate more than one plot.

In addition to looking at the individual coefficients of plot and farm size and the interaction terms in Eqs. (2) and (3), we also calculate the marginal effects of $Service\ provider_i$ on LLL adoption as follows:

$$\frac{\partial P(Y_i = 1)}{\partial Service\ provider_i} = \gamma_2 \Phi\,(\boldsymbol{X}_i) + \gamma_3 Plot\ area \Phi\,(\boldsymbol{X}_i) \quad \text{(Eq.4)}$$

$$\frac{\partial P(Y_i = 1)}{\partial Service\ provider_i} = \delta_2 \Phi\,(\boldsymbol{X}_i) + \delta_3 Total\ cultivated\ area_i\ \Phi\,(\boldsymbol{X}_i) \quad \text{(Eq.5)}$$

These marginal effects are calculated at the mean values of the covariates $\boldsymbol{X}_i$. We show these effects graphically for different numbers of service providers.

4.3 Control variables

The control variables ($\boldsymbol{X}_i$) used in our regression models are chosen based on the existing literature on LLL adoption (Ali et al., 2018; Aryal et al., 2018; Aryal et al., 2020; Sheikh et al., 2022). These variables, their units of measurement, and sample mean values are shown in Table 1. Roger (2003) suggests that the spread of innovation is affected by various social factors, such as gender, caste, and class, as well as societal norms. Ali et al. (2018) find evidence supporting this idea, demonstrating associations between various socioeconomic factors and the adoption of LLL. Aryal et al. (2018) highlight that farmers with more education tend to have better access to information about new technologies, making them more likely to adopt. The caste system, which still plays a significant role in India's social hierarchy, can either facilitate or hinder access to information, markets, and resources, thus also potentially affecting technology adoption (Krishna et al., 2019). Additionally, household wealth was shown to influence technology adoption, mostly in a positive way (Aryal et al., 2018). Such variables are also included in our regression models.

In terms of plot-level characteristics, we include soil type, slope, fertility, and waterlogging. Studies show that soil fertility and slope can influence the decision to adopt LLL and other water-conservation technologies significantly (Abdulai and Huffman, 2014; Ali et al., 2018; Aryal et al., 2018). Households facing water scarcity are also more likely to adopt LLL (Ali et al., 2018).

Table 2: Descriptive statistics of explanatory variables

Variable name	**Description**	**Mean (Std. deviation)**
Village-specific variables (n = 84)		
Share of adopters	Share of LLL adopters in the village (minus the household) in the reference year (2020-21)	0.28 (0.18)
Groundwater level	Groundwater depth at the village level (meters)	27.11 (12.04)
Crop diversity – Kharif	Crop diversity in the Kharif season (Simpson index[#])	0.32 (0.15)
Crop diversity – Rabi	Crop diversity in the Rabi season (Simpson index[#])	0.39 (0.16)
Distance to district HQ	Distance from village centre to district headquarters (km)	19.04 (16.81)
Household-specific variables (n = 1661)		
Age of HH	Age of the household head	53.48 (13.34)
Education of HH	Number of years of education of the household head	7.50 (4.68)
Non-marginalised caste	The household belongs to one of the non-marginalized castes (dummy)	0.69
Majority religion	The religion of the household is a major religion in the state (dummy)	0.59
Number of plots	The total number of plots cultivated by household	2.03 (1.17)
Farm size	Area cultivated by the household (ha)	5.43 (6.98)
Total adult members in the household	Number of adult members in the household	4.48 (1.78)
Women share	Share of adult women in the total number of adults in the household	0.46 (0.14)
Non-farm employment	A household member is employed in non-farm activities (dummy)	0.29
Asset index	Asset index estimated from 20 agricultural productive items	0.00 (1.73)
Service providers in 2020/21	Number of service providers the household has access to in 2020-21	2.30 (2.18)
Discount on first use of LLL	The household received a subsidy for the first event of adoption (dummy)	0.02
Access to information from (dummy)	The household accessed information in the last 12 months (2020-21) (dummy) from the given source	
	Government extension agency	0.38
	Krishi Vigyan Kendra or KVK	0.44
	Progressive farmer	0.64
	Non-Governmental Organisation or NGO	0.15
	Farmer collective	0.39
	Input dealer	0.65

Plot-specific variables (n = 3365)		
Plot size	The size of the plot (ha)	3.12 (3.20)
Service provider distance	Distance of plots from the LLL service provider (km)	2.87 (2.25)
Soil type	Soil type in the plot (dummy)	
	Clayey	0.33
	Loamy	0.65
	Sandy	0.02
Soil erosion	The plot is affected by soil erosion (dummy)	0.06
Waterlogging	The plot is affected by waterlogging (dummy)	0.10
Soil fertility	Soil fertility status in the plots (farmer assessment; dummy)	
	Low fertile	0.04
	Medium fertile	0.35
	High fertile	0.61
Crop in Kharif	Crops grown in the plot during the Kharif season (June to October) 2021 (dummy)	
	Non-Basmati rice	0.51
	Sugarcane	0.30
	Basmati rice	0.09
	Other crops	0.09
Western Uttar Pradesh	The plot is in western Uttar Pradesh (dummy)	0.50

Note: Further details with variables by state are shown in Table A1 in the Appendix. [#]Simpson index (SI) is calculated using the formula $SI = 1 - \sum P_i^2$, where P_i is the share of crop *i* in the total crop area (0 means full specialization and 1 means maximum diversification).

In terms of institutional factors, we consider various variables such as subsidies for first-time use of LLL and the availability of formal and informal extension services. Subsidies are measured as a binary variable, indicating whether or not any discounts are or were available for first-time users. Access to extension services, which offer training on various agricultural practices, is often linked to technology adoption (di Falco et al., 2011; Aryal et al., 2018). However, in India, Ali et al. (2018) found no significant relationship between access to extension services and LLL adoption. Finally, we include village-level characteristics, such as the diversity of crops grown during the Kharif (June to October) and Rabi (November to April) seasons and the distance of the village to the district headquarters.

5 Results and discussion

We start by exploring farmers' awareness and adoption of LLL technology descriptively. Then, we analyse farmers' perceptions about the effects of LLL technology, before presenting and discussing the regression results.

5.1 Awareness of the technology

LLL technology has gained widespread recognition in northwestern India, with 93% of the sample farmers in Punjab and 96% in western Uttar Pradesh being aware of it (Table A1 in the Appendix). This high level of awareness is largely due to various public-sector initiatives like field demonstrations and participatory research trials conducted in the past (Jat et al., 2006; Sidhu et al., 2008). Surveys conducted 15 years ago already indicated the presence of LLL technology in many villages across northwestern India, even though technology adoption was still limited at that time (Krishna et al., 2012). Today, LLL technology adoption is high. Of the farmers being aware of LLL technology, 84% in Punjab and 85% in western Uttar Pradesh had already used it at some point at the time of our survey. In Punjab, 4% of the farmers knowing LLL technology own the machinery themselves and also act as private service providers. In western Uttar Pradesh, only around 1% of the farmers reported to own LLL machinery themselves.

