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Adoption and Economic and Environmental Impact of Laser-assisted Precision Land Leveling in Northwestern India

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Abstract

Globally, agricultural production systems need to become more sustainable to meet future food demand without overexploiting natural resources. Northwestern India, a region with highly intensive agricultural production, is facing a rapid decline in groundwater levels due to excessive water use for irrigation. This dissertation investigates laser-assisted land levelling technology (LLL) that reduces water use for irrigation and has been adopted in northwestern India to manage groundwater depletion. The study examines three interrelated research questions: 1) Why are farmers adopting LLL technology, 2) How did farmers access this technology, and 3) What impact does LLL technology adoption have on groundwater levels? The study uses primary data from 1661 households in 84 villages to determine why and how farmers adopt the technology. Further, combining village-level survey data from 291 villages with monthly observational well data and climate data for 21 years, the study also estimates the effect of LLL adoption on groundwater in northwestern India.

LLL is popular and widely adopted in northwestern India, with 93 % of farmers aware of the technology and 84% adopting it in their farms. Analysis based on qualitative interviews and estimation based on regressions and causal machine learning shows that the widespread adoption of LLL is due to positive perceptions about this technology and other co-benefits, such as a marginal increase in yield and preference for levelled fields. The findings highlight the need to recognise farmers' perceptions and co-benefits, integrate them with benefits designed by researchers, and foster feedback loops and knowledge co-creation to promote LLL adoption.

The emergence of private service providers, an institutional mechanism for renting technology, facilitates the adoption of LLL on small plots and among small farm owners. Regression analysis shows that the number of service providers is positively associated with adoption rates, particularly on smaller plots and farms. Promoting individual service providers increases the access of small farm owners to LLL technology through flexible on-demand services and competitive rental markets.

Furthermore, the analysis reveals that LLL adoption slows down the effect of groundwater decline in northwestern India. Applying a staggered difference-in-difference approach, the study shows that the adoption of LLL at the village level has reduced the decline in groundwater levels by 3.7 meters in the month succeeding the use of technology. However, adopting LLL is not enough to stop or reverse overall groundwater decline. Several technological and policy options that could impact the behaviour of farmers towards saving water for irrigation in agriculture are discussed.

This dissertation contributes to understanding the adoption and impact of LLL technology for groundwater sustainability in three ways. First, it provides insights into designing new dissemination strategies based on farmers' experience. Second, it discusses new institutional approaches – individual service providers, for supporting the adoption of technology by smallholder farmers. Third, it examines the extent to which the adoption of technology at the farm level transforms into system-level effects in terms of the actual impact on groundwater savings, reducing the negative externalities of groundwater exploitation for agriculture.

Zusammenfassung

Weltweit müssen die landwirtschaftlichen Produktionssysteme nachhaltiger werden, um den künftigen Nahrungsmittelbedarf zu decken, ohne die natürlichen Ressourcen übermäßig zu beanspruchen. Der Nordwesten Indiens, eine Region mit sehr intensiver landwirtschaftlicher Produktion, ist mit einem rapiden Rückgang des Grundwasserspiegels konfrontiert. In dieser Dissertation werden Implikationen der Laser-Landnivellierungstechnologie (LLL) untersucht, die den Wasserverbrauch für die Bewässerung reduziert und im Nordwesten Indiens eingesetzt wird. Speziell werden drei Forschungsfragen adressiert: 1) Warum wenden Landwirte die LLL Technologie an, 2) Wie erhalten Landwirte Zugang zu der Technologie, und 3) Welche Auswirkungen hat die Technologie auf das Grundwasser? Die Studie verwendet Primärdaten von 1661 Haushalten aus 84 Dörfern, um herauszufinden, warum und wie die Landwirte die Technologie anwenden. Durch die Kombination von Umfragedaten auf Dorfebene aus 291 Dörfern mit monatlichen Beobachtungsdaten von Brunnen und Klimadaten über 20 Jahre hinweg schätzt die Studie die Auswirkungen der Einführung von LLL auf das Grundwasser im Nordwesten Indiens.

LLL ist im Nordwesten Indiens weit verbreitet und wird von vielen Landwirten angewendet. 93 % der Landwirte kennen die Technologie und 84 % wenden sie in ihren Betrieben an. Die Analyse basierend auf qualitativen Interviews und Schätzungen auf der Grundlage von Regressionen und Kausalanalyse mit maschinellem Lernen zeigt, dass die weit verbreitete Nutzung auf eine positive Wahrnehmung der Technologie sowie andere Nebeneffekte wie einer marginalen Ertragssteigerung und einer Präferenz für geebnete Felder zurückzuführen ist.

Das Aufkommen privater Dienstleistungsanbieter, ein institutioneller Mechanismus für die Vermietung von Technologie, erleichtert die Einführung von LLL bei kleinen Parzellen und Landwirten. Die Anzahl der Dienstleistungsanbieter korreliert positiv mit der Verbreitungsrate, insbesondere bei kleineren Parzellen und Betrieben. Die Förderung von Dienstleistungsanbietern verbessert den Zugang durch flexible, bedarfsgerechte Dienstleistungen und wettbewerbsintensive Mietmärkte.

Die Einführung von LLL verlangsamt den Grundwasserrückgang im Nordwesten Indiens. Unter Anwendung eines „gestaffelten“ (staggered) Differenzierungsmodells zeigt die Studie, dass die Einführung von LLL auf Dorfebene den Rückgang des Grundwasserspegels um 3,7 Meter verringert hat. Die Einführung von LLL reicht jedoch nicht aus, um den Rückgang des Grundwassers aufzuhalten oder umzukehren. Weitere notwendige technologische und politische Maßnahmen werden diskutiert.

Diese Dissertation trägt in dreierlei Hinsicht zum Verständnis der Verbreitung und den Auswirkungen der LLL-Technologie auf die Nachhaltigkeit des Grundwassers bei. Erstens liefert sie Einblicke in die Entwicklung neuer Verbreitungsstrategien auf der Grundlage der Erfahrungen der Landwirte. Zweitens erörtert sie neue institutionelle Ansätze - individuelle Dienstleister - zur Unterstützung der Anwendung von Technologien durch Kleinbauern. Drittens wird untersucht, inwieweit sich die Einführung der Technologie auf Betriebsebene auf die Systemebene auswirkt, d. h. auf die tatsächliche Einsparung von Grundwasser und die Verringerung der negativen externen Effekte der Grundwassernutzung durch die Landwirtschaft.

Dedication

The Rhine

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ATSAF	Arbeitsgemeinschaft Tropische und Subtropische Agrarforschung
ATT	Average Treatment Effect of Treatment on the Treated
CATE	Conditional Average Treatment Effect
CGIAR	Consortium of International Agricultural Research
CGWB	Central Groundwater Board
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
CIMMYT	International Maize and Wheat Improvement Center
DiD	Difference in Difference
DSR	Direct Seeded Rice
GPS	Global Positioning System
HH	Household Head
HQ	Head Quarters
ICAR	Indian Council of Agricultural Research
IRB	Institute Review Board
IRRI	International Rice Research Institute
KVK	*Krishi Vigyan Kendra*
LLL	Laser-assisted precision land levelling, Laser land levelling
NARES	National Agricultural Research and Education System
NGO	Non-Governmental Organisation
ODK	Open Data Kit
OLS	Ordinary Least Square
SI	Simpson Index
SPIA	Standing Panel of Impact Assessment
TWFE	Two-way Fixed Effect
UN	United Nations
USA	United States of America
WUP	Western Uttar Pradesh
ZEF	Centre for Development Research

Chapter 1 : Introduction

1.1 Motivation and relevance

The Green Revolution increased agricultural productivity and ensured food security in developing countries (Evenson & Gollin, 2003; Gollin et al., 2021). In the 1960s, the Green Revolution era started with the transfer of agricultural technologies that were successful in developed countries to developing countries by the Consortium of International Agricultural Research (CGIAR) institutes in collaboration with the National Agricultural Research and Education (NARES) system (Pingali, 2012). The technologies promoted during the Green Revolution era were primarily improved high-yielding crop varieties responsive to fertilizer and irrigation (Gollin et al., 2021; Pingali, 2012). However, over time, due to the Green Revolution, the agricultural production systems in developing countries intensified and resulted in negative externalities such as biodiversity loss and groundwater depletion, raising questions over sustainability of these intensive production systems (Devineni et al., 2022; Kamau et al., 2023; Zabel et al., 2019).

Moreover, the current agricultural production systems are becoming increasingly unsustainable due to the increasing demand for food and overexploitation of natural resources. The global population is expected to reach 9.7 billion in 2050 and about 10.4 billion in the mid-2080s (UN, 2024). At the current population growth rate and socio-economic development, global food demand is projected to increase by 35% to 56% between 2010 and 2050 (Van Dijk et al., 2021). This increase in food demand puts additional pressure on existing natural resources such as groundwater (Boretti & Rosa, 2019). In this context, the challenge is to transition towards a more sustainable food system, which can meet the future food demand, without overexploiting the resources or negatively affecting the environment (Davis et al., 2019).

The northwestern part of India is characterized by an intensive agricultural production system, coupled with an alarming rate of groundwater depletion (Perez et al., 2024). The region encompassing the states of Punjab, Haryana, and Western Uttar Pradesh is considered an extremely high water depletion region globally (Seo et al., 2023). During the Green Revolution, the cropping system in northwestern India shifted from low water-intensive crops like millet with mixed farming to high water-intensive crops like rice and sugarcane (Bjornlund & Bjornlund, 2024). Unlike traditional rice-growing regions where rice is grown in wetlands, in northwestern India, rice is grown under flooded water through irrigation. The widespread cultivation of rice-wheat cropping systems using flood irrigation has led to a rapid decline in groundwater (Joseph et al., 2022; Shekhar et al., 2020). This decline is not only affecting yields, but could result in a 68% decline in cropping intensity (multiple cropping in the same plot), threatening local livelihoods and food security (Jain et al., 2021a).

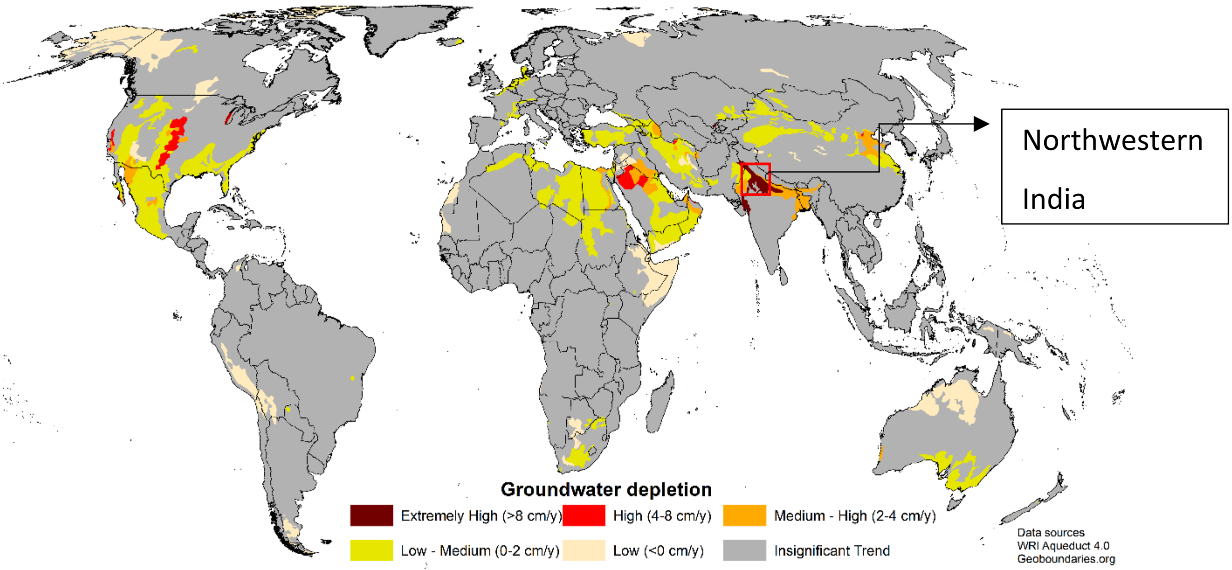


Figure 1.1: Global depletion of groundwater

Note: Extent of depletion is consumptive withdrawal of water on average in cm/yr for the period 1979-2019

Source: World Resource Institute, Aqueduct project 4.0 (Kuzma et al., 2023).

