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RESEARCH ARTICLE

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The adoption of laser land leveler technology and its impact on groundwater use by irrigated farmland in Punjab, Pakistan

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Abstract

This paper investigates the factors that influence the adoption of laser land levelers and their impact on groundwater usage in the Punjab Province of Pakistan. A farm household survey of 504 agriculture producers was conducted in 2019. A discrete-time duration model is used to investigate factors influencing the speed of adoption and an endogenous switching regression (ESR) model is used to evaluate its impact on groundwater usage. About 70% of the surveyed households adopted the technology, and the average time to adoption was 9 years. Key factors accelerating the speed of adoption include strong legal land rights, access to information about the technology, and exposure to the technology. In contrast, long distance to rental market deaccelerates the speed of adoption. The adoption of laser land leveler reduced groundwater use by about 23%. The results imply that institutional arrangements, such as improving access to extension services, exposure to innovation, and legal land rights, can enhance the adoption and diffusion of the technology and conserve groundwater.

KEYWORDS
land management, laserland leveler, discrete-timeduration model, endogenous switching regression, propensityscore matching

1 | INTRODUCTION

Improving the productivity of water resources is essential for ensuring the sustainability of surface water and groundwater used for irrigation in South Asia (Rasul, 2014). This is particularly important given the projected increase in irrigation water demand due to the increasing population, which increases the demand for food produced in these arid and semi-arid regions already facing rising temperatures and variable precipitation (Sivakumar & Stefanski, 2010). The South Asian region is heavily dependent on groundwater for irrigation (Rasul, 2016), and has seen rapid groundwater depletion (Taylor et al., 2013) and increased soil salinity (Shah et al., 2008). Mishra et al. (2016) note that the livelihood of millions of people would be affected by water stress, scarcity, and frequent droughts in the Indo-Gangetic Plains of South Asia. Therefore, farmers in South Asia are under pressure to adopt water-saving technologies in order to ensure the sustainability of food, water, and energy security for future generations (Rasul, 2016).

Highly efficient irrigation technologies, such as drip-irrigation, were introduced in South Asia in the 1980s (Hasanain et al., 2019) to reduce the amount of water used for irrigation. However, their adoption has remained low due to high upfront investment costs, high operational costs, and a lack of knowledge about the technology (Reid Bell et al., 2020). Surface irrigation water loss can be minimized through reasonable land care and better farm-level management practices (Ali, 2011).

Experimental evidence from wheat–rice systems in the Indo-Gangetic Plains has shown that about 10%–25% of irrigation water is lost due to unlevelled fields and poor agronomic practices, resulting in uneven water distribution across farm plots (Kahlown et al., 2000). Uneven farm plots can increase weed growth that reduces crop production, increase irrigation costs, and decreases resource-use efficiency (Jat et al., 2006; Rickman, 2002). A simple agronomic remedy is leveling fields using a laser land leveler (LLL), a climate-smart technology (Gill, 2014) for flattening uneven farmland leading to less than 20 mm variation (Ali et al., 2018). This practice helps ensure the equal distribution of water in the field (Abdullaev et al., 2007) and is necessary for water and soil conservation (Rickman, 2002).

Many experimental and non-experimental studies have identified the direct and indirect benefits of adopting LLL. Direct benefits include improved water application efficiency and productivity (Abdullaev et al., 2007; Ali et al., 2018; Anantha et al., 2021; Aryal et al., 2015; Asif et al., 2003; Bhatt et al., 2021; Hoque & Hannan, 2014; Jat et al., 2006; Jat et al., 2009; Ram et al., 2018; Rizwan et al., 2018; Sattar et al., 2003) and reduced runoff and deep percolation (Abdullaev et al., 2007; Jat et al., 2006; Jat et al., 2009; Sattar et al., 2003). Indirect benefits include energy cost savings (i.e., diesel fuel cost of operating a tube-well), reduced greenhouse gas emissions, enhanced fertilizer use efficiency, improved seed germination, and increased crop yields and crop income (Abdullaev et al., 2007; Aryal et al., 2015; Bhatt et al., 2021; Hoque & Hannan, 2014; Jat et al., 2009; Khatri-Chhetri et al., 2020; Rezaei-Moghaddam & Tohidyan Far, 2019; Rickman, 2002; Rizwan et al., 2018). Environmental benefits due to improved surface drainage include controlling waterlogging, salinity (Miao et al., 2021), and soil erosion (González et al., 2009; Miao et al., 2021; Rezaei-Moghaddam & Tohidyan Far, 2019; Tohidyan Far & Rezaei-Moghaddam, 2020). However, some studies have reported negative impacts of LLL on the soil aeration function, crop root growth (Brye et al., 2005), and crop yield (Walker et al., 2003).

Despite the overall benefits and widespread promotion of LLL through agricultural development programs, its adoption has remained modest in India and Pakistan, with rates of about 55% and 57% (Ali et al., 2018; Aryal et al., 2020). The adoption of LLL is expected to increase the net returns from wheat and rice crops in India by 22% and 34% (Aryal et al., 2020) and by about 27% for both rice and wheat in Pakistan (Ali et al., 2018).

Only a few empirical studies in India and Pakistan have investigated the factors influencing farmers' decisions to adopt LLL technologies (Ali et al., 2018; Aryal et al., 2018; Aryal et al., 2020; Pal et al., 2021) and the associated direct impacts on farm performance (i.e., water conservation as measured by the reduction in the number of irrigations applied to wheat and rice crops) (Ali et al., 2018). These studies suggest that the modest rate of LLL adoption in India and Pakistan could be attributed to factors such as household demographics, farm location, stocks of human, economic and social capital, land tenure status, household wealth, access to markets and credit, expectations about the return on investment, and farm outlays. Only one non-experimental study in India adopted a multi-stage approach that simultaneously models the decision to adopt LLL and its adoption intensity (Aryal et al., 2018).

Prior studies have not examined the timing of LLL adoption. Adoption is often a multi-stage decision-making process that includes decisions on when to trial a new technology, when to adopt, and adoption intensity (Åstebro, 2004). Past studies only employed a static model to investigate adoption at a single period using cross-sectional survey data (Ali et al., 2018; Aryal et al., 2018; Aryal et al., 2020; Pal et al., 2021), without considering factors that might influence the timing of the adoption event. However, duration models can be used to investigate the timing of the adoption event. Unlike binary models, duration models use pseudo panel data that can control for time-varying factors (Burton et al., 2003; Jenkins, 2005; Khataza et al., 2018). Investigating the determinants of the timing of the adoption decision of LLL technology using duration analysis could provide evidence-based and context-specific policies on how to accelerate the speed of LLL technology adoption.