5.2 Adoption of the technology

In the survey, we asked farmers about when LLL and related services became first available in their villages and when they started using this technology themselves. Figure 2 shows that availability and adoption follow a parallel growth trend over time in both regions, whereby adoption occurs with a slight delay. This delay is consistent with Krishna et al. (2012), who showed that LLL technology was available in many villages in the late 2000s but not yet widely adopted at that time. Early adopters already used the technology back then, but more widespread adoption only started after 2010. Education programs spearheaded by the Department of Farm Power and Machinery of the Punjab Government, which began around 2007 and were then upscaled in later years, may have played some role for wider technology adoption. These education programs targeted farmers, machinery operators, and also leaders of local cooperative societies (Sidhu et al., 2008).

Table 2. Perceived impacts of LLL adoption on farming in northwestern India (share of adopters)

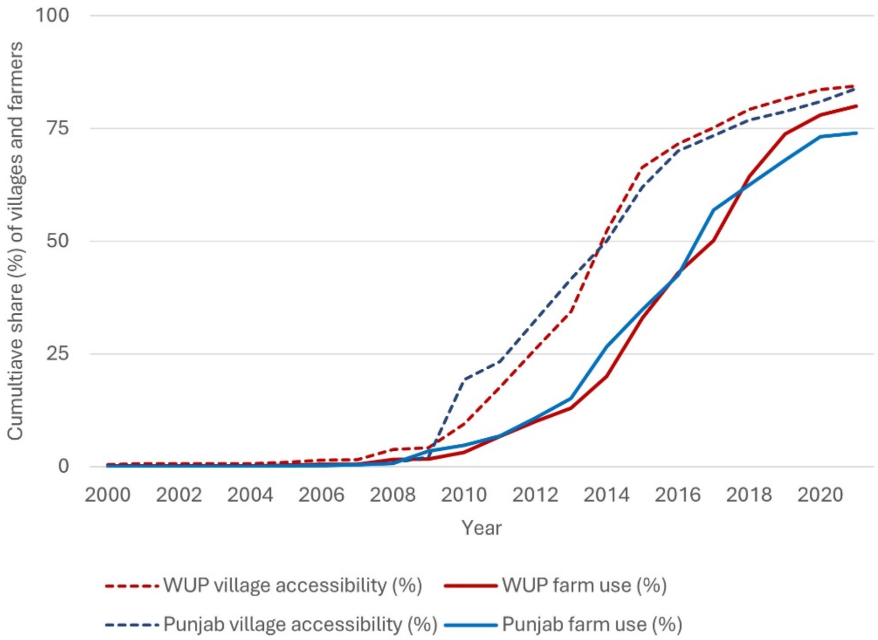


Figure 2: Cumulative share of LLL adopters in northwestern India, 2000-2020
Source: Primary data collected by authors (2021).
Note: WUP, western Uttar Pradesh

In Punjab, the majority of the LLL adopters use service providers from within the same villages, accounting for around 60% of the total (Table A2 in the Appendix). As mentioned, in western Uttar Pradesh fewer farmers own LLL machinery, so service providers often come from outside the village. In both regions, most of the service providers are private enterprises, mostly farmers themselves. Co-operative societies and larger custom hiring centres play some role for LLL services in other parts of India (Villalba et al., 2024), but their role in Punjab and western Uttar Pradesh is small. The reason is probably that many farmers in Punjab and western Uttar Pradesh own a tractor, so buying additional LLL equipment and also renting it or providing the service to others is easier than in regions where very few farmers own a tractor.

Rental charges for LLL machines and services have shown a consistent increase between 2018 and 2021 (Table A2 in the Appendix). In Punjab, the rental fee was Rs. 800 (~$11) per hour in 2021, slightly higher than the Rs. 750 (~$10) charged in western Uttar Pradesh. During the survey, respondents were also asked whether they received any discounts from service providers for their first-time use. While no public programs to subsidize LLL services were in place, 1-2% of the sampled farmers reported to have received such discounts for their initial use. Private service providers have their own pricing strategies and may offer discounts to increase their customer base. In their study in eastern districts of India, Lybbert et al. (2017) found that offering a first-hour service discount can be an effective strategy to increase the likelihood of LLL adoption among smallholders.

Figure 3. looks at the frequency of LLL use among sample farmers. Around 72% of the farmers in Punjab and 74% of the farmers in western Uttar Pradesh have used LLL at least once in their life. However, in Punjab the technology seems to be used more frequently: 63% of the farmers used the technology during the three years prior to the survey (2018-2021) and 37% used in in the last season (2020/21). These usage rates in Punjab are higher than those observed in western Uttar Pradesh (42% and 17%, respectively). One reasons for the less frequent use of LLL in western Uttar Pradesh is the widespread cultivation of sugarcane. Sugarcane is kept in the field for two years, the first year and the ratoon year, meaning that a crop rotation with either wheat or rice takes at least three years to complete. Other possible reasons may relate to differential impacts or perceived impacts of LLL technology, which we analyse below.

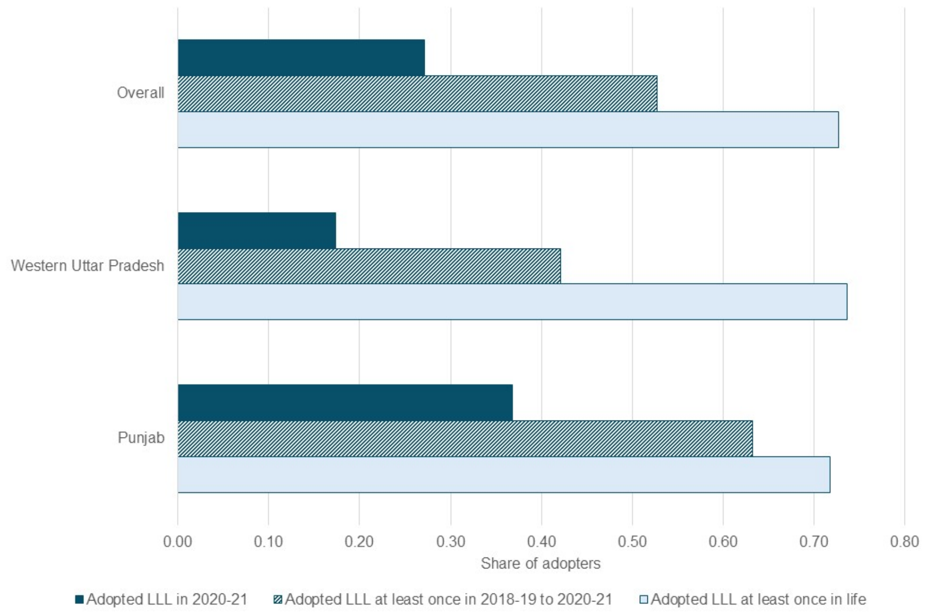


Figure 3. Share of LLL adopters based on the frequency of technology use.
Source: Primary data collected by authors (2021).