There are different solutions proposed and experimented in northwestern India to mitigate groundwater decline. First, a regulatory solution banning transplanting of rice crops before June 10th in Punjab (Punjab Preservation of Sub-soil Act 2009) and Haryana (Haryana Prevention of Sub-soil Act 2009). This is to prevent farmers from transplanting the rice crop with irrigation water before the onset of the rainy season. Though a few earlier studies showed positive effects (Singh, 2009; Tripathi et al., 2016), recent studies have shown negative long-term effects of the policy on groundwater due to 'rebound effects'; farmers increasing the area under rice and pumping capacity resulting in over-extraction of groundwater (Kishore et al., 2024; Sekhri, 2012). Additionally, the late transplanting of rice due to irrigation has reduced the time available to prepare the land for wheat crop after rice cultivation, which in-turn has led to stubble burning (Kant et al., 2022). Second, a recently piloted policy intervention on incentivizing water saving through payments, the World Bank Project on 'save water make money' (*Pani Bachao Paise Kamao* in Hindi), compensates farmers for reduced water use for irrigation. Though the pilot-version of the project has shown a positive impact of the incentive schemes on groundwater conservation (Mitra et al., 2023), an earlier scaled-up version of a similar project has shown no impact due to lack of access to affordable water saving technologies (Fishman et al., 2016).

Third, crop diversification- diversifying or switching to other crops with lower water requirements is a widely promoted solution (Chakraborti et al., 2023; Kamau et al., 2023). Despite several efforts to diversify the cropping system, the existing price support mechanism (minimum support price) disincentives farmers from switching to alternative crops (Chatterjee et al., 2024). Fourth, a promising technology-based solution is the direct-seeded rice (DSR), which is still in the early stages of adoption (Brown et al., 2021; Mishra et al., 2017). Though field trials have shown positive effects, and the government has introduced incentive systems, the DSR technology has not been widely adopted due to lack of demand by farmers and limited supply of DSR renting services by service providers (Brown et al., 2021).

In this study, I examine a technology solution- laser land levelling- also called laser-assisted precision land levelling (LLL). This technology was invented in the United Stated of America (USA) in the 1970s, and later adopted in different parts of the world (Figure 1.2). LLL was subsequently manufactured and disseminated in Italy, Russia, Egypt, India, Pakistan, China, Iran, Vietnam, Cambodia, Nepal, and Tajikistan, among others (Chen et al., 2022). There is a growing interest in promoting this technology in other parts of south-east Asia, especially in Indonesia, Philippines, Myanmar, Sri Lanka, Cambodia and Vietnam (CGIAR Research Program on Rice, 2019a, 2019b). LLL was introduced and promoted in northwestern India in 2001 by the CGIAR, Indian Council of Agricultural Research (ICAR) institutes and State Agricultural Universities (SAUs) as a solution for groundwater depletion in the region (Jat et al., 2006, 2009).

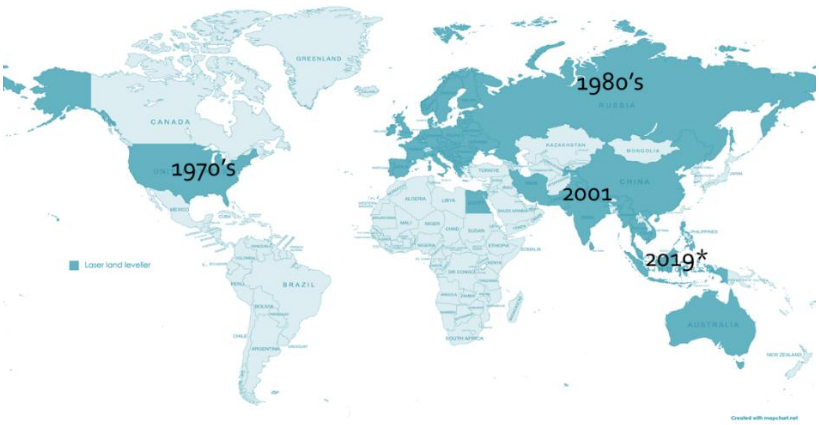


Figure 1.2: Global diffusion of laser land levelling technology

Note: *The technology was reintroduced to south-east Asian countries in 2019 after the initial field trials by the International Rice Research Institute (IRRI) in 2001.

Land levelling is a land preparatory operation before crop sowing to ensure uniform water distribution. This is especially important for rice-wheat cropping systems, where the water is maintained at a certain depth (Jat et al., 2009; Nguyen-Van-Hung et al., 2022). Using LLL on the farm results in a smoother surface (± 2cm), reducing the water required for irrigation (Figure 1.3). It's postulated that the individual water savings from the farm would result in aggregate savings in the groundwater (Jat et al., 2006).

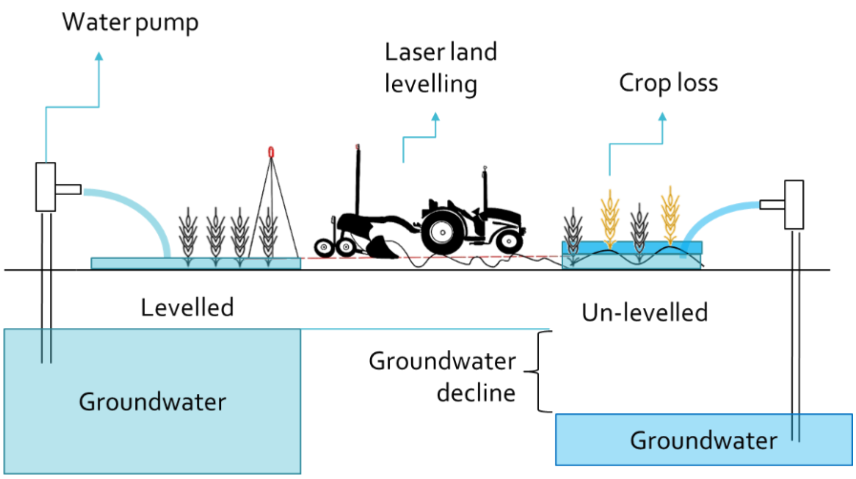


Figure 1.3: LLL mechanism for saving groundwater

1.2 Problem statement and research questions

There are three puzzling questions with respect to the adoption of LLL in northwestern India. First, based on the existing literature on the adoption of LLL, the main advantage is the technology's ability to save water for irrigation. However, in northwestern India, the cost of electricity for irrigation is either negligible or even free, and the extraction cost of water is low. So, are farmers adopting the technology to save groundwater, or are there possibly other reasons? Second, the adoption rate of LLL technology is higher (~80%) than that of most other resource conservation technologies (D'Souza & Mishra, 2018; Fuglie & Kascak, 2001). What is unique about LLL compared to other resource conservation technologies? Third, LLL is an indivisible technology, i.e. unlike seed or fertiliser, the technology cannot be divided based on individual farmer demand (Lu et al., 2016). Indivisible technologies are often not rapidly and widely adopted by smallholder farmers.

The existing literature on the adoption of LLL focuses on assessing the factors determining the early stages of adoption (Ali et al., 2018; Aryal et al., 2018a, 2020; Pal et al., 2022; Sheikh et al., 2022). These studies focus on understanding demand-side factors 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., 2018a, 2020; Pal et al., 2022; Sheikh et al., 2022). However, adoption is a dynamic process that starts before the actual decision to use a technology for the first time and continues even after the first use of the technology. Understanding the adoption process post-initial hurdles of adoption is important in order to address possible adoption constraints effectively (Ishtiaque et al., 2024).

Moreover, studies on the impact of the adoption of LLL focused on impact of LLL adoption on water saving and yield at the farm level (Aryal et al., 2018a, 2020; Lybbert et al., 2018). However, studies assessing the impact of water-saving technologies have shown that the water savings at the farm level may not translate into meaningful reductions at groundwater or aquifer level (Fishman et al., 2023; Joseph et al., 2022; Pfeiffer & Lin, 2014). So, has LLL technology really resulted in saving of groundwater at scale? To address these knowledge gaps in the literature, I have phrased three research questions, which are structured as three separate chapters of this dissertation.

1. Why are farmers adopting LLL technology?
2. How were farmers able to access the technology (indivisible nature)?
3. What is the effect of the adoption of LLL on groundwater levels?

Chapter two focuses on why farmers are adopting LLL technology, specifically at the later stage of adoption, after overcoming the initial hurdles of knowledge and information (Roger, 2003). It assesses the farmers' perception regarding the benefits designed by the technology developers, such as irrigation water saving and yield, to understand how these perceptions influence farmers' decision to continue using the technology. Furthermore, the exploration extends beyond the binary notion of adoption, as the technology is adopted at different frequencies/intervals over time. Understanding the factors motivating farmers to continue adopting technology could help in designing similar technologies and policies for promoting sustainable agricultural intensification.

Chapter three discusses the institutional mechanism for renting LLL, which made the technology accessible to farmers. The analysis explores the relationship between the adoption of LLL and the number of service providers the farmer has access to. The study quantifies the relationship between land size and accessibility of technology by interacting the number of service providers with the plot and farm size. This study helps in understanding supply-side factors, particularly private service providers, for renting LLL in the adoption of technology by farmers.

Chapter four estimates the impact of LLL adoption on groundwater levels. Here, adoption is evaluated at the village level. Technology diffusion in the region occurred over a period of 21 years in a staggered manner. This staggered diffusion is exploited as an identification strategy to estimate the impact. Since 100% of the villages in the region have adopted the technology over time, the analysis provides an opportunity to measure the technology impact at its full adoption potential and to compare effects with those of other policy alternatives.

Overall, this work focuses on an in-depth analysis of technology that could help solve groundwater sustainability issues. The three research questions addressed provide a holistic understanding of the technology and help designing policies and strategies for dissemination of LLL technology in other regions of India and beyond. The study also provides lessons for developing other resource conservation technologies.

1.3 Study area and data collection

1.3.1 Study area context

We collected data from three states in the northwestern region of India: Punjab, Haryana, and Western Uttar Pradesh (Figure 1.4). The region is part of the Indo-Gangetic deltaic plains, characterised by multiple rivers (Ganges, Yamuna, Sutlej, Chenab), alluvial soil deposited by the river under zone 5 and zone 6 of agro-climatic zone: Upper-Gangetic plains and Trans-Gangetic plains. The climate is semiarid, with temperatures ranging from 7^0 C to 42^0 C and average rainfall between 70 cm to 125 cm. The main crops cultivated in the region are rice, wheat, sugarcane, cotton and maize. Private tube wells and canals are the main sources of irrigation.

1.3.2 Data collection

In this section, I provide a summary of the different types of data collected and my contribution in this process. My study is associated with two projects of the International Maize and Wheat Improvement Center (CIMMYT) namely; Project 1. Farmer Adoption and Impacts of Resource Conservation Technologies (Zero Tillage and Laser Leveler) in Punjab funded by the Standing Panel on Impact Assessment (SPIA), Project 2. Farmer Adoption and Impacts of Resource Conservation Technologies in Western Uttar Pradesh funded by the Indian Council of Agricultural Research. In addition to these projects, I conducted my own survey (Project 3) using my PhD funding support from Arbeitsgemeinschaft Tropische und Subtropische Agrarforschung (ATSAF) e.V.