Our study investigates the factors that influence the speed of adoption of LLL technology and its impact on the amount of groundwater applied to wheat crops in three irrigated agro-ecological zones in the Punjab Province of Pakistan (hereafter 'Punjab'). Our study contributes to the literature on agricultural innovation adoption in three ways: (1) it documents the factors affecting the speed of adoption of LLL; (2) it evaluates the diffusion of LLL technology under different subsidy regimes that provide a deeper understanding of potential pathways used to promote the uptake of innovations and agricultural development; and (3) it provides empirical evidence of the impact of technology adoption on groundwater conservation in wheat production, which is important for addressing the problems of increasing water scarcity, soil salinity, and declining groundwater tables in the Punjab Province.

1.1 | Promotion of laser land-leveling technology in Pakistan

The LLL technology was introduced by the Government of Punjab in 1985 to increase surface water irrigation efficiency (Government of Punjab, 2012). The Provincial Government started to promote LLL technology in 2001 under the District Devolution Plan, where it distributed 86 LLL units to District Governments. The District Governments added 40 more LLL units to improve service delivery at the district level. A subsidy scheme dubbed "Strengthening of Laser Land Leveling Services in the Punjab, Pakistan" was implemented by the Provincial Government between 2005 and 2008, distributing 2500 LLL units to farmers and LLL service providers at 50% subsidy (Government of Punjab, 2012). Between 2012 and 2016, under the "Punjab Irrigated Agriculture Productivity Improvement Project" funded by the World Bank, the Provincial Government distributed 5000 LLL units to farmers at the same subsidy rate (50%). Between 2016 and 2018, an additional 4000 LLL units were distributed to farmers at the same subsidy rate under the Annual Development Plan (personal communication with Directorate of On-farm Water

Management, 2021). Therefore, the Provincial Government provided 11,500 LLL units to farmers and LLL service providers under various funding schemes between 2005 and 2018.

The different funding schemes had similar selection criteria for farmer eligibility for subsidies: the land manager had to own a tractor, own not more than 5 hectares[1] of land, and agree to provide LLL rental services to the community at a minimum of 121.5 hectares per unit annually during the scheme period (i.e., 2005–2008 or 2012–2018). All subsidy schemes promoted rental services in the province and subsidy beneficiaries were expected to recoup their investment costs by renting out the machinery to other farmers (Hasanain et al., 2019).

2 | MATERIAL AND METHODS

2.1 | Study sites and data descriptive statistics

A farm household survey was conducted in the Punjab Province from April to June 2019, using a multi-stage stratified sampling procedure to select farm households (Sheikh et al., 2022). First, three agro-ecological zones were purposively selected, representing the irrigated areas of Punjab, namely: (i) rice-wheat zone, (ii) maize–wheat–mix zone, and (iii) cotton–mix zones (adopted from Ahmad et al., 2019). Second, one representative district was selected randomly from within each agro-ecological zone: Hafizabad, Jhang, and Bahawalnagar. The government distributed 35 LLL units in Hafizabad, 105 in Jhang, and 139 in Bahawalnagar from 2005 to 2008, and 193 units in Bahawalnagar, 184 in Jhang, and 116 in Hafizabad from 2012 to 2018. Third, in consultation with the Deputy Director of the Agriculture Extension Department, two *tehsils* were purposively chosen within each selected district—one with a relatively high salt-affected area and the other with relatively normal soil properties. Fourth, in each *tehsil*, two Union Councils (UCs) (administrative unit of a district) were purposively selected. Fifth, in each UC, two *mouzas*were purposively chosen. Sixth, one village was selected randomly from each *mouza* (revenue village) is an administrative unit of a district); and 21 farm households were selected randomly from each village as sample farm households. In total, 504 farm households were interviewed for the survey. Figure 1 shows the distribution of selected districts in Punjab.

Data were collected using a structured questionnaire through face-to-face interviews with land managers. Information was collected from farm households that managed or cultivated agricultural plots