5.3 Farmers' perceptions of technology effects

In the survey, we also asked farmers about their perceptions of technology effects, especially on how LLL influences their farming operations, with a particular focus on their main Kharif season crops. These perceptions are summarised in Table 2, separately for Punjab and western Uttar Pradesh. Farmers' perceptions of LLL are quite positive, which is unsurprising given the high adoption rates and is also in line with previous research (Dessart et al., 2019). In both states, most farmers consider LLL to be yield- and income-increasing, and almost all farmers feel that the technology reduces the quantity of irrigation water use. These views are largely consistent with available impact research, suggesting that LLL can increase yields by about 5% and reduce irrigation water usage by 25% (Ali et al., 2018; Aryal et al., 2020; Larson et al., 2016; Lybbert et al., 2013; Pal et al., 2021; Sheikh et al., 2022). Field-trial results suggest that LLL-related yield gains in rice and wheat can even be higher (Jat et al., 2015).

Despite the positive overall perceptions of LLL in both Punjab and western Uttar Pradesh, some differences between the states can also be observed in Table 2. For instance, a greater proportion of farmers in Punjab (79%) than in western Uttar Pradesh (64%) reported increases in farm income due to LLL. In contrast, a higher percentage of farmers in western Uttar Pradesh (87%) than in Punjab (78%) reported grain yield increases. These differences suggest that there may be regional disparities not only in terms of perceptions but possibly also in terms of actual impacts of LLL technology, which could have an influence on regional adoption rates.

Table 2. Perceived impacts of LLL adoption on farming in northwestern India (share of adopters)

	Punjab (n = 755)				Western Uttar Pradesh (n = 344)			
Perceived effects of LLL adoption on:	Reduces	Increases	No change	Don't know	Reduces	Increases	No change	Don't know
Farm income	0.03	0.79	0.17	0.01	0.02	0.64	0.34	0.00
Grain yield	0.04	0.78	0.17	0.01	0.01	0.87	0.12	0.01
Cost of cultivation	0.26	0.53	0.20	0.00	0.38	0.27	0.34	0.00
Irrigation water use	0.94	0.05	0.01	0.00	0.98	0.01	0.02	0.00
Weed infestation	0.51	0.08	0.40	0.02	0.57	0.01	0.42	0.00
Burning of Kharif crop residue	0.32	0.31	0.35	0.02	0.28	0.01	0.70	0.02
Land use intensity	0.21	0.47	0.28	0.04	0.01	0.22	0.76	0.01

5.4 The role of service providers

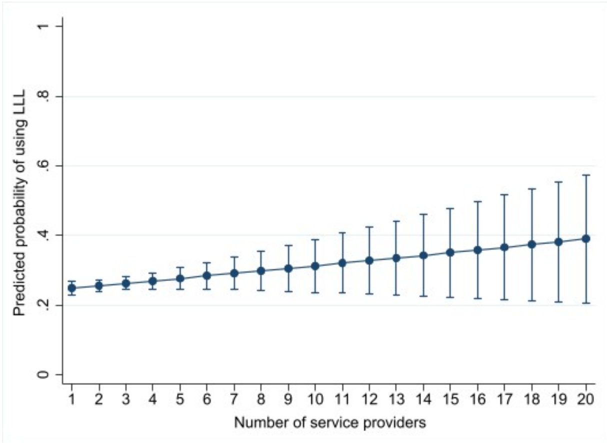
We now present and discuss the regression results, with a particular focus on how the availability of service providers influences farmers' LLL adoption. Results from the probit model explained in Eq. (1) above are summarised in Table 3, column (1). The number of LLL service providers in or nearby the individual farmer's village is positively associated with LLL adoption in 2020/21, even though the coefficient is not statistically significant. The marginal effects for different numbers of service providers are shown in Figure 4a. We see a slight increase in predicted adoption probability with an increasing number of service providers, yet with relatively large confidence intervals. These patterns suggest that the effects of service providers may be heterogenous, which we will further explore below.

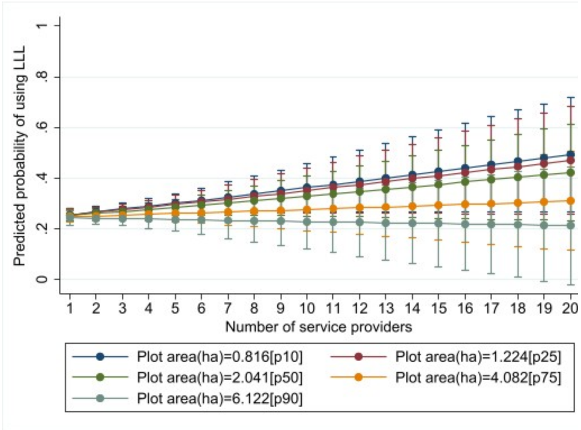
Table 3. Probit model on determinants of LLL adoption (2020/21)

	(1) Model 1	(2) Model 2	(3) Model 3
Service providers in 2020/21	0.021	0.040$^{**|\#}$	0.032$^{*|\#\#\#}$
	(0.014)	(0.019)	(0.017)
Plot size	-0.015	2.E-04$^{|\#}$	
	(0.010)	(0.014)	
Plot size x Number of service providers (interaction)		-0.007$^{\#}$	
		(0.005)	
Farm size			-0.013$^{**|\#\#\#}$
			(0.005)
Farm size x Number of service providers (interaction)			-0.003$^{\#\#\#}$
			(0.002)
Household-level controls	Yes	Yes	Yes
Plot-level controls	Yes	Yes	Yes
Village-level controls	Yes	Yes	Yes
Model intercept	-1.160***	-1.179***	-1.355***
	(0.373)	(0.374)	(0.375)
LR Chi^2	393.18***	395.37***	403.98***
Observations$^{\$}$	2,815	2,815	2,815
Marginal effects of the variables interacted			
Service providers in 2020/21	0.006	0.005	0.005
	(0.004)	(0.004)	(0.004)
Plot size	-0.005	-0.005*	
	(0.003)	(0.003)	
Farm size			-0.006***
			(0.002)

Note: *** shows significance at 1%, ** shows significance at 5%, and * shows significance at 10%. $^{\#\#\#}$ shows joint significance at 1%, and $^{\#}$ shows joint significance at 10%. $^{\$}$The analysis is based on plot-level data from Punjab and western Uttar Pradesh, excluding households owning LLL machinery themselves (124 plots). In western Uttar Pradesh, we dropped plots on which sugarcane ratoon crop was grown in 2020/21 because levelling cannot be done before the sugarcane ratoon crop (436 plots). Full model results are provided in Table A3 in the Appendix.

Relevant control variables were included in estimation with the more detailed results shown in Table A3 in the Appendix. Various socioeconomic variables are positively and significantly associated with LLL adoption, including involvement in non-farm employment, wealth (asset ownership), and discounts on the first-time use of LLL services. A few village-level variables are also positively associated with individual LLL adoption, namely the proportion of LLL adopters in the village and proximity to the district centre. These results are plausible and consistent with earlier research on LLL adoption in India (Aryal et al., 2015; Ali et al., 2018; Lybbert et al., 2018; Pal et al., 2021; Villalba et al., 2024). Most of the plot characteristics (e.g., soil type, soil fertility) and farmer characteristics (e.g., age, education) are not statistically significant.