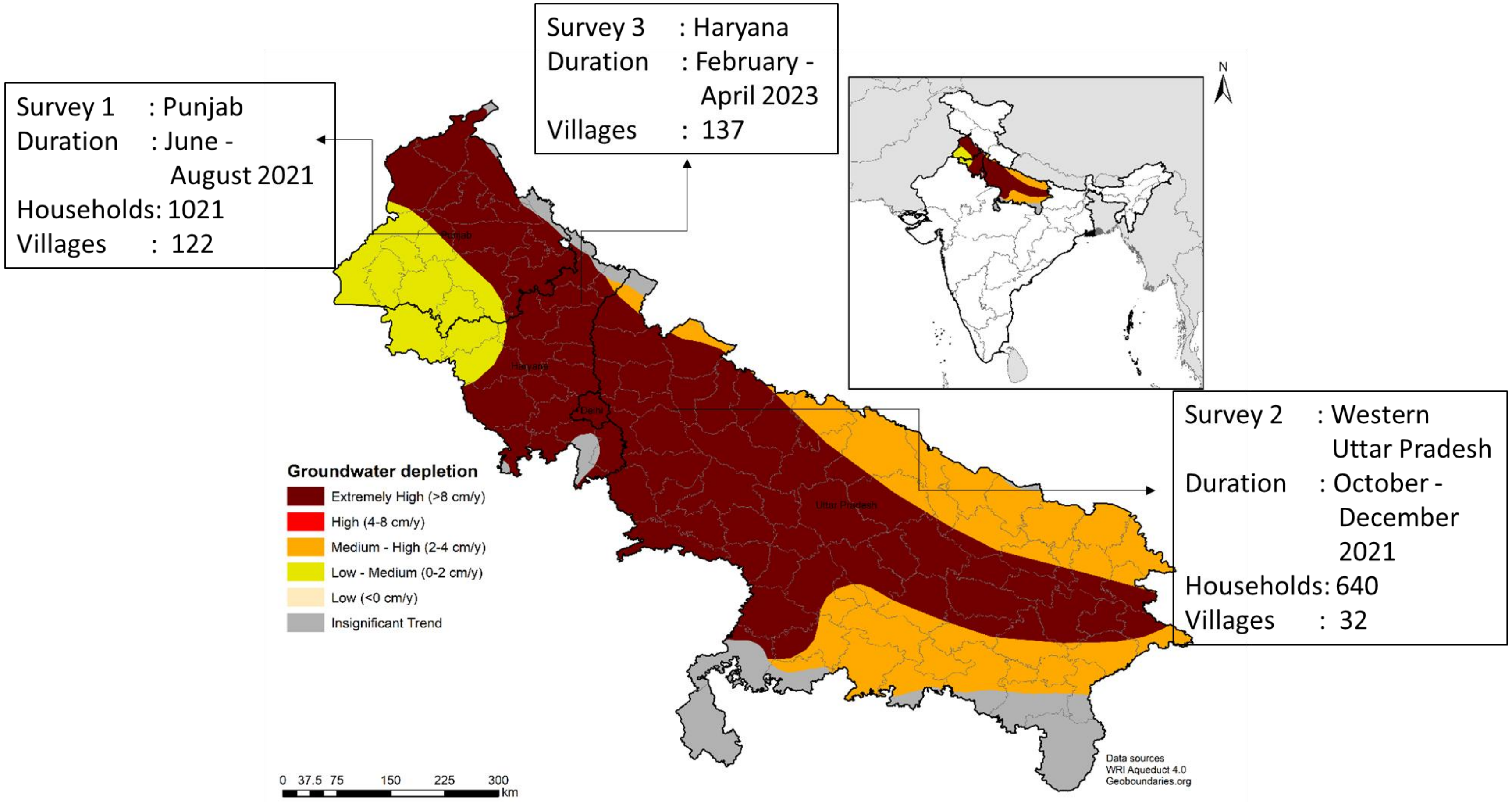


Figure 1.4: Study area visualizing groundwater depletion and timeline of the surveys

Note: Extent of depletion is consumptive withdrawal of water on average in cm/yr for the period 1979-2019
Source: World Resource Institute, Aqueduct project 4.0 (Kuzma et al., 2023).

For my PhD, I was involved in three surveys associated with the three projects mentioned above: first in Punjab, second in western Uttar Pradesh and third in Haryana. The details of the timeline and the duration of the survey are provided in Figure 1.4.

The first survey was carried out in four districts (Ludhiana, Fatehgarh, Patiala and Sangrur) in Punjab state associated with Project 1. Survey 1 had four components: qualitative interviews, a quantitative household survey, measuring irrigation water discharge by pumps in a sub-sample, and a village-level survey. I conducted eight qualitative interviews with farmers and LLL service providers. These interviews were explorative in nature, and the objective was to understand the prevailing cropping practices, groundwater use, and technology adoption mechanism. A verbal consent was obtained from all respondents before the interview. Dr. Vijesh V Krishna received ethical clearance for this study from the Institute Review Committee (IRB) of CIMMYT. I transcribed and translated the recorded interviews and used the data for analysis in Chapter two.

The questionnaire for the household survey was designed by Dr. Vijesh V Krishna, and I contributed to designing the section of the questionnaire on LLL. After the qualitative interviews, the household survey questionnaire was finalised, and a piloting of the questionnaire was done in one of the non-sample villages. The finalized questionnaire was then coded in Open Data Kit (ODK), and tablets were used for the interviews. Twenty enumerators from the region who could speak Punjabi, along with two supervisors were hired for the survey using a survey agency, SurveyJena. I was involved in enumerator training and monitoring during the survey.

In the household survey, data on the household, plot/farm characteristics, adoption of LLL technology (duration, frequency, share of cultivated area) and many other details were collected. The sampling frame of the survey was based on a household survey conducted by CIMMYT in 2018 (See Keil et al. 2019). I calculated the power of sample size based on the decided sample. In addition to the household survey, a village-level survey was conducted in 52 sample villages of the household survey and 70 additional villages in four other districts of Punjab.

The second survey, associated with Project 2, was done in four districts (Baghpat, Shamli, Muzaffarnagar, Muzaffarnagar, and Saharanpur) in western Uttar Pradesh. The ethical clearance for this survey was submitted to IRB of CIMMYT through Dr. Vijesh V Krishna.

Survey 2 had six components: qualitative interviews, a village-level census, a household survey, measuring irrigation water discharge by pumps in a sub-sample, a service provider survey and a village-level survey. For the qualitative part, I interviewed eight farmers and service providers. For the household survey, I conducted the selection of households from the village census list, re-designing the questionnaire based on the questionnaire from Survey 1. The survey tool was designed by me in ODK and surveyed using tablets. We hired another 20 enumerators through a survey agency who could speak Hindi from the region. Further details of the sampling procedure and survey are given in chapter three.

The village-level survey was carried out with three key informants in each village and a survey of laser land leveller service providers (1-2 per village or in the vicinity of the sampled village). The questionnaire was developed and programmed in ODK, and three enumerators did the survey. I was directly involved in monitoring the enumerators in Bahpat and Shamli districts and visited one-third of the villages in the village-level survey. Additionally, I also visited two villages in western Uttar Pradesh and collected water pump velocity data using an ultra-sonic flow meter and volumetric methods.

There were a few major challenges in Surveys 1 and 2, which had some implications for the data collected. First, the survey period coincided with the farmer's protest in the region (Jodhka, 2021). This led to severe trust and suspicion among farmers of anyone visiting the village for the survey. Additionally, the data on water, horsepower (hp) of the irrigation pump used, and stubble burning are of sensitive nature since there are regulations that can mean some of the farmers' practices are actually illegal (Krishna & Mkondiwa, 2023). These issues were known to some extent before the survey, but after the experience in Survey 1, additional efforts such as to build trust among the community by doing three rounds of visits were done in Survey 2. In the first round, we visited the village head and collected basic details of the village. The second visit involved a focus group discussion and a census of the households in the village. During the third visit, we surveyed the sampled households.

The third survey (Survey 3) was a village-level survey in Haryana funded through Project 3. I obtained the ethical clearance for the survey from the Center for Development Research (ZEF). We surveyed 137 villages from six districts in Haryana. Chapter four mentions the details of the sampling and information collected. For chapter four, we combined the village-level data collected from survey 1 and survey 2, making the total sample size 291 villages. I also collected secondary data on the monthly groundwater levels from the Central Groundwater Board (CGWB) for the period from 2000 to 2021. In addition, I also extracted monthly weather (rainfall) from the Climate Hazards Center, University of California Santa Barbara- Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (CHIRPS, n.d.).

1.4 Dissertation outline

The dissertation is further structured into five chapters. In Chapter two, we examine how the benefits designed by the technology developers affect adoption decisions and how the perceived benefits play a role in adoption in Punjab, India. Chapter three focuses on how LLL technology was widely adopted in northwestern India and specifically probes the role of private service providers. Chapter four is on the impact of the adoption of LLL on groundwater levels in northwestern India. Chapter five provides the overall conclusion and discusses policy implications and limitations of the study.

Chapter 2 : Perceived and designed benefits of resource conservation technologies: insights from adoption of laser land levellers in India[1]

Abstract

Farmers often adopt resource conservation technologies for different reasons, including profitability but also other benefits around social, psychological, and behavioral norms. During initial product development, some of these benefits may have been explicitly targeted, while other benefits may not have been initially targeted but can nevertheless, have strong influence on the question of whether farmers adopt a technology or not. In this paper, we analyze different benefits that can explain the adoption of laser land levelling (LLL), a resource conservation technology widely adopted in northwestern India. We use primary data from 1021 households randomly selected from 52 villages in Punjab, northwestern India. Using an embedded mixed approach employing qualitative interviews and machine learning causal forests, we aim to better understand and estimate different benefits of LLL adoption. Unlike previous studies that looked at one-time binary adoption decisions, we also consider differential effects depending on the frequency of technology adoption. The study reveals that LLL impacts yield increase and water savings less than initially thought. However, farmers' favorable perceptions, along with factors like electricity availability, compatibility with other technologies, and its aesthetic appeal, have led to broader adoption of the technology. The implications of the study findings for technology development, use and dissemination are discussed.

Keywords: mixed method, embedded QUAN(qual) approach, frequency of use, machine learning causal forest
JEL codes: N5, O13, Q15, Q25

[1] This is a joint paper with Martin C. Parlasca. A previous version was presented at an organized symposium titled “Technology and policies for groundwater management in South Asia”, at the International Conference of Agricultural Economists (ICAE), New Delhi, India on August 3, 2024.

Subash Surendran-Padmaja developed the research idea, collected and analyzed the data, and wrote the manuscript with support from Martin C. Parlasca. The coding in the software package R was assisted by Maxwell Mkondiwa.

2.1 Introduction

In a linear technology transfer system, technologies are developed and transferred to farmers with the intention of offering benefits such as increasing yield, reducing cost, or improving net income (Ogundari & Bolarinwa, 2018). Among farmers, profitability is often the key factor driving adoption decisions (Michler et al., 2019; Wang et al., 2023). This is one reason resource conservation technologies are less frequently adopted (D'Souza & Mishra, 2018; Fuglie & Kascak, 2001). Surprisingly, LLL, a resource conservation technology designed to reduce water use during rice cultivation, has seen widespread adoption in northwestern India (Aryal et al., 2020; Villalba et al., 2024). This is unexpected, particularly because the financial cost of water extraction in the region is very low, making water-saving technologies less financially compelling.

While profitability is an important motivator, adoption decisions are also influenced by other factors such as perception, social norms, and behavioral values (Okello et al., 2019; Shang et al., 2021). In this paper, we explore the reasons behind the adoption of LLL and the roles that both designed benefits and farmers' perceived benefits play in this process. To date, research on LLL has predominantly focused on the technical advantages offered by the technology, with little attention given to how farmers' attitudes and perceptions influence adoption (Caffaro et al., 2020; Swart et al., 2023).

This article addresses two key questions: 1) How do the benefits designed by the technology developers affect adoption decisions? and 2) What role do perceived benefits play in the adoption of LLL? To investigate these questions, we employ a mixed method, combining data from a survey of 1,021 farm households in Punjab, India, with qualitative insights from in-depth interviews with eight farmers. Additionally, we examine the effect of different frequency of LLL use, a factor that is highly praxis relevant, but often overlooked in previous studies, which typically treat adoption as a one-time decision. Recommendations for LLL use vary, suggesting application every three to five years, depending on crop and system (Aryal et al., 2018a; Chen et al., 2022;

Nguyen-Van-Hung et al., 2022). We estimate the impact of different usage frequencies on both yield and water savings.

Doing so, this article aims to contribute to the literature in two significant ways. First, it investigates technology adoption from both the perspectives of technology developers and farmers, offering insights into how these perspectives influence adoption. Second, the study employs innovative methodologies, including mixed methods and machine learning causal forest analysis, to better understand the complex factors behind LLL adoption.

The remainder of the paper is structured as follows: the conceptual and analytical framework section outlines the key concepts and hypotheses, followed by the data and methodology section, which describes the study area, household survey, and interviews. Results from the qualitative and quantitative analyses are then presented and discussed before concluding with a summary of findings, limitations, and policy implications.

2.2 Conceptual framework

In the classical adoption literature model, farmers' decision-making is modelled based on the key behavioral assumption of profit maximization (Feder et al., 1985). However, technology adoption is a dynamic learning process involving learning by using and learning from others (Sunding & Zilberman, 2001). The drivers of adoption can depend on the stage of adoption of learning process (Pannell, 2007). While profit maximization is an important consideration in the later stages of adoption, social and cognitive considerations play an important role in the early stages (Weersink & Fulton, 2020).

Though improved profitability and lower risk are important for farmers, they may not be the only objectives (Weersink, 2018); rather, farmers' goals are heterogeneous. Barnes et al., (2019) showed that in addition to profit maximization, farmers' attitudes towards a technology and information support influence the adoption of precision agricultural technologies. Based on this literature, we have conceptualized two hypotheses testing both profit maximization and other heterogeneous goals and perceptions of farmers.

First, we hypothesize:

H1a: The adoption of laser levelling technology is influenced by farmers' positive perceptions about the benefits of the technology.

H1b: The adoption of laser levelling technology is influenced by heterogeneous goals of the farmer.

Perceptions regarding the benefits of a technology are formed by either learning from others, demonstration, or one's own experience (Mottaleb, 2018). LLL was introduced in the region in 2001, and nearly all farmers are aware of the technology or have used it at least once. Therefore, farmers have experience and an established perception of technology. We additionally explore other goals or factors, technology-specific or contextual factors not previously captured in the literature. For hypothesis H1b, since we do not use any *a priori* assumption regarding factors in this case, this sub-hypothesis is explorative. We use both qualitative and quantitative approaches to examine the hypothesis.