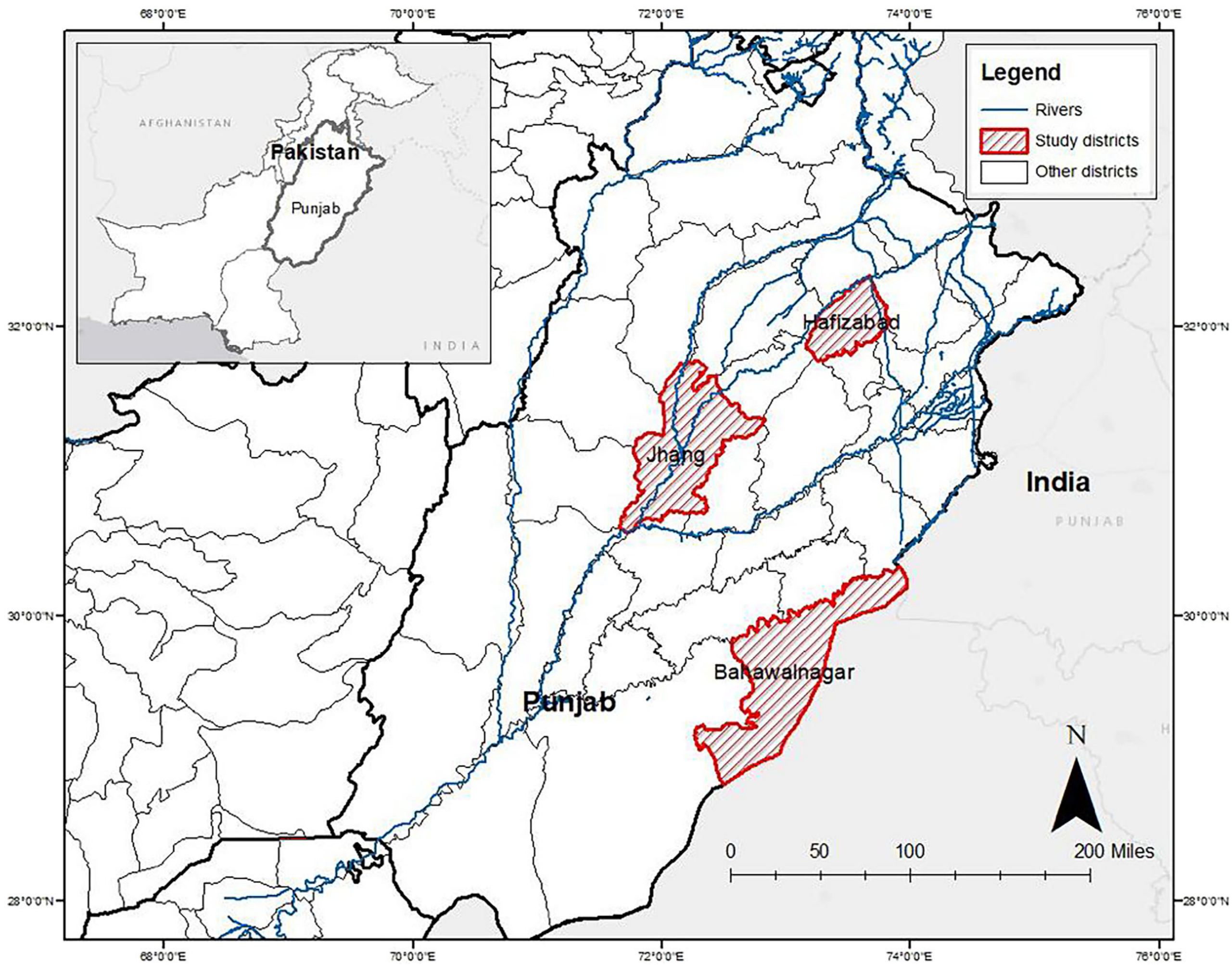

FIGURE 1 Map of the study areas in Punjab, Pakistan [Colour figure can be viewed at wileyonlinelibrary.com]

during the 2018–2019 cropping seasons: *Kharif* (summer season) 2018 and *Rabi* (winter season 2019). One section of the questionnaire was designed to capture information on the adoption of soil and water conservation technologies, including the LLL technology. Land managers were asked when they first adopted LLL technology, their future aspirations pertaining to its use, how they gained awareness of the technology, and their farm area under LLL technology in the current period. The descriptive statistics of the policy variables used in the empirical analysis and their mean differences between adopters and non-adopters of LLL are presented in Table A1.

Of the total households surveyed, about 70% (353 farm households) adopted LLL technology (Table A1). The mean adoption time[2] based on land managers' recall is about 9 years, with a minimum of one year. The intensity of adoption indicated that, of those defined as adopters, on average, land managers committed 65% of their current (i.e., 2018–2019 survey period) farm acreage to LLL technology. That is, most land managers had integrated LLL technology into their existing agronomic practices and passed the trialing phase, which is consistent with the adoption definition of Loevinsohn et al. (2013). Figure 2 shows the cumulative distribution of LLL adopters by year. The adoption pattern indicates considerable uptake of LLL technology during the 2012–2018 subsidy periods.

The age and education of adopters and non-adopters did not statistically differ, but adopters had more farming experience than non-adopters did. Land managers had acquired information about LLL technology through various sources including: (1) extension services and water management directorates; (2) peer progressive farmers and agricultural input dealers in the village; and (3) friends and relatives. About 30% of adopters had acquired information about LLL technology from extension services and water management directorates, 21% from peer progressive farmers and agricultural input dealers in the village, and 49% from friends and relatives. About 59% of LLL adopters had strong legal land entitlements (i.e., *Fard-e-malkiat*[3] *and Intaqalnama*).

Family labour was used as a proxy for labour availability. The availability of family labour could decrease the speed of LLL adoption because it can be used to level farm plots manually. Family labor engaged in farm operations is converted into adult equivalent units (AEU)[4] (Khataza et al., 2018). The average family labour available for adopters in the sample was 2.22. Most adopters were close to LLL rental markets with an average distance of 7 km. There was no significant difference in land managers' perception of groundwater quality and groundwater cost (m^3ha^{-1}) between adopters and non-adopters. However, wheat yields significantly differed between adopters and non-adopters. Following Bundervoet (2010), tropical livestock units (TLU) were computed to convert the herds found on farms to a common unit to account for heterogeneity across livestock classes using $TLU_i = \sum n \times \omega_{li}$, where ω_{li} is the weightage of the l livestock class[5] owned by land manager i, and n is the total number of livestock in a particular class. On average, adopters had about 4.4 TLU units, with no significant difference between adopters and non-adopters.

Following Watto and Mugera (2015), the volume of groundwater withdrawal (m^3) was estimated using an approximation equation:

$$GW_i = \frac{t_i \times 129{,}574.1 \times BHP_i}{\left[\left(d_i + (255.5998 \times BHP_i^2)/d_i^2 \times DM_i^2\right)\right]}, \quad (1)$$

where GW_i denotes the quantity of groundwater extracted in litres by the ith land manager and applied to wheat crop, t_i is total groundwater irrigation time (hours), BHP_i is engine power (horsepower), d_i is