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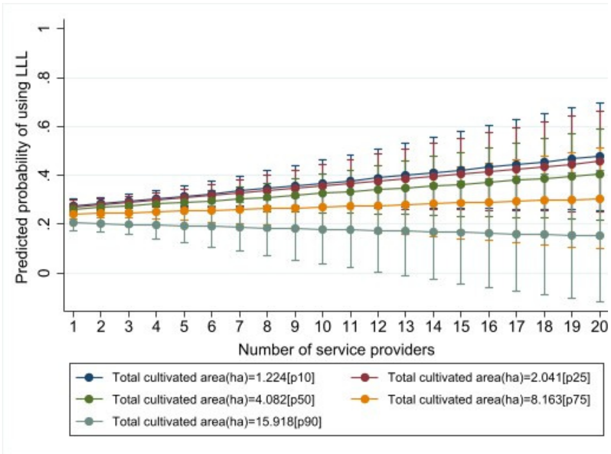

Figure 4. Marginal effects of the number of service providers on LLL adoption

Source: Estimated from regression models (1) to (3) in Table 3.

Note: Marginal effects calculated at sample mean values. Adjusted predictions with 95% confidence intervals. The vertical axis shows the predicted probability of LLL adoption. In panels b and c, predictions are shown for the 10th (p10), 25th(p25), 50th(p50), 75th(p75) and 90th(p90) percentile values of plot size and farm size, respectively.

5.5 Heterogenous effects of service providers

As explained, we are also interested in understanding whether the local availability of service providers has differential effects on LLL adoption by plot and farm size. The results from the probit models explained in Eqs. (2) and (3) are summarised in Table 3, columns (2) and (3). In model (2), we include plot size and an interaction term between plot size and the number of service providers locally available. Both variables are not significant individually, but they are jointly significant with the number of service providers. In model (2), the effect of the number of service providers is now also significant and larger than in model (1), suggesting the following interpretation: when controling for plot size and interaction effects, the number of service providers locally available influences LLL adoption positively. Further, the negative interaction term coefficient suggests that the positive adoption effect of service providers decreases with increasing plot size, or, in other words, the service provider effect is larger on small plots than on large plots.

To provide more clarity, using the estimates from model (2), we plot the marginal effects of service provision on adoption for different plot sizes in Figure 4b. As can be seen, the number of service providers has a larger positive effect on LLL adoption on smaller plots than on larger plots. In other words, the proliferation of service providers in the local contexts makes the technology more accessible to farmers with small plots. These results support our hypotheses H1 and H2.

Model (3) in Table 3 (column 3) and Figure 4c show alternative estimates where farm size (area cultivated) is used instead of plot size. The effects are consistent with those of model (2). The number of service providers is positively and significantly associated with LLL adoption, but the negative interaction term coefficient suggests that this effect is primarily observed among smaller farms. Interestingly, farm size as such has a significantly negative association with LLL adoption, meaning that larger farms are somewhat less likely to adopt LLL technology than smaller farms. This negative association may be related to larger farms already having higher yields and easier access to irrigation water, which would lower the marginal benefits of LLL and thus decrease their incentives to adopt. However, a more detailed analysis of the impacts of LLL on small and large farms is beyond the scope of this study and would deserve further scrutiny in follow-up research.

The analysis in Table 3 captures the determinants of LLL adoption in 2020/21, corresponding to the last season prior to the survey. However, even adopters do not use LLL technology in every season. The frequency of LLL use depends on several local agroecological factors (Nyugen-Van-Hung et al., 2022). In Table 4, we estimate the same probit models but now redefining the adoption variable to look at LLL use in any of the three years prior to the survey (2018/19 to 2020/21). The findings in Table 4 are similar to those in Table 3. When controling for plot size and farm size, the number of service providers has a positive effect on LLL adoption, especially among the smaller farms and those with smaller plos. These results underscore the importance of customizing agricultural support services to the specific needs of different farm sizes.

Table 4. Probit model on determinants of LLL adoption in at least one of the previous three years (2018/19-2020/21)

	(1) Model 1	(2) Model 2	(3) Model 3
Service providers in 2020/21	-0.003	0.013#	0.024###
	(0.012)	(0.016)	(0.015)
Plot size	0.018**	0.030***|#	
	(0.008)	(0.011)	
Plot size x Number of service providers (interaction)		-0.006#	
		(0.004)	
Farm size			0.010***|###
			(0.004)
Farm size x Number of service providers (interaction)			-0.005***|###
			(0.002)
Household-level controls	Yes	Yes	Yes
Plot-level controls	Yes	Yes	Yes
Village-level controls	Yes	Yes	Yes
LR Chi^2	521.34***	523.73***	527.66***
Observations$	3,237	3,237	3,237
Marginal effects of the variables interacted			
Service providers in 2020/21	-0.001	-0.002	-0.004
	(0.004)	(0.004)	(0.004)
Plot size	0.006**	0.006**	
	(0.003)	(0.003)	
Farm size			8.E-05
			(0.001)

Note: *** shows significance at 1%, ** shows significance at 5%, and * shows significance at 10%. ### shows joint significance at 1%, and # shows joint significance at 10%. $The analysis is based on plot-level data from Punjab and western Uttar Pradesh, excluding households owning LLL machinery themselves (124 plots). Full model results are provided in Table A4 in the Appendix.

6 Summary and conclusion

In this article, we have used LLL as an example to better understand how private service providers can facilitate inclusive dissemination of indivisible technologies among smallholder farmers with fragmented plots. We have analysed how improved access to LLL renting services, measured by the number of service providers locally available either in the village or nearby, influences individual technology adoption and use. We hypothesised that (H1) a larger number of service providers would lead to more adoption, and that (H2) this effect would also and especially be observed for small farms and small plots. The study results confirm these two hypotheses. Our regression estimates show that the number of service providers is positively associated with the likelihood of LLL adoption and that the marginal effect of service providers is larger on small farms and plots than on large farms and plots. In other words, small farms and plots benefit over-proportionally from better access to LLL service provision. Important to note is that the service providers in northwestern India are predominantly private enterprises, mostly farmers themselves.

Our findings presents a compelling case for re-evaluating traditional agricultural technology scaling models to include individual service providers for broader and more inclusive adoption. From a policy perspective, policies that promote transparent service provision in competitive rental markets can therefore help to foster smallholder-inclusive technological change. More generally, our results suggest that an institutional environment that accommodates the specific needs of different types of farms can enhance broad-based innovation in the small farm sector, thus contributing to sustainable productivity growth and environmental efficiency.