Second, we hypothesize:

H2a: The adoption of LLL is positively associated with an increase in the yield of rice and wheat

H2b: The adoption of LLL is positively associated with savings in irrigation water in rice and wheat.

To test these hypotheses, we follow the profit maximization assumption. Instead of profits, studies have used physical output (yield) or imputed shadow values to the unmarketed production, assuming that the output can be stored or sold (Emerick et al., 2016; Evenson & Gollin, 2003). Unlike other agricultural technologies, since LLL is adopted at different frequencies, we test how the different frequencies of adoption influence the yield and irrigation water use by quantifying the magnitude of the effect.

2.3 Materials and methods

2.3.1 Study area and sampling

This study focuses on the Punjab state of northwestern India, which has India's fastest groundwater depletion zones (CGWB, 2021). Four districts in Punjab (Ludhiana, Fatehgarh Sahib, Sangrur, and Patiala) were selected since farmers in these districts grow rice and wheat following the rice-wheat cropping system (Figure 2.1). In the rice-wheat cropping system, rice is planted in June-July and harvested in November, followed by wheat sown in November and harvested in February-March. LLL is done from April to May before rice planting.

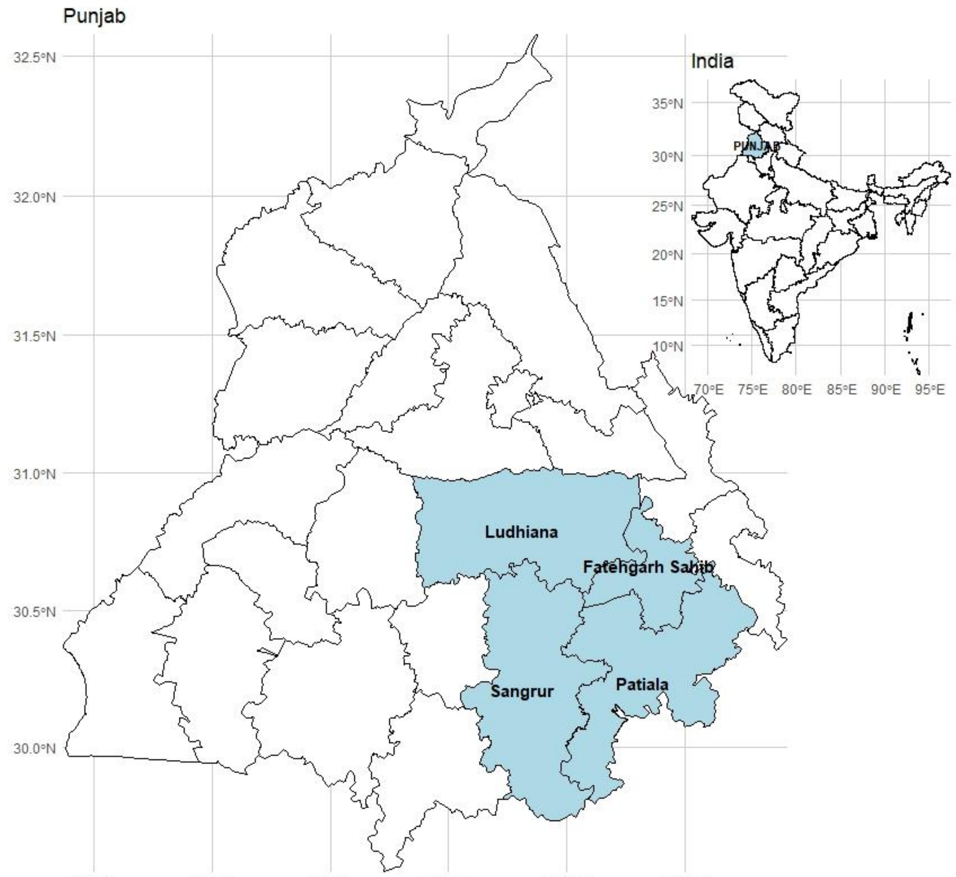


Figure 2.1: Study area

Note: The study districts are highlighted in light-blue colour.

For the study, we conducted eight qualitative interviews with farmers and laser land service providers in June 2021. The details of the interview respondents are provided in Appendix 1 Table 6.1. The responses are referred in the manuscript based on the number given in column 1 of the Appendix 1 Table 6.1. Followed by a qualitative survey, we surveyed 1021 households selected randomly from 52 villages in four selected districts of Punjab from June to August 2021. From the surveyed household, we collected data on household and farm characteristics, LLL adoption, and service provision. We collected details of the bio-physical characteristics and input-output data of crops cultivated on the largest plots for the last two seasons before the survey. Additionally, we collected village-level data from a key informant's survey in all the villages (52 key-informant survey).

We focus on two main outcomes: yield (kg/ha) and irrigation hours per hectare (h/ha) of the crops grown in Punjab, India. We asked the farmers the total production of rice and wheat for the largest plot and divided it by the area of the plot to calculate yield (kg/ha). To calculate the total hours of irrigation, we asked farmers to state the number of irrigation and hours required for irrigation for each plot in a crop season. We multiplied the number of irrigation and hours of irrigation to calculate the total hours. Then, we divided them by the plot area to get irrigation hours per hectare (h/ha). The crop-wise information was collected for one major plot per household (1021 plots).

To assess the benefits of using LLL, we considered the frequency of using LLL technology. The frequency of adoption is classified into four categories: 1) last year, 2020-21, 2) once in the last three years, 3) before the last three years, and 4) never used LLL. So instead of comparing the plots with different frequencies of use from a time-series data, we are measuring the outcome (yield/irrigation use) of a plot at time (t) with plots levelled in t vs t-n, where n is the lagged time. This approach is used since we have a cross-sectional data on outcome, with the knowledge about when the plot levelled last time. One of the main challenges in using this approach is identifying the causal effect, as cross-sectional data limits the ability to control for time-varying confounding variables.

2.3.2 Analytical framework

2.3.2.1 Mixed method approach- embedding QUAN(qual) approach

Using mixed-method approaches in studies quantifying impact can deepen the understanding of the mechanism behind impact (Nakasone et al., 2024). But unlike Nakasone et al., (2024), we use an embedded research design, Quan(qual)—a predominantly quantitative study with qualitative data (Fetters & Tajima, 2022). The advantage of the embedded approach over the simple comparison of qualitative and quantitative data is that it offers more nuanced and actionable insights compared to isolated analyses.

We use insights from qualitative surveys at the start of the study to design the quantitative survey and at the end to triangulate the results from the quantitative analysis (Figure 2.2). In-depth, unstructured interview focused on the guiding questions regarding farmers' crop cultivation practices and irrigation systems, why they use the LLL technology and how they access it. Follow-up questions were based on respondents' responses. The objective of the qualitative surveys was to understand farmers' prevailing practices and opinions.

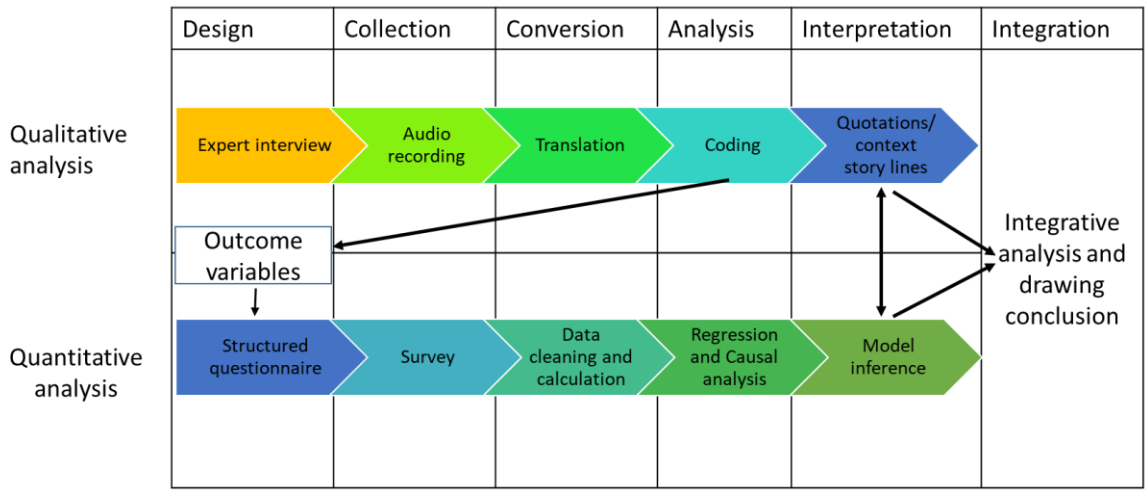


Figure 2.2: Mixed method embedded QUAN(qual) approach used in the study

Source: Developed by authors based on American Psychological Association, (2020) The interviews were conducted in Punjabi/Hindi, and took between 30 to 60 minutes. A verbal consent was sought before the interview and the interviews were audio-recorded and translated into English. We manually open-coded the translated interview texts, using a deductive approach in coding, in which we selected the part of the interviews that relates to the benefits of the technology (Saldana, 2015). The deductive approach in coding is useful in order to better understand the nuanced context and perception of the technology among farmers.

2.3.2.2 Model specifications for quantifying benefits

To assess the different benefits, we regress the frequency of levelling (K) with the outcome variable controlling for covariates. We start with a simple model OLS model in a matrix form as Eq. 2.1.

$$Y = \tau W + \theta X + \varepsilon \qquad \text{Eq. 2.1}$$

Where Y is the vector of outcomes (Yield, irrigation hours), W is the matrix of treatment variable (frequency of levelling), τ is the vector of treatment effects for k-1 treatment groups, X is a matrix of control variables: household head, household, plot level, institutional, and village level characteristics, and θ is the vector representing the coefficient of variable in the matrix. These variables are selected based on the existing studies which explored the factors affecting adoption (Ali et al., 2018; Aryal et al., 2018b, 2020; Sheikh et al., 2022). ε is the error term independently distributed with zero mean and finite variance. The average treatment effect on the treated (ATT) can be estimated from the coefficients of the treatment variable.

2.3.4.3 Effect estimation using machine learning causal forests

The treatment effect estimated using the linear model (Eq. 2.1) and an OLS estimator is based on three assumptions: 1) W is unconfounded given X, 2) the cofounders X have a linear effect on Y, and 3) the treatment effect τ is constant. We have built an identification strategy for the first assumption by defining our research questions and hypothesis, collecting relevant data, and identifying and controlling for confounding variables (Lewbel, 2019). Our identification strategy is, therefore, based on the assumption of selection-on-observables, the effect is identified if we have controlled for all the confounders.

However, treatment effects may also be biased due to misspecification of functional forms (Storm et al., 2020). Machine learning techniques like random forest have shown to be useful in this context (Chernozhukov et al., 2024). Instead of relying on parametric specifications we, therefore, use machine learning methods. Machine learning algorithms combine the best practices from semi-parametric statistics for estimation with machine learning for prediction. To this end, we use causal forest, a machine learning casual inference learning method that extends random forest (Breiman, 2001). Random forest can specify subgroups and run separate regressions for each subgroup to obtain different estimates of τ, relaxing the assumption of constant treatment effects.

In a random forest model, several decision trees are built using a bootstrapped random sample and a subset of the variables (X). The splitting of the sub-groups (leaves) is done greedily based on the variable values that maximize the squared difference in subgroup means. This process is repeated for *n* trees, and an average of prediction from each tree gives the estimate of outcome (Y). Similarly, in causal forests, instead of decision trees, causal trees are built using an 'honest' data-splitting approach to maximize the treatment effect across groups without overfitting (Athey & Imbens, 2016). Causal forest estimates the treatment effect (τ) for a target sample X=x referred to as conditional average treatment effect (CATE) by estimating a residual-on-residual regression on samples with similar treatment effects (Athey et al., 2019; Wager & Athey, 2018).

To estimate CATE, we use the generalized random forest (grf) package, specifically the multi-arm causal forest package developed by Athey et al., (2019); Athey & Imbens, (2016). First, we use the honest split of data by 50% for training and testing tests. We use the default setting in the *grf* package for hyperparameters. Second, we estimate the CATE of LLL on outcomes (yield and irrigation hours). Third, to understand which variables are critical for estimating treatment effect, we employ the variable importance statistics in the *grf* package in R and visualize using variable importance plots

(Appendix Figure 6.1). Fourth, we compute the best linear for CATE using forest prediction (on testing data) and mean forest prediction to check the quality of the random forest estimate (Chernozhukov et al., 2024). More detailed steps involved in estimating CATE using the *grf* package are detailed by (Mulungu et al., 2024).