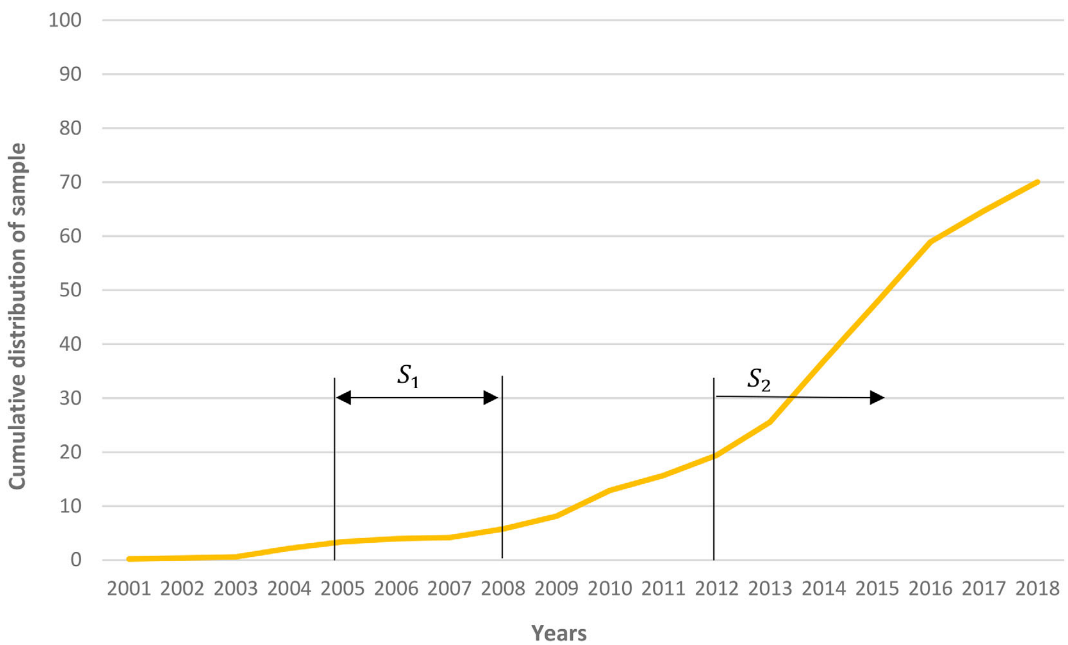

FIGURE 2 Cumulative distribution of the number of adopters. S_1 is the 2005–2008 subsidy scheme; S_2 is the 2012–2018 subsidy scheme [Colour figure can be viewed at wileyonlinelibrary.com]

reported bore depth (meter), and DM_i is suction pipe diameter (inches). Finally, GW_i is divided by 1000 to convert litres to m^3. The result shows that the amount of groundwater applied to wheat significantly differed between adopters and non-adopters.

2.2 | Theoretical framework

With LLL adoption, land managers anticipate deriving indirect observable private benefits (i.e., increased yield or net income, reduced irrigation requirement) and direct unobservable private benefits (i.e., environmental benefits such as reduced soil salinity, reduced soil erosion risk, and improved groundwater security). The random utility theory (McFadden, 1973) can be used to model the choices encountered by land managers when deciding to adopt LLL technology or not. Alcon et al. (2011) explicitly explain the dynamic nature of the adoption process that allows a distinction between early and late adopters, which is not possible when the adoption decision is considered at a point in time (Ali et al., 2018; Aryal et al., 2020). In a dynamic adoption process, land managers learn about the technology (i.e., its appropriateness, compatibility with existing farmland conditions, institutional factors that influence its adoption, and expected net benefits) over time and then make a discrete decision to adopt at a particular time. Under the random utility framework, the expected utility for the ith land manager in any production year p_t from the adoption of LLL technology can be represented as $\pi_{ai}(p_{it})$, which is compared to the expected utility without adoption ($\pi_{nai}(p_{it})$). The ith land manager will adopt in the production year p_t if the expected utility (benefit) from adopting is greater than the utility of not adopting, that is, $D_i^* = [\pi_{ai}(p_{it}) - \pi_{nai}(p_{it})] > 0$. Here D_i^* is the expected net utility by the ith land manager in production year p_t. However, each land manager's adoption decision varies as they anticipate benefits differently, which are contingent on their socio-economic conditions (S), farm characteristics (F), institutional factors (I), and the region's natural endowments (R). The probability of the ith land manager adopting LLL technology (P_i) when they expect positive net utility ($D_i^* > 0$) is expressed as:

$$P_i = f(S,F,I,R). \tag{2}$$

A discrete-time duration function was used to model the key determinants influencing the speed of LLL technology adoption. From the adoption of LLL, land managers can expect reductions in needed groundwater for wheat crops, reducing the extraction cost to land managers and producing environmental benefits such as reducing soil salinity, minimizing soil erosion risk, and improving groundwater security.

2.3 | Empirical framework

2.3.1 | Discrete-time duration model of the technology adoption

Duration analysis (DA) has been used widely to study the adoption or dis-adoption of agricultural technologies, considering time as a continuous or discrete variable. Duration models analyze the length of time taken before an event occurs. However, events are often intrinsically discrete (adopt or not adopt) in agriculture, as land managers do not use technology continuously over the production season. The discrete intervals are usually reported in integer years, making the discrete time duration model more suitable to examine the dynamic nature of the adoption process (An & Butler, 2012; Burton et al., 2003). A few studies have used the discrete-time duration framework to model the dynamic nature of the adoption process. Some examples include the adoption of recombinant bovine somatotropin (rbST) in dairy production in California (An & Butler, 2012), conservation agriculture in Malawi (Khataza et al., 2018), organic agriculture in the UK (Burton et al., 2003), burley tobacco in the US (Tiller et al., 2010), drip-irrigation in southeastern Spain (Alcon et al., 2011), acacia plantation by smallholders in Indonesia (Permadi et al., 2018), and survival of registered farms in Italy (Bassi et al., 2010).

The discrete-time duration model is used to characterize the time until an event occurs, which in our context explains the transition from a state of non-adoption of LLL to a state of actual adoption of the technology. This is the duration (T) from when the LLL technology was introduced by the government and made accessible to farmers to the time when individual farmers adopt it. In this study, the beginning of the duration is early 1985, when LLL technology was introduced and made accessible to land managers. The time ends when the land manager adopted the LLL technology at time t. If a land manager had not adopted the practice by 2018, when the study was conducted, the duration is referred to as right-censored (Jenkins, 2005).

Let the discrete adoption time be a random year $T \geq 0$, representing a length of time before adoption, while t is the time at which the actual technology adoption occurs, which can be represented by the probability density function $f(t)$. The survival function $(S(t))$ defines the probability that adoption will not be realized until time, t, that is, $S(t) = \Pr(T \geq t) = 1 - F(t)$. The hazard function, $h(t)$, evaluates the likelihood of adoption of a given technology, which is the conditional probability that a land manager who had not yet adopted LLL technology, chooses to adopt it in the period, dt. It can be expressed as (Alcon et al., 2011):

$$h(t) = \lim_{dt \to 0}\left[\frac{\Pr(t \leq T < t+dt \mid T \geq t)}{dt}\right] = \lim_{dt \to 0}\frac{F(t+dt) - F(t)}{dt(1-F(t))} = \frac{f(t)}{S(t)}. \tag{3}$$

In the parametric hazard model specification, the most common specification used to augment the effects of both baseline hazard and covariates on a hazard function, commonly known as the proportional hazard (PH) model, is expressed as follows (Jenkins, 2005):

$$h(t|X,\beta) = h_0(t).\exp(X\beta'), \tag{4}$$

Where: $h(t|X,\beta)$ is hazard rate at time t; $h_0(t)$ is a baseline hazard function that is time-dependent and common to all land managers in the sample, while $\exp(X\beta')$ is a relative hazard conditional on covariates and varies for each land manager given their heterogeneous conditions. β is a vector of unknown parameters to be estimated that characterizes the distribution function of the hazard rate. In the parametric continuous-time DA, the baseline hazard function, h_0, commonly follows either an exponential or Weibull distribution, whereas either logistic or complementary log-log specification for discrete-time DA (Jenkins, 2005).