A few limitations of our study should be mentioned. First, our regression estimates show associations between the number of service providers and LLL adoption, which should not be interpreted as rigorously-identified causal effects. Second, the results from northwestern India cannot simply be generalized to other countries and regions. In Punjab and western Uttar Pradesh, many farmers own a tractor, which facilitates the purchase of LLL equipment and the emergence of competitive rental markets. The ramifications may be different in settings where most farmers do not own a tractor. Third, while LLL is an indivisible technology, its characteristics may be peculiar. For instance, LLL is typically not used by farmers every year, so farmers who own the machinery are particularly interested to also rent it out to others for more efficient use. Follow-up research with data from other regions and referring to other types of technologies may be useful to further add to our understanding of how the adoption of indivisible technologies in the small farm sector can be promoted through suitable institutional mechanisms.

References

Abdulai, A., Huffman, W. 2014. The adoption and impact of soil and water conservation technology: An endogenous switching regression application. Land Economics. 90(1), 26-43. https://www.jstor.org/stable/24243729

Ali, A., Hussain, I., Rahut, D.B., Erenstein, O. 2018. Laser-land leveling 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. https://doi.org/10.1016/j.foodpol.2018.03.018

Aryal, J. P., Rahut, D. B., Jat, M. L., Maharjan, S., Erenstein, O. 2018. Factors determining the adoption of laser land leveling in the irrigated rice-wheat system in Haryana, India. Journal of Crop Improvement. 32(4), 477–492. https://doi.org/10.1080/15427528.2018.1457584

Aryal, J.P., Khatri-Chhetri, A., Sapkota, T.B., Rahut, D.B., Erenstein, O. 2020. Adoption and economic impact of laser land levelling in the irrigated rice-wheat system in Haryana, India using endogenous switching regression. Natural Resource Forum. 44, 255-273. https://doi.org/10.1111/1477-8947.12197

Aryal, J.P., Mehrotra, M.B., Jat, M.L., Sidhu. H.S. 2015. Impacts of laser land leveling in rice–wheat systems of the north– western Indo-Gangetic plains of India. Food Security. 7(3), 725–738. https://doi.org/10.1007/s12571-015-0460-y

Bailey, A., Williams, N., Palmer, M., Gerring, R., 2000. The farmer as service provider: The demand for agricultural commodities and equine services. Agricultural System. 66(3), 191-204. https://doi.org/10.1016/S0308-521X(00)00047-0

CGIAR Research Program on Rice. 2019. Laser land leveling in Indonesia, Philippines, Myanmar, Sri Lanka. Reported in Rice Annual Report 2019. Innovations. https://hdl.handle.net/10568/122417

CGWB, 2021. Department of water resources, river development, and Ganga rejuvenation. Central Ground Water Board (CGWB), Ministry of Jal Shakti, Government of India. https://cgwb.gov.in/

Chen, G., Hu, L., Luo, X., Wang, P., He, J., Huang, P., Zhao, R., Feng, D., Tu, T. 2024. A review of global precision land-levelling technologies and implements: Current status, challenges, and future trends. Computer and Electronics in Agriculture. 220, 108901. https://doi.org/10.1016/j.compag.2024.108901

Daum, T., Villalba, R., Anidi, O., Mayienga, S.M., Gupta, S., Birner, R. 2021. Uber for tractors? Opportunities and challenges of digital tools for tractor hire in India and Nigeria. World Development. 144: 105480. https://doi.org/10.1016/j.worlddev.2021.105480

David, P.A. 1966. The mechanization of reaping in the Ante-bellum Midwest. In industrialization in two Systems: Essays in honor of Alexander Gershenkron, ed. H. Rosovksy, 3–39. New York: Wiley.

Dessart, F.J., Barrerio-Hurle, J., van Bavel, R. 2019. Behavioural factors affecting the adoption of sustainable farming practices: A policy-oriented review. European Review of Agricultural Economics. 46(3), 417-471. https://doi.org/10.1093/erae/jbz019

di Falco, S., Veronesi, M., Yesuf, M. 2011. Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. American Journal of Agricultural Economics, 93(3), 825–842. https://doi.org/10.1093/ajae/aar006

Evenson, R.E., Gollin, D. 2003. Assessing the impact of the Green Revolution, 1960 to 2000. Science, 300(5620), 758–762. https://www.science.org/doi/10.1126/science.1078710

Feder, G., Just, R.E., Zilberman, D. 1985. Adoption of agricultural innovations in developing countries: A survey. Economic Development and Cultural Change. 33(2), 255-298. https://www.jstor.org/stable/1153228

GoI (Government of India). 2023. Agricultural Input Survey 2015-16. Department of Agriculture and Farmers Welfare. Ministry of Agriculture and Farmers Welfare, India. https://inputsurvey.dacnet.nic.in/databasehome.aspx

Gulati, K., Lybbert, T.J., Spielman, D.J. 2017. Diffusing to level fields: Evolution of laser land leveling technology markets in India. Agricultural and Applied Economics Association Annual Meeting, Chicago, Illinois, July 30- August 1, 2017. https://ageconsearch.umn.edu/record/258387/files/AAEA%202017_Gulati.pdf

Hu, Y., Li, B., Zhang, Z., Wang, J. 2022. Farm size and agricultural technology progress: Evidence from China. Journal of Rural Studies. 93, 417-429. https://doi.org/10.1016/j.jrurstud.2019.01.009

Ishtiaque, A. Krupnick. T.J., Krishna, V.K., Uddin, M.N., Aryal, J.P., Srivastava, A.K., Kumar, S., Shahazad, M.F., Bhatt, R., Gardezi, M., Bahinipati, S.S., Nazu, S.B., Ghimire, R., Anik, A.R., Sapkota, T.B., Ghosh, M., Sudebi, R., Sardar, A., Uddin, K.M.Z., Khatri-Chhetri, A., Rahman, M.S., Balwinder-Singh., Jain, M. (2024). Overcoming barriers to climate-smart agriculture in South Asia. Nature Climate Change. https://doi.org/10.1038/s41558-023-01905-z

Jain, M., Fishman, R., Mondal, P., Galford, G. L., Bhattarai, N., Naeem, S., Lall, U., Balwinder-Singh, DeFries, R. S. 2021. Groundwater depletion will reduce cropping intensity in India. Science Advances, 7, eabd2849. https://www.science.org/doi/10.1126/sciadv.abd2849

Jat, M.L., Singh, Y., Gill, G., Sidhu, H., Aryal, J. P., Stirling, C., Gerard, B. 2015. Laser assisted precision land leveling: Impacts in irrigated intensive production systems of South Asia.