There are several advantages of using a machine learning approach over conventional approaches in estimating treatment effects (Wager & Athey, 2018). First, classical quasi-experimental approaches such as nearest-neighbour matching and kernel matching perform well only with a small set of covariates and break down when a more significant number of covariates are used. Machine learning approaches such as causal forest perform better in settings with many covariates and complex interactions among covariates (Stetter et al., 2022). Moreover, the specific advantage of using the machine learning causal forest model is that it could also account for multi-collinearity in the data by splitting it into subsets. The algorithm is less reliant on the assumptions of the conventional models regarding the presence of unobserved confounders. The machine learning causal model is 'doubly robust'; the estimators are unbiased in determining whether the specification of at least one model (treatment or control model) is correct (Chernozhukov et al., 2024).

2.4 Results and discussion

2.4.1 Descriptive analysis

The data collected from the survey is classified based on outcome (yield and irrigation hours), treatment (frequency of levelling) and control variables. The summary of control variables used for this study is shown in Table 2.1. The distribution of yield and irrigation of wheat and rice crop is give in Figure 2.3. The average yield of rice is 7131 kg/ha and wheat is 4884 kg/ha. The average hours of irrigation in rice plots are 416 h/ha and wheat plots is 6 h/ha. The average values of the irrigation hours in rice is higher than the estimations from previous studies, example Srivastava et al., (2015) estimated the average hours of irrigation in case of rice is 285 h/ha. The distribution of the data shows they are not normally distributed. The non-normal distribution of outcome variable such

Table 2.1: Descriptive statistics for the control variables used in the analyses

Variable name	**Mean**	**Standard deviation**
Village-specific variables (n = 52)		
Share of adopters	36.40	18.78
Groundwater level	104.52	38.52
Crop diversity – Kharif	0.273	0.104
Crop diversity – Rabi	0.33	0.15
Distance to district headquarters (HQ)	2.32	2.03
Household-specific variables (n = 1021)		
Age of household head (HH)	52.544	13.206
Education of HH	7.334	4.622
Non-marginalised caste	0.94	
Majority religion	0.95	
Number of plots	1.66	0.84
Total cultivated area	2.72	2.63
Total adult members in the household	4.35	1.58
Women share	43.63	15.37
Non-farm employment	0.07	
Asset index	2.31e-09	1.69
Service providers in 2020-21	2.89	2.27
Discount on first use of LLL	0.02	
Access to information from (dummy)		
Government extension agency	0.44	
Krishi Vigyan Kendra or KVK	0.49	
Progressive farmer	0.58	
Non-Governmental Organisation or NGO	0.15	
Farmer collective	0.48	
Input dealer	0.46	
Plot-specific variables (n =1664)		
Plot area	6.92	6.44
Soil type		
Clayey	0.45	
Loamy	0.50	
Sandy	0.05	
Soil erosion	0.04	
Waterlogging	0.12	
Soil fertility		
Low fertile	0.02	
Medium fertile	0.36	
High fertile	0.62	
Rice crop variety[$]	0.55	
Rice crop duration[$]	0.09	
Wheat crop variety[$]	0.93	
Wheat nitrogen application[$]	183.08	61.61
Pump house power (hp)	14.80	5.41

Note: [$]The number is only based on the main plot in which the crop is cultivated. The description of the variables is given in Appendix Table 6.2.

as yield is commonly observed in agricultural data (Baul et al., 2024). The issue of non-normal data may be due to measurement error, population characteristics or heteregenous treatment effects (Okorie et al., 2023).

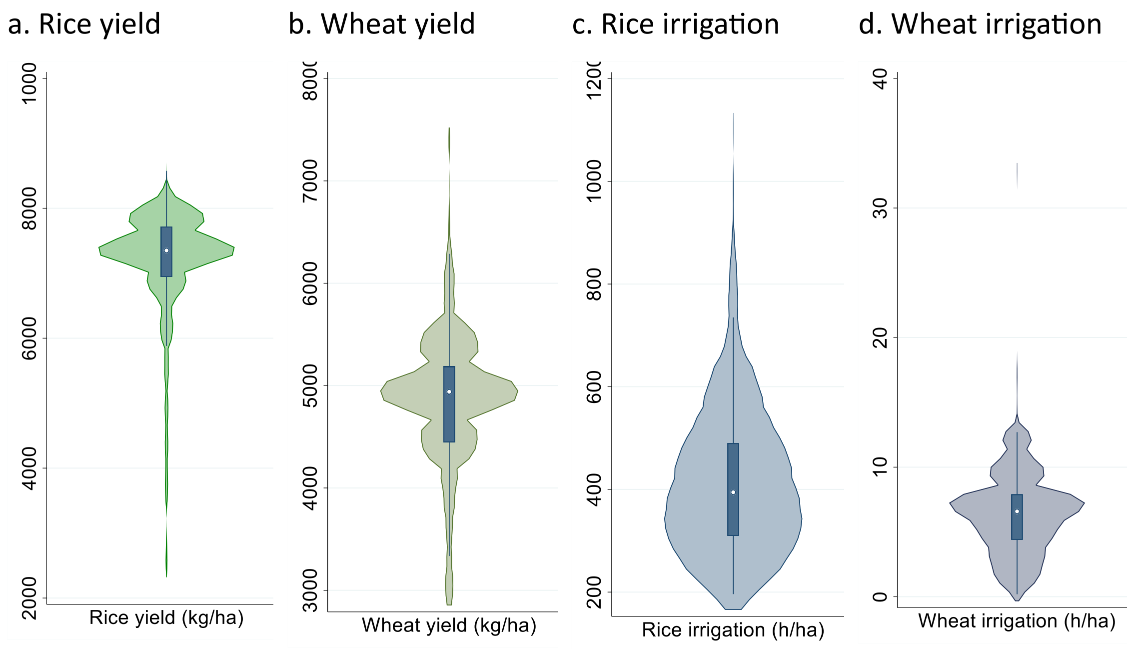


Figure 2.3: Distribution of yield and irrigation of wheat and rice crop in Punjab, India

Note: Violin plot is a combination of a kernel density plot and box plot showing the distribution of outcome variable for the largest plot cultivated in the rice and wheat growing season. The skewness and kurtosis normality test show that the data is not normally distributed.

The frequency of adoption of LLL technology at the plot level is given in Table 2.2. Irrespective of the difference in the plot numbers across crops and outcomes, we observe a similar pattern of frequency of technology use. About 30-40% of the plots were levelled in the year in which the data was collected (2020-21), and 30% of them were levelled in last three years before 2020-21, and 10% of them were levelled before last three years (before 2018) and about 20-27% of the plots were never levelled. This pattern reveals that about 60-70% of the plots were levelled once in last four years. This is in-line with the recommended use of LLL once in three to four years (Aryal et al., 2018b; Chen et al., 2022; Nguyen-Van-Hung et al., 2022).

Table 2.2: Frequency of technology use in rice and sugarcane plots in Punjab, India

Levelling frequency	Rice (% share)		Wheat (%share)	
	Plots from which the yield data was collected	Plots from which the irrigation data was collected	Plots from which the yield data was collected	Plots from which the irrigation data was collected
Never	27.90	23.91	24.88	19.35
Before three years	10.03	10.37	10.65	10.84
Last three years	29.00	30.57	29.85	29.84
2020-21	33.07	35.15	34.63	39.97
N	1007	916	1005	1421

Note: The levelling frequency is based on the last year in which the levelling was carried out in the plot. Yield data was collected data from the farmer's largest plot in each season. The figures in parentheses are percentages. N= number of plots.

2.4.2 Perception of farmers towards the effect of LLL

During the qualitative interview, all the farmers responded that LLL reduces water use and increases yield. Rice crops need standing water and with the eight-hour schedule of electricity availability, farmers irrigate every day for the first 60 days (two-thirds of the crop period). Farmers know the amount of water required to irrigate their plots and use submersible water pumps with horsepower according to the plot area. If the land is undulated, they must irrigate more to maintain the water level at six inches. One of the interviewed farmer stated, “Before using LLL, it takes 3 to 4 hours to irrigate an acre (2.3 acre=1 hecatre) of land… after LLL (used in the plot), it takes two hours.” The reduction in water use is expressed as hours required to irrigate the field.

The second benefit mentioned was higher crop yield. We asked the farmers how levelling could help in increasing the yield. Farmers narrated two pathways in which levelling leads to an increase in crop yield. First, levelling would result in a uniform distribution of fertilizer, which could increase yield. In undulated land, when the water level goes down, the plants in the exposed land get affected, and when the water level is high, the submerged plant dies. These pathways were noted in the technology's agronomic field experiments. It improves the uniform application of water, resulting in better crop standing, reduced water stress, survival of seedlings and improved nutrientwater interactions, leading to increased yield (Jat et al., 2006). These results imply that the farmers have realized the benefits researchers envisaged while designing the technology.

In the interviews, farmers also explained other benefits of using the technology. The technology suits machinery such as mechanical rice transplanters and direct-seeded rice transplanters. Mechanized rice transplanting is emerging in the region and has led to increased use of LLL. The plots are also levelled using LLL to create beds for sowing vegetable crops like cabbage and potato. These benefits, which emerged from the narratives in the in-depth interview, were not discussed in the existing literature.

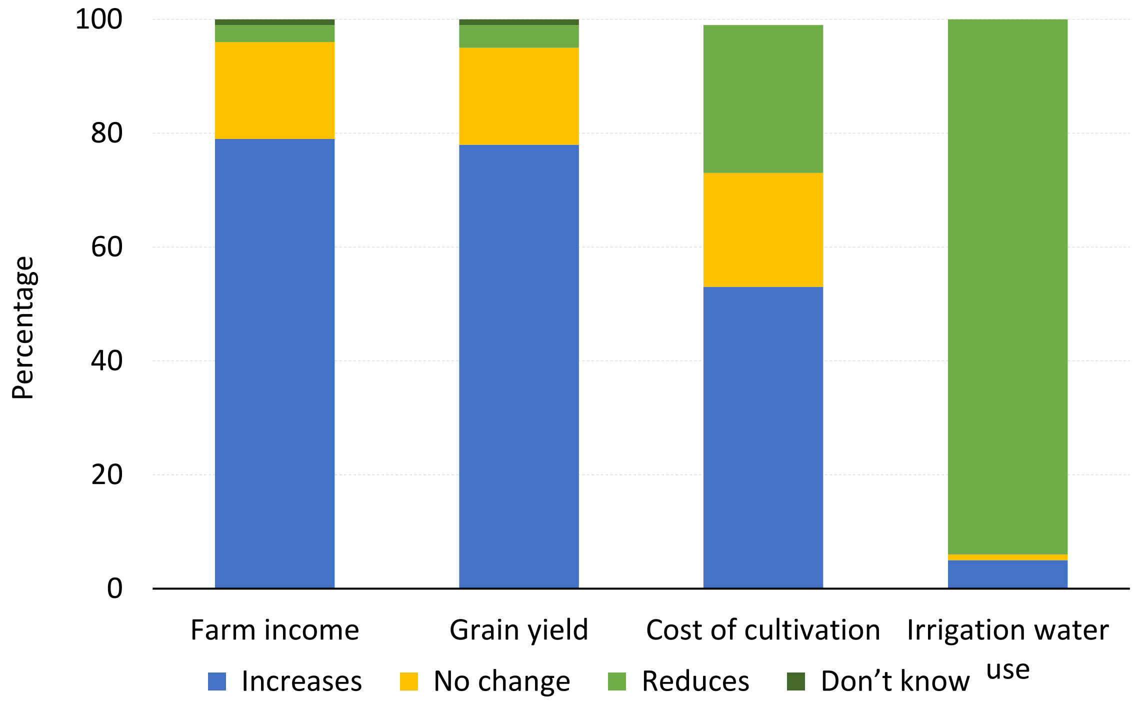


Figure 2.4: Perception of farmers towards the effect of LLL technology

Following qualitative interviews in the primary survey we quantified the perceived benefits mentioned by the farmers. In the survey, we asked the farmers to categorize the benefits from LLL (income, yield, cost of cultivation and irrigation water use) into four categories (“reduces”, “increases”, “no change” and “don’t know”). The share of responses in these four categories is given in Figure 2.4. About 80% of the respondents stated that the LLL increases farm income and crop yield. About 53% of the respondents also stated it reduces the cost of cultivation. The reduction in the cost of cultivation could be due to the reduced use of fertilizer. One respondent farmer mentioned, "In a non-levelled land, 2.5 bags of fertilizer (urea) is required, while in a levelled land, two bags are enough." About 94% of the respondents also stated that LLL reduces water use. The qualitative survey and quantitative data, therefore, suggest that farmers have different benefits from using LLL.