In our study, the hazard function [Equation (4)] is parameterized using a complementary log-log specification (clog–log) because it is the discrete-time equivalent of the continuous-time PH model (Jenkins, 2005; Rabe-Hesketh & Skrondal, 2008). The log [−log(.)] transformation of multiplicative function [Equation (4)] into a linear functional form is specified as follows:

$$\ln[-\ln(1-h(t,X))] = h_0(t)\exp[X(t)\beta + e_i] = \alpha\gamma_t + X\beta' + e_i, \quad (5)$$

Where: $h(t,X)$ is the hazard rate for the tth time interval; X is a vector of covariates which consist of cross-sectional data and time-varying covariates, γ_t is a time-variable summarizing the pattern of duration dependence (baseline hazard), α and β are the parameters to be estimated. All coefficients are computed in terms of hazard ratios (HR) which are reported in the exponential form ($e^{\beta'}$). The coefficient is interpreted as a proportional shift in the hazard function to a unit change in the explanatory variable (Beyene & Kassie, 2015). An HR greater (less) than one implies a positive (negative) impact on the probability of LLL adoption (Khataza et al., 2018). The significance of the exponential form is relative to one (i.e., the null hypothesis of HR testing for p-values different from one).

Moreover, e_i is a random error term representing unobserved farm household specific characteristics. It is assumed that the error term is uncorrelated with X. The presence of unobserved heterogeneity can lead to biased estimates of duration dependence. To account for the unobserved heterogeneity, we include the error term in Equation (5), which is assumed to be normally distributed with zero mean and finite variance σ^2 (Jenkins, 2005). The random error term e_i can be interpreted as the impact of the unobserved factors influencing the hazard ratio. In the discrete-time DA model, the gamma error distribution is commonly used (Alcon et al., 2011).

The maximum likelihood estimation method is used to estimate Equation (5) using the discrete-time DA. Following Jenkins (2005), the data is organized into a person-time format for each farm household. To estimate the duration hazard model, the dependent variable is dichotomous, with a value of 1 if adoption has taken place in time $t \le T$. In this scenario, it consists of a sequence of zeros (since the introduction of the technology in 1985) terminating when the adoption takes place with a value of 1 in the termination year. If the land manager had not adopted LLL technology at the end of the survey year 2018 ($T > t$). In this case, a sequence of zeros will occur from the introduction of LLL technology until the end of the study period. Discrete-time DA can incorporate time-varying (e.g., subsidy schemes) and time-invariant variables in the model that can influence the dependent variable. The variables used in the discrete-time DA model are reported in Table A1.

2.3.2 | Endogenous switching regression

In a non-randomized experimental situation like the adoption of LLL technology, one would expect that the adoption is not random, which could lead to selection bias when considering the outcomes of adoption. This non-random nature of sample selection makes it difficult to directly compare the mean outcomes (i.e., groundwater use) of adopters and non-adopters. In the presence of selection bias, traditional ordinary least squares and t-tests can produce misleading and inconsistent results. To account for this, we estimate an endogenous switching regression (ESR) that addresses the selection bias problem arising from unobservable heterogeneities in the sample data (Abdulai, 2016; Di Falco et al., 2011; Lokshin & Sajaia, 2004; Ma & Abdulai, 2016; Shiferaw et al., 2014). The detailed specification of the two-stage ESR model is in Appendix I. In the current study, we are interested in the direct impact of the LLL technology on groundwater usage, especially the average treatment effects (ATT). Only those farm households who used groundwater to irrigate wheat during 2018–2019 were considered. To evaluate the impact of LLL adoption on the volume of groundwater applied to the wheat crop (m^3ha^{-1}), the observed and unobserved counterfactual outcomes for LLL adopters can be estimated (Lokshin & Sajaia, 2004) as follows:

Adopters of LLL technology (observed):

$$E\left[GW_i^a|L_i=1\right] = \delta_i^a Z_i + \sigma_\mu^a \lambda_i^a. \quad (6.1)$$

Adopters of LLL technology (counterfactual):

$$E\left[GW_i^{na}|L_i=1\right] = \delta_i^{na} Z_i + \sigma_\mu^{na} \lambda_i^a, \quad (6.2)$$

Where: GW_i indicates the volume of groundwater extracted in liters by the ith land manager to irrigate the wheat crop[6] for both adopters (GW_i^a) and non-adopters (GW_i^{na}). In a counterfactual scenario, if the adopters chose not to adopt the LLL technology, what would be the average volume of groundwater applied to wheat crops (m^3ha^{-1})? (The counterfactual is implemented by using data associated with the adopters, but the coefficients associated with non-adopters). In this case, the average treatment effect on treated farms (those adopting LLL) (Lokshin & Sajaia, 2004) to estimate unbiased effects is written as:

$$ATT = E\left(GW_i^a \mid L_i=1\right) - E\left[GW_i^{na}|L_i=1\right] = Z_i\left(\delta_i^a - \delta_i^{na}\right) + \lambda_i^a\left(\sigma_\varepsilon^a - \sigma_\varepsilon^{na}\right). \quad (7)$$

2.3.3 | Propensity score matching (PSM)

We also use the PSM method to check the robustness of our findings from the ESR model by estimating the counterfactual and average treatment effects on treated farm households. The PSM approach minimizes the bias arising from two systematically different groups, addressing the problem of self-selection (Rajeev & Sadek, 2002; Rosenbaum & Rubin, 1983). The PSM is a three-stage process: (1) a parametric binary response model is used to calculate propensity scores for each farm household; (2) a matching method is used to match each adopter with a non-adopter with a similar propensity score, with all unmatched farm households discarded (Rajeev & Sadek, 2002). We used the NNM (nearest-neighbor matching) and KBM (kernel-based matching) matching techniques (Caliendo & Kopeinig, 2008); (3) the matching quality is inspected, with the average treatment effect estimated if the matching quality is acceptable; if not, steps two and three are repeated using a different matching method. The volume of applied groundwater saved (m^3)ha^{-1} is the outcome of interest in this study.