In Lal, R., and Stewart, B. A. (Eds.). Advances in soil science. 323–52. Boca Raton, FL: CRC Press, Taylor and Francis Group. https://www.taylorfrancis.com/chapters/mono/10.1201/b18759-17/laser-assisted-precision-land-leveling-impacts-irrigated-intensive-production-systems-south-asia-rattan-lal-stewart

Jat, M.L., Chandna, P., Gupta, R., Sharma, S.K., Gill, M.A. 2006. Laser land leveling: A precursor technology for resource conservation. Rice-Wheat Consortium Technical Bulletin Series 7. New Delhi, India: Rice-Wheat Consortium for the Indo-Gangetic Plains. pp 48. http://www.knowledgebank.irri.org/csisa/images/FactsheetsAndReferences/Techbulletins/lasertechbull.pdf

Krishna, V. V., Aravalath, L. M., Vikraman, S. 2019. Does caste determine farmer access to quality information? PLoS ONE, 14(1). https://doi.org/10.1371/journal.pone.0210721

Krishna, V., Mehrotra, M.B., Teufel, N., Bishnoi, D.K. 2012. Characterizing the cereal systems and identifying the potential of conservation agriculture in South Asia. Socio-Economics Program Working Paper 5. Mexico, D.F.: CIMMYT. https://repository.cimmyt.org/handle/10883/1357?show=full

Larson, N., Sekhri, S., Sidhu, R. 2016. Adoption of water-saving technology in agriculture: The case of laser levelers. Water Resources and Economics, 14, 44–64. https://doi.org/10.1016/j.wre.2015.11.001

Lu, L., Reardon, T., Zilberman, D. 2016. Supply chain design and adoption of indivisible technology. American Journal of Agricultural Economics. 95(5), 1419-1431. https://doi.org/10.1093/ajae/aaw076

Lybbert, T. J., Magnan, N., Bhargava, A. K., Gulati, K., Spielman, D. J. 2013. Farmers' heterogeneous valuation of laser land leveling in eastern Uttar Pradesh: An experimental auction to inform segmentation and subsidy strategies. American Journal of Agricultural Economics. 95(2), 339–345. https://doi.org/10.1093/ajae/aas045

Lybbert. T.J., Magnan, N., Spielman, D.J., Bhargava, A.K., Gulati, K. 2018. Targeting technology to increase smallholder profits and conserve resources: Experimental provision of laser land-leveling services to Indian farmers. Economic Development and Cultural Change. 66(2), 265–306. https://www.journals.uchicago.edu/doi/10.1086/695284

Nguyen-Van-Hung, Balingbing, C., Sandro, J., Khandai, S., Chea, H., Songmethakrit, T., Meas, P., Hitzler, G., Zwick, W., Viriyangkura, L., Bautista, E., Gummert, M. 2022. Precision land levelling for sustainable rice production: case studies in Cambodia, Thailand, Philippines, Vietnam, and India. Precision Agriculture. 23, 1633-1652. https://link.springer.com/article/10.1007/s11119-022-09900-8

Pal, B.D., Kapoor, S., Saroj, S. 2021. Adoption of climate-smart agriculture technology in drought-prone area of India – implications on farmers' livelihoods. Journal of Agribusiness in Developing and Emerging Economics, 12(5), 824-848. https://doi.org/10.1108/JADEE-01-2021-0033

Paudel, G. P., Khanal, A. R., Rahut, D. B., Krupnik, T. J., McDonald, A. J. 2023. Smart precision agriculture but resource constrained farmers: Is service provision a potential solution? Farmer's willingness to pay for laser-land leveling services in Nepal. Smart Agricultural Technology, 3, 100084. https://doi.org/10.1016/j.atech.2022.100084

Roger, E.M. 2003. Diffusion of Innovation. 5th Edition. Free Press, New York, NY.

Ruzzante, S., Bilton, A. 2021. Adoption of agricultural technologies in the developing world: A meta-analysis dataset of the empirical literature. Data in Brief, 38 (October 2021), 107384. https://doi.org/10.1016/j.worlddev.2021.105599

Ruzzante, S., Lavarta, R., Bilton, A. 2021. Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature. World Development, 146, 105599. https://doi.org/10.1016/j.worlddev.2021.105599

Schut, M., Leeuwis, C., Thiele, G. 2020. Science of scaling: Understanding and guiding of innovation for societal outcomes. Agricultural Systems. 184: 102908. https://doi.org/10.1016/j.agsy.2020.102908

Sheikh, A.T., Mugera, A., Pandit, R., Burton, M., Davies, S. 2022. The adoption of laser land leveller technology and its impact on groundwater use in irrigated farm lands in Punjab, Pakistan. Land Degradation and Development. https://doi.org/10.1002/ldr.4290

Sidhu, B.S., Kandlikar, M., Ramankutty, N. 2020. Power tariffs for groundwater irrigation in India: A comparative analysis of the environmental, equity, and economic tradeoffs. World Development. 128: 104836. https://doi.org/10.1016/j.worlddev.2019.104836

Sidhu, H.S., Mahal, J.S., Dhaliwal, I.S., Bector, V., Singh, M., Sharda, A., Singh, T. 2008. Chapter 8. Tractor operated laser land leveler. In: Singh, S. (Ed). Success stories. Coordinating Cell, AICRP on Farm Implements and Machinery, Central Institute of Agricultural Engineering, Nabi Bagh, Berasia Road, Bhopal-462 038, India.

Sunding, D., Zilberman, D. 2001. The agricultural innovation process: Research and technology adoption in a changing agricultural sector. In Handbook of Agricultural Economics, ed. B. Garner and G. Rausser, 207–61. New York: Elsevier. https://doi.org/10.1016/S1574-0072(01)10007-1

Tripathi, A., Mishra, A.K., Verma, G. 2016. Impact of preservation of subsoil water Act on groundwater depletion: The case of Punjab, India. Environmental Management, 58(1), 48-59. https://doi.org/10.1007/s00267-016-0693-3

Van Loon, J., Woltering, L., Krupnik, T.J., Baudron, F., Boa, M., Govaerts, B. 2020. Scaling agricultural mechanization services in smallholder farming system: Case studies from sub-Saharan Africa, South Asia, and Latin America. Agricultural Systems. 180, 102792. https://doi.org/10.1016/j.agsy.2020.102792

Villalba, R., Joshi, G., Daum, T., Venus, T.E. 2024. Financing climate-smart agriculture: A case study from Indo-Gangetic Plains. Mitigation Adaptation Strategies for Global Change. 29,33. https://doi.org/10.1007/s11027-024-10127-3