Even though farmers' perceived use of LLL seems to reduce irrigation hours, the preference for saving water as a motivation factor for adopting LLL is puzzling since electricity is free. In 1997, free electricity and free canal water were introduced to support farmers in Punjab (Gupta, 2023; Sarkar & Das, 2014). Since free electricity was introduced, farmers switched from canal to groundwater. About three-fourths of the total irrigated area in Punjab is irrigated using groundwater. In the interview, farmer stated that the process of irrigation as

The pumping (for irrigation) depends on availability of electricity. To avoid overloading the grid connection, electricity is made available (by the government) on a rotation basis (3-day rotation) for eight hours each day. In the last two years, we have created a WhatsApp group that informs about the shifts. The pumps have automatic switches that turn on the pumps for irrigation when electricity is available.

With the changes in the policy, the government and farmers have created new institutions and mechanisms. Though electricity is free, there is a sense of constraint and preparedness ensuring that water is available for irrigation.

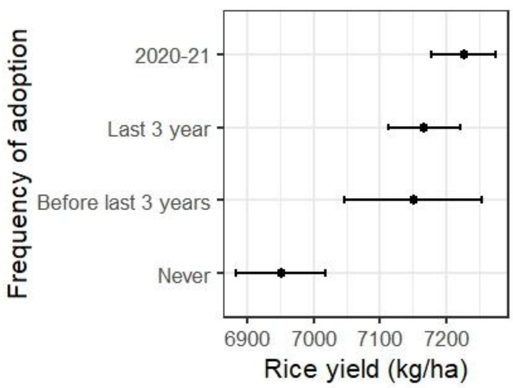
Farmers also stated various specific reasons for adopting LLL. One of the farmers stated that the field looked good after levelling. The benefit of the farm looking tidy (levelled) is considered a sign of skilled farming, a bourdieusian perspective (Burton, 2012; Gosnell et al., 2019). Burton, (2012) conducted a cross-cultural study of Germany and Scotland on 'tidy' features such as straight colour and evenly coloured fields. He concluded the relationship between how farmers perceive 'tidy' landscapes as a sign of skilled farming. Gosnell et al., (2019) similarly observed the relationship of aesthetics as a norm with the ‘good farmer’ in the case of climate-smart regenerative agriculture. We observed that farmers view levelling as ‘looking good’, and we infer that this is one of the reason for the wide-spread adoption of LLL since it is related to the norm of a ‘good farmer’ or skilled farmer. Another farmer responded that with levelling he could reduce the width of the bund. Another farmer who cultivates responded that levelling helps create raised beds for cultivating potatoes. This validates our hypothesis that adoption is not only a question of productivity but is influenced by the heterogenous goals of farmers.

2.4.3 Quantifying the magnitude of benefits from LLL

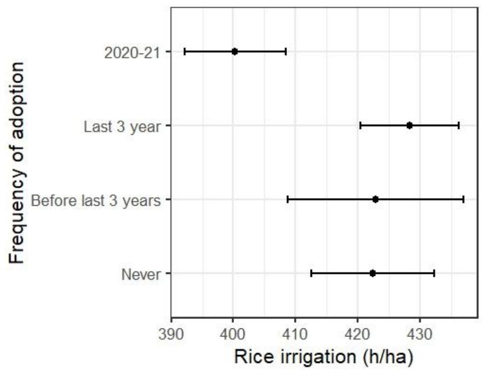
We calculated the average yield and irrigation hours of rice and wheat crops reported by farmers and compared them at different frequencies of LLL (Figure 2.5). The average rice yield for plots levelled before three years (7150 kg/ha), last three years (7167 kg/ha), and 2020-21 (7226 kg/ha) are statistically significantly different from the plots in which LLL has never used [base category] (6951 kg/ha). The mean difference in rice yield for the three frequency levels compared to the base category is 200 kg/ha, 216 kg/ha and 276 kg/ha. Based on this estimation, the average increase in yield is 3-4 % from the average yield in the base category. Assuming the market prices in 2020-21 (~0.26 $ per kg of rice), the rice yield gain (200 kg/ha= ~42$) could cover 80% of the cost of levelling (53$ @10$ h/ha). This back of the envelope estimations suggest that there are yield gains from technology which could partially cover the cost of using the technology.

The average hours of irrigation in rice are lowest for plots levelled in 2020-21 (400 h/ha), followed by levelled before three years (422 h/ha) and last three years (428 h/ha). The average difference is 22 h/ha in plots levelled in 2020-21 compared to the base category (“never”). These differences are somewhat smaller than the estimates from the previous studies (Ali et al., 2018; Aryal et al., 2018b; Larson et al., 2016; Lybbert et al., 2018; Pal et al., 2022; Sheikh et al., 2022).

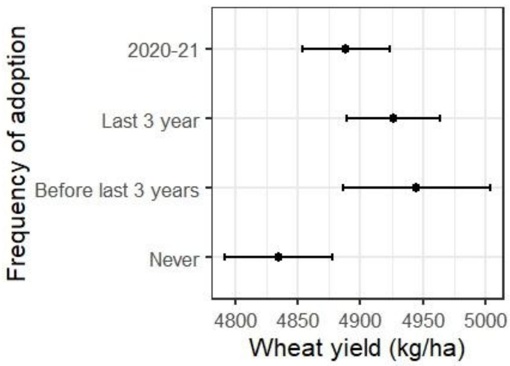
a. Rice yield



b. Rice irrigation



c. Wheat yield



e. Wheat irrigation

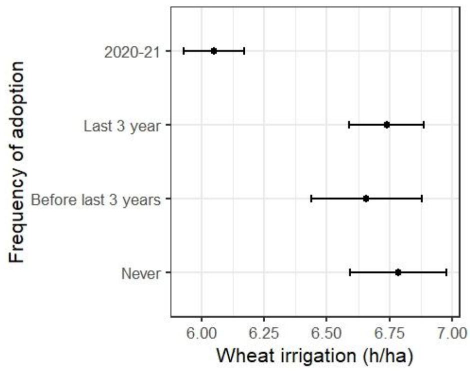


Figure 2.5: Yield and irrigation by frequency of LLL in rice and sugarcane in northwest India

Note: The average values are shown in the plot with a 95% confidence interval. The average values are given in Appendix Table 6.3.

We estimate the average effect of the frequency of LLL by controlling for other factors using OLS regression. The coefficients from the model for the variable on the frequency of LLL give us the average treatment effects. The effect on rice yield is positive but statistically non-significant if levelling is done in the last three years (53.99 kg/ha) and last year, 2020-21 (85.4 kg/ha). The irrigation hour in rice was negative for the plots in which levelling was done in 2020-21. There was no statistically significant increase in the yield of wheat. However, the irrigation hours were negative in all frequencies of levelling but statistically significant for plots levelled in 2020-21.

The effect estimates from the OLS model are lower than the average difference in frequency of levelling compared with the base category in the summary statistics

(Figure 2.5). This may be caused by imprecise estimates due to non-normal outcomes (Baul et al., 2024; Esen et al., 2024).

Next, we estimate the conditional average treatment effect using a machine-learning causal forest approach (Table 2.3). The estimates show that the average effect plots levelled in the last three years (233.8 kg/ha) and last year (2020-21) (242.43 kg/ha) had a statistically significant effect. In the in-depth interview, a farmer also stated that the effect of LLL on rice yield was 100 to 200 kg/ha. Even in CATE estimates, we do not find a statistically significant effect in the case of rice irrigation and wheat yield. Plots levelled in the last three years and 2020-21 have statistically significantly lower hours of irrigation. The estimates from CATE are higher than the estimates from OLS but lower than the effects reported in previous studies based on filed experiments (Jat et al., 2015) observational studies (Ali et al., 2018; Aryal et al., 2020; Larson et al., 2016; Pal et al., 2022; Sheikh et al., 2022)and randomized control trails (Lybbert et al., 2018) in India.

The distribution of CATE values by quartiles (4 quartiles) is shown in Figure 2.6. There is a noticeable variability with each quartile. The range of CATE values is widest in the case of the first and fourth quartile in all outcomes. This indicates that there is a substantial heterogeneity in the treatment effect. The CATE values for rice yield and rice and wheat irrigation hours are right-skewed. This indicates that the distribution is not normal, and could be influenced by certain covariates across the quartiles. Such heterogeneous effects of technology are important for understanding the effects of technology (Stetter et al., 2022).

Table 2.3: Magnitude of effect of LLL

Levelling frequency	**Rice yield (kg/ha)**		**Rice Irrigation (h/ha)**		**Wheat(kg/ha)**		**Wheat Irrigation (h/ha)**	
	OLS	CATE	OLS	CATE	OLS	CATE	OLS	CATE
Before three years	25.858	45.307	-0.380	2.523	21.877	-40.399	-0.411	-0.464
	(112.733)	(138.585)	(17.340)	(16.828)	(75.458)	(80.172)	(0.356)	(0.296)
Last three years	130.245	215.193**	-0.472	13.723	-0.600	-86.709	-0.196	-0.598**
	(87.049)	(95.597)	(13.390)	(14.919)	(59.029)	(71.433)	(0.278)	(0.237)
Last year	187.506**	227.463**	-25.423*	-9.457	-11.638	-136.266	-0.351	-0.666**
(2020-21)	(86.476)	(96.019)	(13.261)	(13.097)	(58.223)	(72.132)	(0.273)	(0.221)

Note: OLS- Ordinary least square (Refer appendix Table 6.4 for full model) CATE- Conditional average treatment effect (Refer Appendix Figure 6.1 for variable importance plot). The figures in the parenthesis are standard errors. ** shows significance at 5%, *Shows significance at 10%.

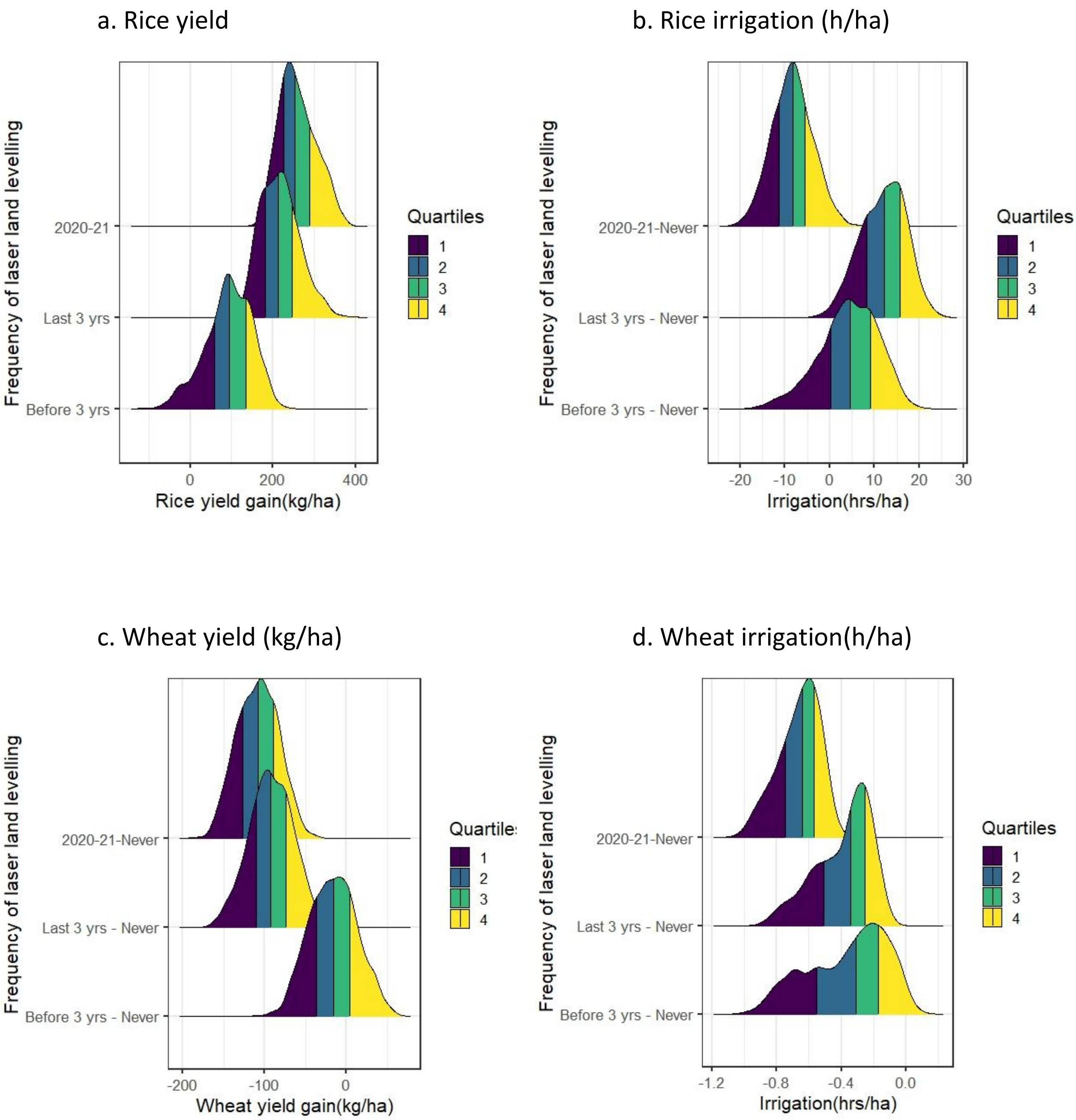


Figure 2.6: Distribution of CATE estimates of yield and irrigation by frequency of LLL in rice and wheat

We test for the robustness of the CATE estimates using best linear fit mean forest prediction and differential forest prediction (Table 2.4). The coefficient of the mean for prediction is close to one, and significance shows that the estimates are robust and wellcalibrated. However, the coefficient from the differential forest prediction is not significant for all the outcomes. The estimates for the upper and lower quartiles are imprecise and we exercise caution in drawing inferences from these sub-groups.