3 | RESULTS

The results of the speed of LLL technology adoption are presented in Table 1, and the determinants of LLL adoption are presented in Table 2. The ATT in terms of volume of groundwater (m^3)ha^{-1} applied to wheat crops are presented in Table 3. All models were estimated using STATA 15 software.

3.1 | Effect of covariates on speed of adoption

We use the clog–log model to estimate the HR with robust standard errors (Table 1). The effects of unobserved heterogeneity were also tested for and reported. The likelihood ratio test shows that the estimated variance parameter (σ^2) is statistically insignificant implying that unobserved heterogeneity is not present; so, the null hypothesis of $\sigma^2 = 0$ is not rejected.

The information acquisition from extension services, water management directorates, progressive farmers, and agricultural input dealers have HRs > 1 and are highly significant ($p < 0.05$) compared to information acquired through friends and relatives, suggesting that information is crucial for accelerating the speed of LLL adoption. The distance to LLL rental market has an HR < 1, implying that a greater distance to LLL rental markets increases the time to adoption. Secure and legal land rights (i.e., *Fard-e-Malkiat* and *Inteqalnama*) have a statistically significant HR > 1, indicating that having strong land property rights accelerates the speed of LLL adoption. The variable for customary rights has an HR > 1 but was not statistically significant.

The HR for farm size is >1 and statistically significant, indicating those managers of large-scale farms are likely to adopt LLL technology sooner than managers of small-scale farms. Farms located at the middle and tail-end of the watercourse have statistically significant HR > 1, also suggesting that those locations accelerate the speed of adoption compared to farms located at the head of the watercourse. Contrary to expectations, the parameter that indicates land managers' perceptions about good groundwater quality has significant HR < 1, implying that their perception of good groundwater quality decelerated their speed of adoption. Moreover, relative to the no subsidy scheme, the government's subsidy scheme during the 2005–2008

TABLE 1 Summary of complementary log-log model results

Variables	Hazard ratios
Land managers' age at adoption	0.936*** (0.010)
Land managers' education (≥12 years)	1.252 (0.218)
Farming experience (years)	1.062*** (0.012)
Family labour engaged in agriculture	0.903** (0.039)
Secure and legal land rights	1.260* (0.177)
Customary land rights	1.136 (0.200)
Access to credit	1.139 (0.149)
Extension services and water management directorates	1.711*** (0.220)
Peer progressive farmers and agricultural input dealers in the village	1.389** (0.199)
Farm size (≥5 hectares)	1.454*** (0.201)
Farm location at the middle of the watercourse	1.366** (0.215)
Farm location at the tail of the watercourse	1.352** (0.196)
Poor land quality perception	0.794 (0.133)
Perception: good groundwater quality	0.809* (0.098)
Tropical livestock unit (TLU)	0.969** (0.015)
Distance to rental market	0.969** (0.014)
Subsidy Schemes 2005–2008	0.919 (0.249)
Subsidy Schemes 2012–2018	9.521*** (1.549)
Log of time duration	1.836*** (0.054)
Rice–wheat zone	1.467** (0.224)
Maize–wheat–mix zone	1.381** (0.223)
Constant	0.065*** (0.024)
Log likelihood	−1091.263
Likelihood-ratio test ($\sigma^2 = 0$)	0.000 ($p = 0.496$)
Number of observations	5460
Number of farm households	504

Note: standard errors in parentheses. Null hypothesis is that HR = 1.
*$p < 0.1$ **$p < 0.05$ ***$p < 0.01$

periods had an HR that did not significantly differ from one. However, the subsidy schemes during the 2012–2018 period significantly reduced the time to LLL adoption with HR > 1. We modelled the baseline hazard as a log of time duration (i.e., the number of years since the introduction of LLL technology until the study period) in the discrete-time duration model. The baseline hazard function rises with elapsed survival time, that is, the adoption of technology increases with increasing period at risk.

3.2 | Average treatment effect of LLL on groundwater (m^{3}ha^{-1}) applied to wheat crops

The factors that influence land managers' decision to adopt LLL technology and the impact of this on the volume of groundwater used are presented in Table 2. The selection and outcome equations (Appendix I)

TABLE 2 The determinants of LLL technology adoption and their impact on groundwater (m^3ha^{-1}) applied to wheat crop

Variables	Selection (yes = LLL adopters; otherwise, 0)	Adopters (groundwater [m^3ha^{-1}] applied)	Non-adopters (groundwater [m^3ha^{-1}] applied)
Land manager's age	−0.650** (0.316)	−172.2 (109.1)	−230.0 (178.1)
Land manager's education	−0.105 (0.207)	−20.56 (67.98)	−241.0** (108.3)
Farming experience (years)	0.456*** (0.150)	89.78 (55.08)	170.6* (90.64)
Family labour (AE)	−0.072 (0.126)	−3.925 (46.59)	73.33 (60.19)
Access to credit	0.372** (0.160)	31.47 (58.21)	76.61 (141.8)
Secure and legal land rights	0.522*** (0.154)	147.2*** (54.35)	97.39 (92.40)
Customary land rights	0.423** (0.190)	120.5 (73.90)	5.095 (119.6)
Farm size (≥5 hectares)	0.241* (0.144)	92.10* (51.58)	−19.13 (96.35)
Farm location at the middle of the watercourse	0.270 (0.173)	162.5*** (61.60)	−93.70 (108.5)
Farm location at the tail of the watercourse	0.294* (0.154)	75.64 (57.52)	−33.33 (82.61)
Poor land quality	−0.303* (0.178)	−66.89 (64.46)	192.9 (130.3)
Good ground water quality	0.039 (0.139)	−5.133 (50.05)	−1.786 (82.48)
Tropical livestock units (TLU)	−0.031 (0.048)	−3.999 (16.47)	−3.276 (28.65)
Rice–wheat zone	0.090 (0.181)	−337.2*** (57.93)	−269.7*** (104.0)
Maize–wheat–mix zone	0.155 (0.195)	−64.35 (69.99)	−94.11 (105.9)
Extension services and water management directorates	0.167 (0.124)		
Peer progressive farmers and agricultural input	0.254* (0.146)		
Distance to rental market	−0.229*** (0.075)		
Fuel and maintenance cost		373.5*** (32.85)	456.8*** (93.76)
Constant	1.186 (0.93)	−1861*** (358.8)	−2027** (832.9)
lnsigma0			6.032*** (0.092)
lnsigma1		6.045*** (0.053)	
ρ^{na}			0.232 (0.294)
ρ^{a}		1.759*** (0.241)	
Wald chi^2	49.54***		
Log likelihood	−3382.942		
Wald test of independent equations	18.94***		
Number of farm households	434		