Appendix

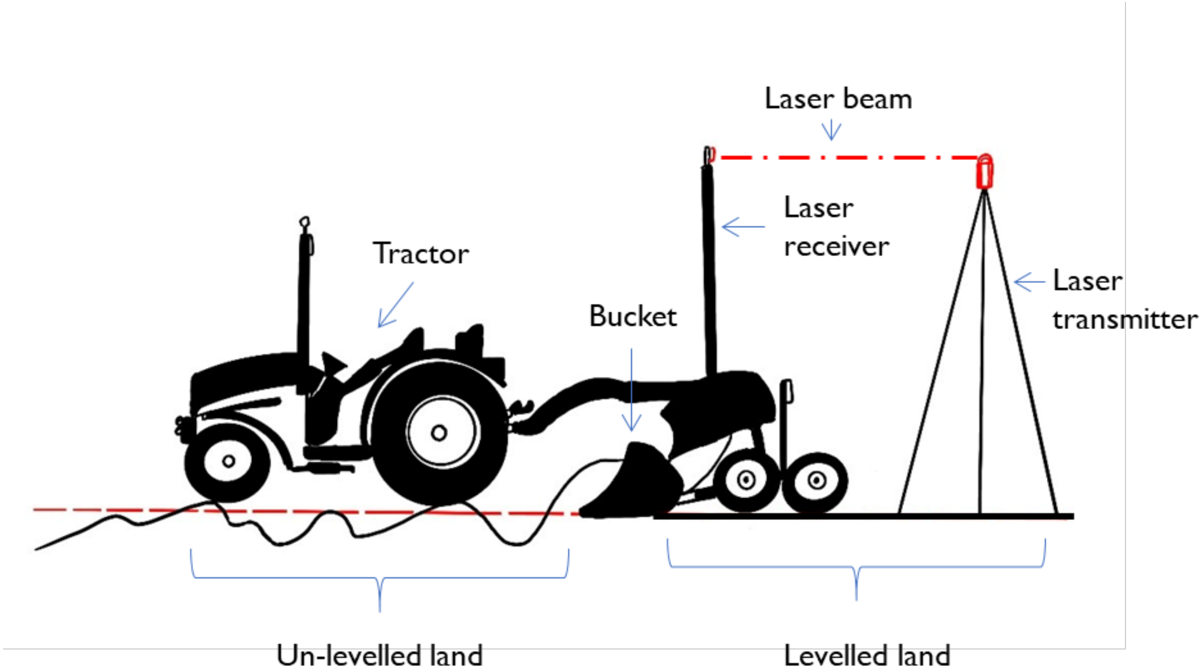

Figure A1. Laser land levelling technology

Source: Created by authors

Note: The technology consists of a tractor-mounted bucket scrapper with a receiver, a control box in the tractor, and an independent transmitter on a tripod. The transmitter transfers signals as a laser beam (which is why the technology is called laser land leveller) to the receiver attached to the bucket scrapper, which removes or adds soil using a hydraulic system. The tractor operator can further adjust the levels using the control box in the tractor. See Rickman (2002) for more details. For a video animation, see: https://www.youtube.com/watch?v=kRAwyr6oK7Q

Table A1. Knowledge and adoption of LLL in northwestern India (% of farmers)

	Status	**Punjab (rice-wheat system)**	**Western Uttar Pradesh (sugarcane-rice/wheat system)**
1	Heard of technology, but don't know how it works	2.63	0.33
2	Know how it works, but I have never seen it working	0.32	0.17
3	Know how it works and have seen it in field demonstrations	1.26	0.66
4	Know how it works and have seen it in other farmers' fields	10.85	13.79
5	User/non-service-provider	79.56	84.05
6	User/service-provider	4.11	0.83
7	Non-user/service-provider	0.95	0.00
8	Others	0.32	0.17
	Heard about laser land levelling[$]	**92.94**	**94.06**
	Used the technology (row no. 5+6)	**83.67**	**84.88**

Note: Rows numbered 1 to 8 are calculated based on the respondents who know about the technology (Punjab N=949; western Uttar Pradesh N=616). [$]Calculated based on household level sample data (Punjab N =1021; western Uttar Pradesh N=640). Used the technology refers to adoption at least once any time in the past.

Table A2. LLL technology trends in northwestern India (2018-2021)

LLL usage characteristics	**Punjab (rice-wheat system)**				**Western Uttar Pradesh (sugarcane-rice/wheat system)**			
	2018	2019	2020	2021	2018	2019	2020	2021
User (% of farmers)								
Before Kharif	87.15	85.49	93.07	91.88	87.79	83.44	82.89	84.81
Before Rabi	12.15	13.99	6.93	7.81	12.21	16.56	17.11	15.19
Both before Kharif and Rabi	0.69	0.50	0.00	0.31	0.00	0.00	0.00	0.00
Service provider (% of farmers)								
Own	3.82	4.15	4.82	5.63	2.91	0.00	5.26	5.06
Relative	2.08	1.04	2.11	1.25	0.00	0.00	0.00	1.27
Village	62.5	58.55	65.06	57.19	26.74	26.49	39.47	34.18
Outside village	29.51	32.64	25.9	34.69	70.35	73.51	55.26	59.49
Co-operative	2.08	3.11	2.11	1.25	0.00	0.00	0.00	0.00
Mean number of service providers locally available	1.67	1.72	1.66	2.15	2.05	2.48	2.47	2.44
Mean rental charge (Indian Rupees)	698.0	723.2	774.3	801.8	650.9	664.9	717.4	747.2

Note: Calculated based on the sub-sample of adopters (Punjab N =755; western Uttar Pradesh N=510).

Table A3. Probit model on determinants of LLL adoption (2020/21, full model results)

	(1) Model 1	(2) Model 2	(3) Model 3
Service provision and interaction variables			
Service providers in 2020-21	0.021	$0.040^{**\mid\#}$	$0.032^{*\mid\#\#\#}$
	(0.014)	(0.019)	(0.017)
Plot size	-0.015	$2.E\text{-}04^{\mid\#}$	
	(0.010)	(0.014)	
Plot size x Number of service providers (interaction)		$-0.007^{\#}$	
		(0.005)	
Farm size			- $0.013^{**\mid\#\#\#}$
			(0.005)
Farm size x Number of service providers (interaction)			$-0.003^{\#\#\#}$
			(0.002)
Household-level variables			
Age of HH	-0.004	-0.004	-0.003
	(0.002)	(0.002)	(0.002)
Education of HH	0.006	0.006	0.008
	(0.006)	(0.006)	(0.006)
Non-marginalised caste	0.063	0.061	0.065
	(0.083)	(0.083)	(0.083)
Majority religion	-0.164	-0.160	-0.158
	(0.170)	(0.170)	(0.170)
Total adult members in the household	0.009	0.008	0.014
	(0.015)	(0.015)	(0.015)
Women share	-0.001	-0.001	-2.94E-04
	(0.002)	(0.002)	(0.002)
Non-farm employment	0.291***	0.287***	0.317***
	(0.080)	(0.080)	(0.080)
Asset index	0.093***	0.095***	0.105***
	(0.021)	(0.021)	(0.021)
Number of plots	-0.002	-0.003	0.022
	(0.024)	(0.024)	(0.025)
Discount on first use of LLL	0.755***	0.759***	0.785***
	(0.190)	(0.190)	(0.192)
Access to information from			
Government extension agency	0.093	0.092	0.105
	(0.065)	(0.065)	(0.065)
KVK	0.049	0.048	0.040
	(0.064)	(0.064)	(0.065)
Progressive farmer	-0.029	-0.029	-0.027
	(0.060)	(0.060)	(0.060)