Though the machine learning causal approach helps increase the precision of estimates, overall, the effect of LLL on yield and irrigation is lower. We find statistically significant results in the case of rice yield to the extent of 3-5% for plots levelled once in the last three years and last year (2020-21). However, the difference in the yield estimate for levelling every year and levelling once every three years is not statistically significant. This suggests that levelling more than once in three years may not offer many benefits in terms of yields.

Table 2.4: Evaluation of quality of the causal forest estimates

	Rice yield	Rice Irrigation	Wheat yield	Wheat irrigation
Mean forest prediction	1.001** (0.550)	1.025** (0.566)	1.109 (0.952)	0.978** (0.470)
Differential forest prediction	-0.174 (1.019)	-1.637 (1.432)	-246.727 (15.178)	0.097 (1.022)

Note: Stand errors in parenthesis are one-sided heteroskedasticity-robust standard errors. ** shows significance at 5%.

With respect to irrigation, we did not find any statistically significant results. This differs from previous studies showing a significant impact of LLL on reducing irrigation hours. One plausible explanation is that if we measured the irrigation hours based on farmers' responses. Abay et al., (2023) have discussed the issue of measurement errors and misperceptions in self-reported data by farmers on plot size and argue that farmers are misperceiving rather than misreporting. Since there are multiple irrigation schedules over a period of time, it would also lead to recall bias. Self-reported irrigation hour is the common approach used in studies that assessed the impact of LLL on water saving (Aryal et al., 2018b, 2020; Lybbert et al., 2018). An alternative to this approach is quantifying water use using measurement devices, e.g., a flow meter (Knapp et al., 2018)). Our study tried to use an ultra-sonic flow meter to check the water flow velocity from the pumps. However, among the 30 samples we collected, we faced several challenges in collecting data, due to resistance of farmers from collecting such data, since water use is a politically a highly sensitive topic in the region. Rusted tubes, inaccessible pumps, availability of electricity due to the rotation of power caused further issue in using the ultra-sonic flow meters.

2.5 Conclusion and policy implication

This paper used LLL as a case study to understand why farmers adopt resource conservation technologies. We used a mixed-method approach to assess why farmers are adopting the technology, which allowed the exploration of factors that were not previously considered. We find that the effect of LLL on designed benefits such as increased yield and water saving is lower than previously estimated. However, farmers' positive perceptions about the benefits and other factors, such as electricity availability, compatibility of LLL with other technologies, and aesthetic value, have resulted in wider technology adoption. These findings provide new insights beyond the traditional notion of designed benefits and profit maximization as the key drivers behind technology adoption.

Before generalizing the findings for policy, a few limitations must be considered. First, our study is based on cross-section data, and the challenges of measuring the outcomes, especially irrigation hours, must be considered before drawing inferences. Future studies could explore alternative approaches for measuring irrigation water in challenging settings. Second, the insights from the qualitative data need to be explored further to understand the role of technology development and extension institutions in shaping perceptions of technology.

Our study provides three key insights on technology development, use, and dissemination. First, technology development is a continuous process, so even after the farmers adopt a technology, further studies are required to evaluate potentials and other co-benefits. Second, our findings indicate that farmers interact with technology, and their perception is based on their experience evaluating the designed benefits and the context in which they work. Third, the institutions involved in disseminating technology could also use other benefits realized by farmers to promote the technology.

Our study shows that even in the case of linear technology transfer, there is a scope for a feedback loop and the co-creation of knowledge.

Chapter 3 : Private service provision contributes to widespread innovation adoption among smallholder farmers: Laser land levelling technology in northwestern India[1]

Abstract

Adoption of indivisible technologies – like agricultural machinery – is challenging since it's not easily divisible and costly, differentiating it from many other agricultural technologies, such as new seeds and fertilisers. This study investigates key institutional factors promoting the adoption of laser land levelling (LLL), a water saving technology that has gained wide popularity among farmers in northwestern India. The main objective is to evaluate how individual private service providers, offering LLL on a rental basis to farmers, are pivotal to 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. Our study, for the first time, shows that individual service provision is an alternative institutional mechanism for re-evaluating traditional agricultural technology scaling models for wider and more inclusive adoption.

Keywords: adoption, agricultural machinery; indivisible agricultural technology, smallholder farmers
JEL codes: O13, Q13, Q15, Q25

[1] This chapter is a joint paper with Martin C. Parlasca, Matin Qaim, and Vijesh V.Krishna. A previous version of the chapter is published as a journal article: Surendran-Padmaja, S., Parlasca, M.C., Qaim, M. & Krishna, V.V. 2025. Private service provision contributes to widespread innovation adoption among smallholder farmers: Laser land levelling technology in northwestern India. Agricultural Water Management. 312: 109411. https://doi.org/10.1016/j.agwat.2025.109411 and as a ZEF Discussion Paper: Surendran-Padmaja, S., Parlasca, M.C., Qaim, M. & Krishna, V.V. 2024. Private service provision contributes to widespread innovation adoption among smallholder farmers: Laser land levelling technology in northwestern India. ZEF-Discussion Paper on Development Policy No. 346, Center for Development Research, Bonn, May, 2024. A previous version was also presented at an organized symposium titled "Technology and policies for groundwater management in South Asia", at the International Conference of Agricultural Economists (ICAE), New Delhi, India on August 3, 2024.

Subash Surendran-Padmaja developed the research concept, collected and analyzed the data, and wrote the paper with support from the other co-authors.

3.1 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 (Belton et al., 2024; Ruzzante et al., 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 LLL, a water saving 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 (Keil et al., 2019, 2021; 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; Jones-Garcia & Krishna, 2021; Mottaleb et al., 2019; 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., 2018b, 2020; Pal et al., 2022; 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 3.2, we provide some more background on the LLL technology and how it was introduced in the Indian context. In section 3.3, we discuss the theoretical framework of the technology adoption analysis, whereas in section 3.4 we introduce the empirical approach. The empirical results are presented and discussed in section 3.5, while section 3.6 concludes.

3.2 LLL technology and service providers

LLL 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., 2022). 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., 2018b). 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 & 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., 2021a).

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 (Chen et al., 2022; Jat et al., 2006). 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 3.1).

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., 2018b; 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 (GoI, 2023; Jat et al., 2006; Sidhu et al., 2008). 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).

Figure 3.1: Laser land levelling technology operated at night in northwestern India, highlighting the demand for the technology

Photo source: Dr. Anirudh Mar (Special arrangement)
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

3.3 Theoretical background

The earliest literature explaining the adoption of indivisible technologies is the threshold model by David, (1996). 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 & 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.

3.4 Material and methods

3.4.1 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 3.2). 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, 2018b, 2020; Gulati et al., 2017; Larson et al., 2016; Lybbert et al., 2018; Paudel et al., 2023).

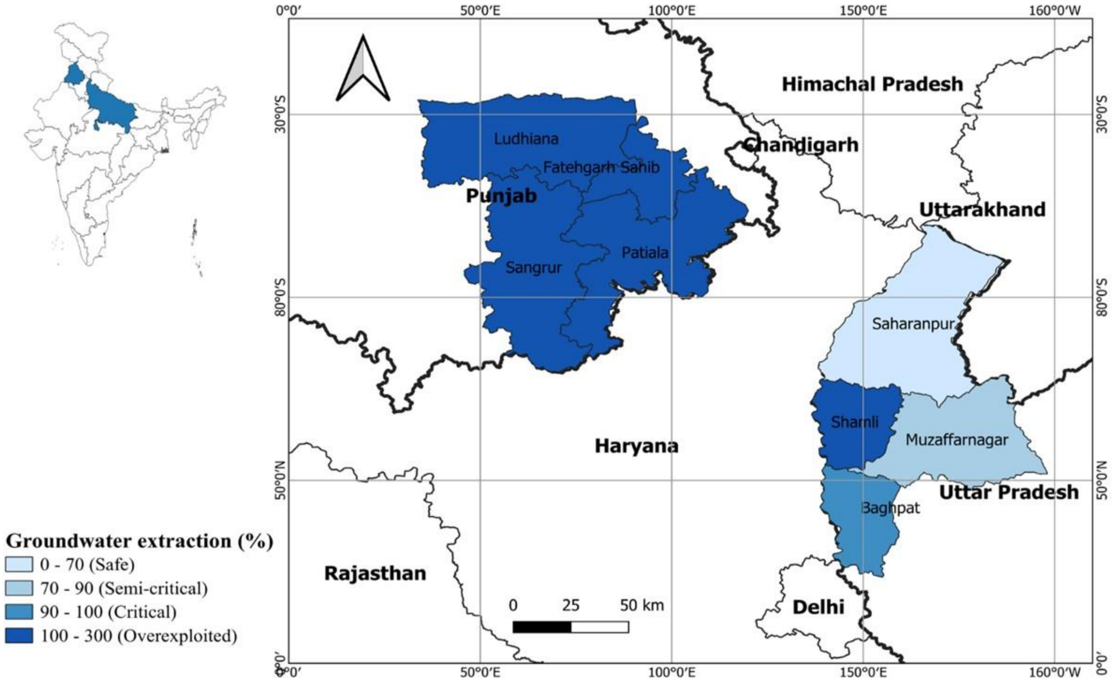


Figure 3.2: Map of study area showing groundwater extraction rates at the district level

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 3.2).

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).

3.4.2 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:

$$P(Y_i = 1) = \Phi\ (\beta_0 +\ \beta_1 Service\ provider_i +\ \theta \boldsymbol{X}_{ik} +\ \mu_i) \qquad \text{Eq. 3.1}$$

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. 3.1 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:

$$P(Y_i = 1) = \Phi\ (\gamma_0 + \gamma_1 Plot\ size_i + \gamma_2 Service\ provider_i + \gamma_3\ Service\ provider_i \times\ Plot\ size_i + \Gamma\boldsymbol{X}_{ik} + \varepsilon_i) \quad \text{Eq. 3.2}$$

$$P(Y_i = 1) = \Phi\ (\delta_0 + \delta_1 Farm\ size_i + \delta_2 Service\ provider_i + \delta_3 Farm\ size\ \times Service\ provider_i + \Delta\boldsymbol{X}_{ik} + \varepsilon_i) \quad \text{Eq. 3.3}$$

In Eq. 3.2 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. 3.3 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 Eq. 3.2 and Eq. 3.3, we also calculate the marginal effects of $Service\ provider_i$ on LLL adoption as follows:

$$\frac{\partial P(Y_i = 1)}{\partial Service\ provider_i} = \gamma_2 \Phi\ (\boldsymbol{X}_i) + \ \gamma_3 Plot\ size_i \Phi\ (\boldsymbol{X}_i) \qquad \text{Eq. 3.4}$$

$$\frac{\partial P(Y_i = 1)}{\partial Service\ provider_i} = \delta_2 \Phi\ (\boldsymbol{X}_i) + \ \ \delta_3 Farm\ size_i\ \Phi\ (\boldsymbol{X}_i) \qquad \text{Eq. 3.5}$$

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.

3.4.3 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 3.1.

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., 2018b). Such variables are also included in our regression models.

Table 3.1: 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

Variable name	Description	Mean (Std. deviation)
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 Appendix Table 6.1. #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 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 & Huffman, 2014; Ali et al., 2018; Aryal et al., 2018b). Households facing water scarcity are also more likely to adopt LLL (Ali et al., 2018).

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 (Jones-Garcia & Krishna, 2021). Access to extension services, which offer training on various agricultural practices, is often linked to technology adoption (Aryal et al., 2018b; di Falco et al., 2011). However, in Pakistan, 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.

3.5 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.

3.5.1 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 (Appendix Table 6.5). 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.

3.5.2 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 3.3 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).

In Punjab, the majority of the LLL adopters use service providers from within the same villages, accounting for around 60% of the total (Appendix Table 6.6). 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.