Note: robust standard errors in parentheses.
**p* < 0.1 ***p* < 0.05 ****p* < 0.01

TABLE 3 Average treatment effect of LLL on the volume of groundwater (m^3 ha^{-1}) for wheat crop

	Mean outcome (m^3 ha^{-1})				
Techniques	Adopters	Non-adopters	ATT	*p*-values	Percentage saving
ESR	278.24	359.03	−80.79	0.000	−22.50
NNM	275.75	355.32	−79.56	0.002*	−22.39
KBM	275.75	340.86	−65.11	0.003*	−19.10

Abbreviations: ATT, average treatment effect for the treated; KBM, kernel-based matching; NNM, nearest-neighbor matching.
**p*-values are calculated by using bootstrap standard errors at 200 replications.

are jointly estimated using the full information maximum likelihood (FIML) estimation (Lokshin & Sajaia, 2004). The selection equation is estimated using the probit model,[7] which explains the probability of LLL adoption given a set of covariates (see column 2, Table 2). The outcome equations estimate the factors that influence the amount of groundwater applied conditional on either being an adopter or not (see columns 3 and 4, Table 2). The outcome equations show that the coefficient for tube-well operational costs (i.e., diesel or electricity cost and maintenance cost of the machinery) has a positive and significant impact on the amount of groundwater applied to wheat crops for both adopters and non-adopters. It indicates that under prevailing market prices, as the tube-well operational costs (i.e., diesel or electricity cost and maintenance cost of the machinery) increase, the volume of groundwater applied to wheat crops by non-adopters is much higher compared to adopters. The variable representing the rice-wheat zone has a negative and statistically significant influence on the quantity of groundwater used for wheat crops relative to the cotton–mix zone for adopters and non-adopters, implying heterogeneity in the use of groundwater across regions for adopters.

An interesting finding in the lower part of Table 2 is the estimated correlation coefficients (ρ^a and ρ^{na}) of covariance terms. First, the result shows that the covariance term for adopters (ρ^a) is statistically significant, indicating the presence of selection bias in adoption decisions. It implies that LLL technology adoption may not have the same influence on non-adopters if they prefer to adopt (Lokshin & Sajaia, 2004). Second, ρ^a and ρ^{na} had the same sign, indicating that land managers prefer to adopt LLL technology based on hierarchical sorting (Ma & Abdulai, 2016). Third, the sign of ρ^a is positive, suggesting negative selection bias (Ma & Abdulai, 2016); that is, land managers with lower-than-average groundwater use to irrigate wheat crops are more likely to adopt LLL technology. The result is plausible since the LLL technology adoption is expected to reduce groundwater usage.

The unbiased estimates of the ATT on the treated farms (Equation 7) for groundwater use are reported in Table 3. Unlike the simple mean differences test reported in the Appendix Table A1, these ATT estimates account for unobserved heterogeneity resulting from observable and unobservable characteristics. The results show that the ATT on groundwater used (m^3ha^{-1}) is negative (-80.79) and highly significant ($p < 0.01$), implying that LLL technology adoption significantly reduces groundwater application by 22.5%. This is consistent with the results from the PSM[8]; irrespective of the matching algorithms used, LLL technology adoption reduced groundwater application by about 19% to 22%.

4 | DISCUSSION

One of the key research findings was that secure and legal land entitlements significantly accelerated the speed of LLL technology adoption. The literature shows that the lack of secure and legal land rights creates inefficiencies in the land market (Spielman et al., 2016), whereas secure and legal land rights can improve the land rental market (Besley, 1995; Soto, 2000) and encourage land managers to make long-term investments (Ali et al., 2014; Gebremedhin & Swinton, 2003). Moreover, Tarfasa et al. (2018) revealed that establishing secure land rights increases the adoption of soil conservation practices in Ethiopia while Sheikh et al. (2022) found that secure land rights accelerate the adoption of gypsum technology used to rehabilitate irrigated salt-affected farmland in Pakistan's Punjab. In addition, secure and legal land rights can aid land managers to use the land as loan collateral (Sheikh et al., 2022). Therefore, these findings suggest that improving legal land rights has the potential to enhance the speed of LLL adoption.

Access to information plays a crucial role in lowering uncertainty about the appropriateness of LLL technology and speeds up the diffusion process. If land managers are uncertain about the outcome of the technology, they may choose to defer the adoption decision until reliable information about technology becomes available (Genius et al., 2014; Ghadim et al., 2005), an important predictor of adoption (Baumgart-Getz et al., 2012). Extension services are major sources of agricultural information for land managers in Pakistan. Yigezu et al. (2018) reported that access to extension services reduced the time to adoption of zero tillage technology in Syria. Moreover, access to extension services may enhance the adoption of climate-smart technologies, as reported in Ghana (Issahaku & Abdulai, 2020; Martey et al., 2020) and India (Aryal et al., 2020). In addition, information acquired through informal sources such as peer progressive farmers and input dealers could potentially accelerate the speed of LLL adoption. Small-scale land managers are often exposed to agricultural innovations from progressive farmers. Likewise, input dealers play a crucial role at the village level where they support land managers by providing agricultural inputs and information on agricultural innovations. Thus, information acquired through both formal and informal sources is crucial for enhancing knowledge about LLL technology in the study area.