NGO	0.029	0.030	0.021
	(0.084)	(0.084)	(0.085)
Farmer collective	-0.090	-0.094	-0.089
	(0.061)	(0.061)	(0.061)
Input dealer	0.029	0.030	0.032
	(0.068)	(0.068)	(0.068)
Plot-level characteristics			
Service provider distance	-0.010	-0.010	-0.010
	(0.013)	(0.013)	(0.013)
Soil type (reference: clay)			
Loamy	-0.008	-0.010	-0.011
	(0.063)	(0.063)	(0.063)
Sandy	-0.055	-0.060	-0.043
	(0.170)	(0.170)	(0.170)
Soil fertility (reference: low fertile)			
Medium fertile	-0.073	-0.074	-0.051
	(0.145)	(0.145)	(0.145)
High fertile	-0.090	-0.091	-0.072
	(0.138)	(0.138)	(0.138)
Soil erosion	0.161	0.154	0.153
	(0.116)	(0.117)	(0.117)
Water logging	0.069	0.071	0.076
	(0.087)	(0.087)	(0.087)
Crop in Kharif (reference: Basmati rice)			
Non-Basmati rice	0.126	0.131	0.151
	(0.136)	(0.136)	(0.136)
Sugarcane	0.220*	0.215*	0.226*
	(0.116)	(0.116)	(0.116)
Others	0.036	0.046	0.053
	(0.130)	(0.130)	(0.129)
Western Uttar Pradesh	-0.269	-0.269	-0.165
	(0.238)	(0.238)	(0.240)
Village level characteristics			
Groundwater level	2.01E-04	1.59E-04	2.51E-04
	(0.001)	(0.001)	(0.001)
Crop diversity – Kharif	-0.131	-0.143	-0.126
	(0.254)	(0.255)	(0.255)
Crop diversity – Rabi	-0.017	-0.018	-0.018
	(0.270)	(0.270)	(0.270)
Share of adopters	0.023***	0.023***	0.023***
	(0.002)	(0.002)	(0.002)
Distance to district HQ	0.002	0.001	0.002
	(0.002)	(0.002)	(0.002)
Model intercept	-1.160***	-1.179***	-1.355***
	(0.373)	(0.374)	(0.375)

LR Chi^2	393.18***	395.37***	403.98***
Observations$^{\$}$	2,815	2,815	2,815

Note: *** shows significance at 1%, ** shows significance at 5%, and * shows significance at 10%. $^{\#\#\#}$ shows joint significance at 1%, and $^{\#}$ shows joint significance at 10%. $^{\$}$The analysis is based on plot-level data from Punjab and Western Uttar Pradesh, excluding households owning LLL machinery themselves (124 plots). In Western Uttar Pradesh, we dropped plots in which sugarcane ratoon crop was grown in 2020/21 because levelling cannot be done before the sugarcane ratoon crop (436 plots).

Table A4. Probit model on LLL adoption in at least one of the previous three years (2018/19 to 2020/21, full model results)

	(1) Model 1	(2) Model 2	(3) Model 3
Service provision and interaction variables			
Service providers in 2020/21	-0.003	0.013$^{\#}$	0.024$^{\#\#\#}$
	(0.012)	(0.016)	(0.015)
Plot size	0.018**	0.030$^{***\|\#}$	
	(0.008)	(0.011)	
Plot size x Number of service providers (interaction)		-0.006$^{\#}$	
		(0.004)	
Farm size			0.010$^{***\|\#\#\#}$
			(0.004)
Farm size x Number of service providers (interaction)			-0.005$^{***\|\#\#\#}$
			(0.002)
Service provider distance	0.016	0.015	0.014
	(0.011)	(0.011)	(0.011)
Household-level variables			
Age of HH	-0.005***	-0.005***	-0.005***
	(0.002)	(0.002)	(0.002)
Education of HH	0.010*	0.010*	0.010*
	(0.005)	(0.005)	(0.005)
Non-marginalised caste	0.074	0.072	0.074
	(0.066)	(0.066)	(0.066)
Majority religion	0.049	0.051	0.052
	(0.171)	(0.171)	(0.171)
Total adult members in the household	0.002	0.001	0.001
	(0.012)	(0.012)	(0.013)
Women share	-0.003*	-0.003*	-0.003*
	(0.002)	(0.002)	(0.002)

Non-farm employment	0.176***	0.172***	0.172***
	(0.063)	(0.063)	(0.063)
Asset index	0.140***	0.140***	0.148***
	(0.020)	(0.020)	(0.020)
Number of plots	-0.044**	-0.045**	-0.059***
	(0.019)	(0.019)	(0.020)
Discount on first use of LLL	1.019***	1.017***	1.010***
	(0.230)	(0.230)	(0.232)
Access to information from			
Government extension agency	0.070	0.072	0.066
	(0.057)	(0.057)	(0.057)
KVK	-0.105*	-0.106*	-0.094*
	(0.056)	(0.056)	(0.056)
Progressive farmer	-0.040	-0.041	-0.050
	(0.055)	(0.055)	(0.055)
NGO	0.092	0.092	0.085
	(0.075)	(0.075)	(0.076)
Farmer collective	0.102*	0.100*	0.100*
	(0.053)	(0.053)	(0.053)
Input dealer	0.137**	0.138**	0.138**
	(0.066)	(0.066)	(0.066)
Plot-level characteristics			
Service provider distance	0.016	0.015	0.014
	(0.011)	(0.011)	(0.011)
Soil type (reference: clay)			
Loamy	0.018	0.013	0.006
	(0.057)	(0.057)	(0.057)
Sandy	0.050	0.044	0.039
	(0.167)	(0.167)	(0.168)
Soil fertility (reference: low fertile)			
Medium fertile	0.068	0.070	0.074
	(0.124)	(0.124)	(0.125)
High fertile	0.052	0.054	0.057
	(0.119)	(0.119)	(0.119)
Soil erosion	0.167	0.163	0.160
	(0.102)	(0.102)	(0.102)
Water logging	0.105	0.108	0.122
	(0.080)	(0.080)	(0.080)
Crop in Kharif (reference: Basmati rice)			
Non-Basmati rice	0.233**	0.237**	0.225*
	(0.118)	(0.118)	(0.118)
Sugarcane	-0.064	-0.068	-0.076
	(0.092)	(0.092)	(0.092)
Others	-0.110	-0.106	-0.143
	(0.110)	(0.110)	(0.109)
Western Uttar Pradesh	0.352	0.354	0.376*

	(0.223)	(0.223)	(0.225)
Village level characteristics			
Groundwater level	0.004***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)
Crop diversity – Kharif	0.349	0.330	0.349
	(0.220)	(0.221)	(0.220)
Crop diversity – Rabi	-0.249	-0.245	-0.278
	(0.250)	(0.250)	(0.251)
Share of adopters	0.023***	0.023***	0.023***
	(0.002)	(0.002)	(0.002)
Distance to district HQ	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)
Model intercept	-1.130***	-1.142***	-1.085***
	(0.340)	(0.340)	(0.342)
LR Chi^2	521.34***	523.73***	527.66***
Observations$	3,237	3,237	3,237

Note: *** shows significance at 1%, ** shows significance at 5%, and * shows significance at 10%. ### shows joint significance at 1%, and # shows joint significance at 10%. $The analysis is based on plot-level data from Punjab and Western Uttar Pradesh, excluding households owning LLL machinery themselves (124 plots).