We find that in general large-scale farmers (cultivating ≥5 hectares) adopted LLL technology earlier than small-scale farmers. According to Mellor and Malik (2017), large-scale farmers account for only 2% of the poverty incidence of total rural households (including landless) in Pakistan, implying that they have better financial capacity to invest in new technologies like the LLL technology compared to small-scale farmers. These results are consistent with other general technological studies, which reported that farm size positively and significantly influences the speed of adoption (Baumgart-Getz et al., 2012). Moreover, Jara-Rojas et al. (2013) found that farm size is an important factor explaining the adoption of soil and water conservation measures in central Chile while Anugwa et al. (2022) notes that it is an important predictor of farmers' choices for climate-smart agricultural technologies in Nigeria. However, Betela and Wolka (2021) found that farm size had a negative association with the adoption of soil and water conservation measures in southwest Ethiopia.

The 2005–2008 government subsidy schemes had a lesser impact on accelerating the adoption of LLL technology compared to the 2012–2018 subsidy schemes. Of the total LLL units distributed in the sampled districts, about 87.6% more LLL units were distributed in Hafizabad during the 2012–2018 period, followed by 79.9% in Jhang and 77.1% in Bahawalnagar (Government of Punjab, 2012). The distribution of LLL units explains that during the 2012–2018 period, more LLL units were available in the districts as compared to the subsidy scheme during 2005–2008. It has improved land managers' exposure to the technology and accelerated the speed of adoption. In addition, short distances to LLL rental services accelerated the speed of adoption. Empirical studies have found that long distances to input markets reduced the propensity to adopt sustainable agriculture technologies (Manda et al., 2016; Teklewold et al., 2013). Aryal et al. (2020) found that access to market positively influenced the adoption of climate-smart agriculture in India. Hence, availability, exposure, and accessibility to LLL technology through rental markets can improve the speed of adoption. The provincial government may need to promote LLL technology in hotspot areas where the adoption rate is still low.

Farms located at the middle and tail of the watercourse were more likely to adopt LLL technology. Given the flood irrigation system, canal water is often wasted due to conveyance losses, and water scarcity often occurs at the tail of the watercourse (Sheikh et al., 2022). When land is flood irrigated, any degree of undulation in the soil surface can seriously reduce water and land productivity (Gill, 2014). Land managers, therefore, use canal water with groundwater to meet crop water requirements, with about one-fifth of irrigated land salinized due to groundwater irrigation (Shahid et al., 2018). Reducing the amount of groundwater used for irrigation could reduce soil salinization, increase profitability, and contribute to resource conservation, motivating land managers to invest in water-saving technologies to save overall groundwater use and impede additional salts in the soil that can hinder plant growth and development.

The adoption of LLL technology, on average, reduces the amount of groundwater extracted to irrigate wheat crops by 19% (PSM) to 22% (ESR). These findings are consistent with irrigation water savings of 22% in the rice-wheat system (Naresh, 2011), about 25%–30% in rice (Bhatt & Sharma, 2009), and 10%–13% in wheat (Jat et al., 2009).

5 | CONCLUSIONS AND POLICY IMPLICATIONS

Laser land levelers have been actively promoted as a climate-smart agriculture technology for their environmental benefits, which include reducing soil salinity, minimizing soil erosion risk, and improving groundwater security. Our study aimed to investigate the factors influencing the speed of adoption of LLL technology and its impact on groundwater usage. The main results imply that institutional factors like secure and legal land rights, access to information about the technology, and government support to meet the initial cost of investment in the technology can accelerate the speed of LLL adoption.

Adoption could be accelerated further by fast-tracking ongoing efforts of the Provincial Government to digitize the land record system to improve legal land rights. Land managers with access to information on LLL technology are early adopters compared to those with no access to information. Adoption could be accelerated by improving information delivery mechanisms through extension services to educate land managers on the appropriateness of the technology and its environmental benefits. Additionally, other information-sharing avenues, such as land managers-to-progressive farmers' interactions and suggestions from input dealers, could be effective in sharing knowledge about the technology at the village level.

This study contributes to the literature on the adoption of agricultural innovations that require a high initial investment. The Provincial Government introduced two subsidy schemes to deal with the problem of market failure. The LLL units were distributed to land managers and LLL service providers. This improved availability, exposure, and access to the technology through rental markets in the study areas. These subsidy schemes created an enabling environment for LLL rental markets to extend services to land managers who could not afford to buy LLL units due to the high initial investment required. The Provincial Government has achieved tremendous success by improving the adoption rate among land managers. This result has two policy implications: (1) the government should pave the way for pulling out of granting subsidies and allow the private sector to move in and let the rental market works in a competitive environment; (2) the Provincial Government should invest in improved extension services and develop strategies to enhance land managers' awareness about the technology in areas where the technology has not been promoted.

Adopting LLL technology could reduce the volume of groundwater extracted and address the problem of increasing water scarcity, soil salinization, soil erosion, and declining groundwater tables in Punjab. However, these findings are specific to the wheat crop, so further research is needed to assess the impact of adopting LLL on groundwater use in other water-intensive crops like rice, sugarcane, cotton, and maize.

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ENDNOTES

[1] 1 hectare = 2.47 acres.

[2] Adoption time is defined as the year when LLL technology was introduced by the Provincial Government (1985) until adoption occurs.

[3] *Fard Malkiat* is known as a record of rights that is maintained for the determination of rights for immovable property. It is proof that you own the property, and is required for the sale, mutation and transfer of rights.

[4] One full working day, one adult male (≥15 years of age) coded as one AEU, whereas one adult female equivalent to 0.8 AEU, and one child (5–14 years) represents 0.5 AEU.

[5] Class means type of animals, that is, goats, sheep, buffalos, cows, camels, poultry.

[6] See Appendix I.

[7] The probit model results in Table 2 are inconsistent with the results from the duration model (Table 1), as they do not account for time-varying information (Abdulai & Huffman, 2005; Foster & Rosenzweig, 2010). Notably, the factors that are significant in the selection stage of the ESR model (see Table 2) differ from the hazard model (see Table 1) due to the model assumptions and the set of variables used. However, the binary model would require adjustments to allow time-varying variables to achieve consistent estimates compared with the duration model (see Burton et al., 2003).

[8] See Table C1 for bias reduction after matching.

DATA AVAILABILITY STATEMENT

Data available on request due to privacy/ethical restrictions.

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