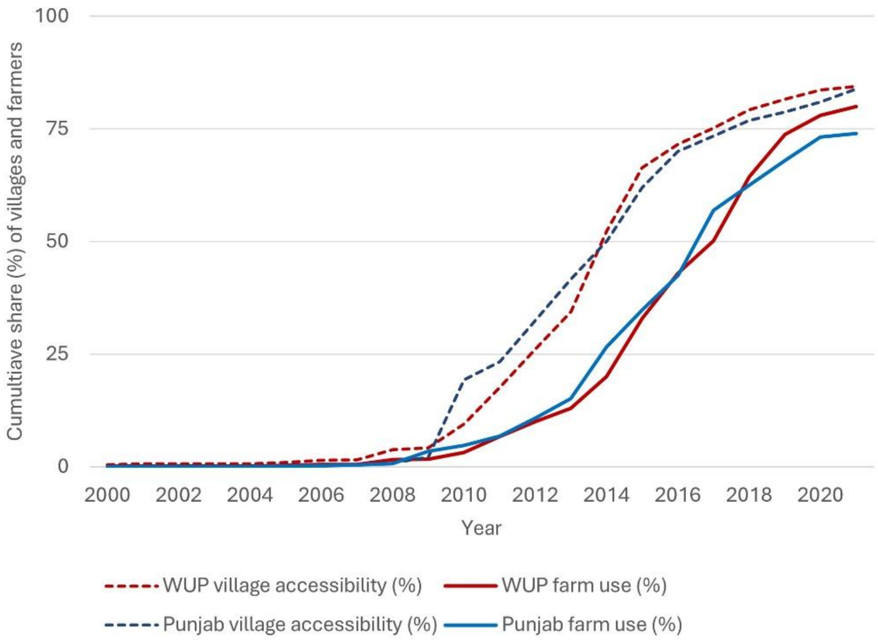


Figure 3.3: Cumulative share of LLL adopters in northwestern India, 2000-2020

Note: We restructured the data from a cross-sectional form to a panel form for the years 2000 to 2021 based on farmer recall, with a new dummy variable equal to one since the laser land leveller was first accessible in the village and adopted in the respondent's farm. WUP – western Uttar Pradesh.

Rental charges for LLL machines and services have shown a consistent increase between 2018 and 2021 (Appendix Table 6.6). 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., (2018) found that offering a first-hour service discount can be an effective strategy to increase the likelihood of LLL adoption among smallholders.

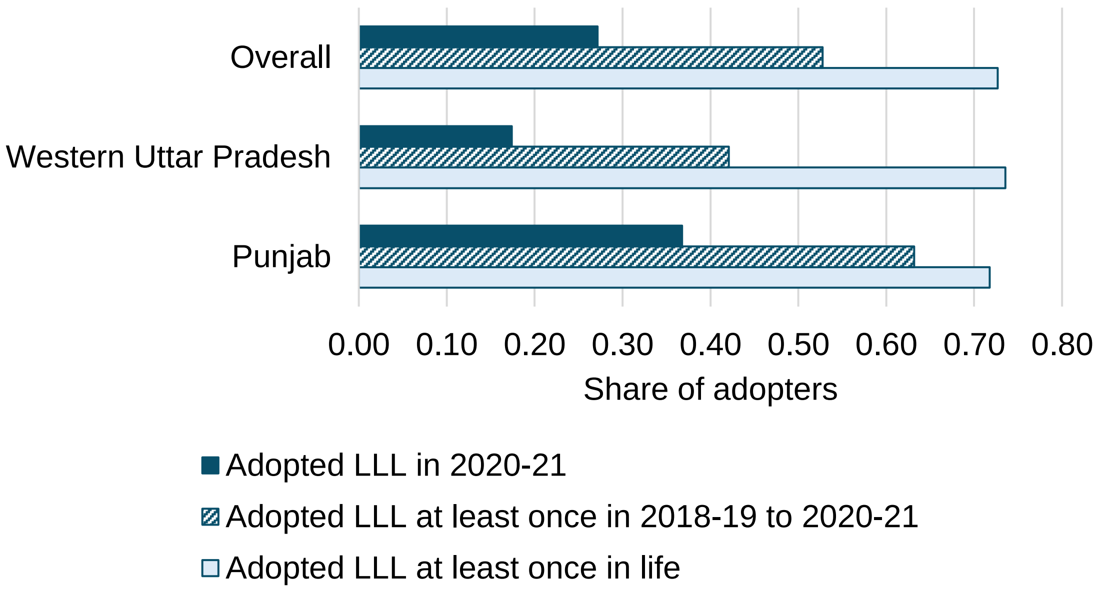


Figure 3.4: Share of LLL adopters based on the frequency of technology use

Source: Primary data collected by authors (2021).

Figure 3.4: Share of LLL adopters based on the frequency of technology use

Figure 3.4 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.

3.5.3 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 3.2, 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., 2018; Pal et al., 2022; Sheikh et al., 2022). Field-trial results suggest that LLL-related yield gains in rice and wheat can even be higher (Jat et al., 2006).

Table 3.2: 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

Note: n- number of adopters

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 3.2. 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.

3.5.4 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. 3.1 above are summarised in Table 3.3, 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 3.5a. 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.

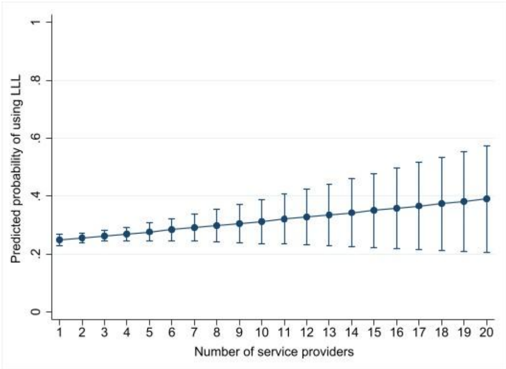
Relevant control variables were included in estimation with the more detailed results shown in Appendix Table 6.7. Various socioeconomic variables are positively and significantly associated with LLL adoption, including involvement in non-farm employment, wealth (asset ownership), and discounts on the 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.

Table 3.3: Probit model on determinants of LLL adoption (2020/21)

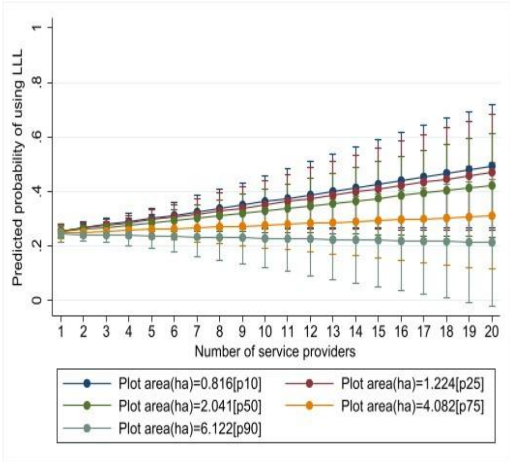
	(1) Model 1	(2) Model 2	(3) Model 3
Service providers in 2020/21	0.021	0.040**|#	0.032*|###
	(0.014)	(0.019)	(0.017)
Plot size	-0.015	2.E-04|#	
	(0.010)	(0.014)	
Plot size x Number of service providers (interaction)		-0.007#	
		(0.005)	
Farm size			-0.013**|###
			(0.005)
Farm size x Number of service 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 Appendix Table 6.7.

5a.



5b.



5c.

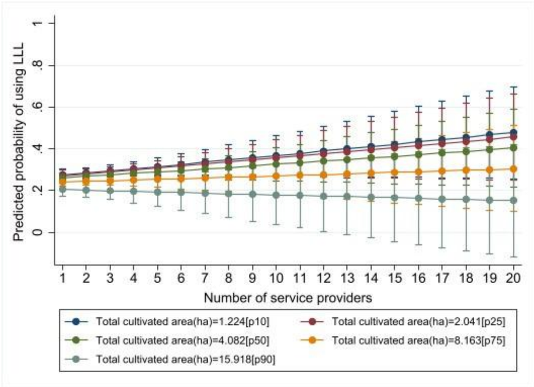


Figure 3.5: Marginal effects of the number of service providers on LLL adoption

Source: Estimated from regression models (1) to (3) in Table 3.3.
Note: The figure shows marginal effects calculated at sample mean values and adjusted predictions with 95% confidence intervals. The vertical axis shows the predicted probability of LLL adoption. In panels 5b and 5c, predictions are shown for the 10^{th} (p10), 25^{th}(p25), 50^{th}(p50), 75^{th}(p75) and 90^{th}(p90) percentile values of plot size and farm size(total cultivated area), respectively.

3.5.5 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 Eq. 3.2 and Eq. 3.3 are summarised in Table 3.3, 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 3.5b 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 3.3 (column 3) and Fig. 5c 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 3.3 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 (Nguyen-Van-Hung et al., 2022). In Table 3.4, 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 3.4 are similar to those in Table 3.3. When controlling 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 plots. These results underscore the importance of customizing agricultural support services to the specific needs of different farm sizes. This is the first study which shows the role of individual service providers as an institutional mechanism for the adoption of invisible technology.

Table 3.4: 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 Appendix Table 6.8.

3.6 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 and are different from custom hiring centers and co-operatives.

Our findings presents a first-hand 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.

Chapter 4 : Laser land levelling technology mitigates groundwater decline in northwestern India[1]

Abstract

Groundwater levels are declining globally due to intensive extraction for agriculture. While various technologies and policies have been introduced to slow down this decline, their effectiveness is debated because water savings at the farm level do not always translate into improvements at the groundwater level. We assess the impact of laser-assisted precision land levelling, a technology that reduces irrigation water use, one of the most successful technologies in the post-Green Revolution era with respect to area under adoption and the number of adopters in northwestern India and Pakistan. We combine primary data collected from 291 villages in northwestern India with groundwater data from 3286 observational wells for a period of 21 years (2000-21). Since the technology was introduced in villages at different times, we employ a staggered difference-in-difference approach to estimate the effect of laser land levelling (LLL) adoption at the village on the groundwater level. We find a rapid decline in groundwater levels in the study region by up to 20 meters from 2000-21. Our analysis shows that the adoption of LLL has reduced groundwater decline by 3.7 meters in May, the month directly succeeding in the use of technology. This finding suggests that LLL mitigated the effect of groundwater decline in northwestern India. We relate this effect to the widespread adoption of LLL and the fact that the technology directly changes farmers' irrigation practices. Yet, considering the intensity of the extraction rates, technology alone cannot solve the current decline in groundwater in northwestern India.

Keywords: groundwater conservation, sustainable production system; agricultural technology, staggered difference in difference
JEL codes: O13, Q14, Q16, Q25

[1] This is a joint paper with Christoph Kubitza, Trevor Tisler, Vijesh V Krishna, and Matin Qaim. Subash Surendran-Padmaja developed the research idea, collected and analyzed the data, and wrote the paper with support from the other co-authors.

4.1 Introduction

Globally, the groundwater as permanent aquifer storage is declining at a rate of 17 km^3/year (Hasan et al., 2023). The depletion of groundwater is primarily due to the withdrawal of groundwater for irrigation (Wada et al., 2014). This decline is a major threat to global food security, not only in the countries growing crops based on irrigation systems but also in those importing, since 11% of the non-renewable groundwater is embedded in the international trade of crop commodities (Dalin et al., 2017). Northwestern India is experiencing one of the fastest rates of groundwater depletion in the world (Seo et al., 2023). Under the current scenario, modelling results show that in the overexploited regions in northwestern India, groundwater levels could decline at a rate of 2.8 m/year (Shekhar et al., 2020). The widespread cultivation of rice-wheat cropping systems, combined with extensive flood irrigation, subsidy on electricity for irrigation is attributed as the primary driver of this rapid groundwater depletion (Joseph et al., 2022). While heavily input-intensive, these cropping systems are essential to local food security and contribute to 63% of the calorie intake of the people in the region (DeFries et al., 2015). The declining groundwater level is, however, already negatively impacting crop yields (Bhattarai et al., 2021) and increase in energy required for extraction and investment for deepening groundwater wells (Sayre & Taraz, 2019). With the current rate of groundwater decline will result in a 68% reduction in cropping intensity based on estimates, which is a major threat for local livelihoods and food security (Jain et al., 2021b).

Several technologies and policies exist to address the groundwater decline caused by agricultural production in India (Devineni et al., 2022; Kumar et al., 2022). Two widely studied policy-based solutions include banning the sowing of rice crops before June (Kishore et al., 2024; Tripathi et al., 2016) and incentivising water savings using payments (Fishman et al., 2016; Mitra et al., 2023). Their impact on groundwater decline has been ambiguous, with studies showing positive (Mitra et al., 2023; Tripathi et al., 2016), negative (Kishore et al., 2024; Sekhri, 2012), and no effects (Fishman et al., 2016). Another widely promoted solution is diversifying or switching to crops with lower water requirements (Chakrabortty et al., 2023). Despite several efforts to diversify the cropping system, India's prevailing price support mechanism provides little incentive for farmers to switch to alternative crops (Chatterjee et al., 2024). Given this policy framework, interim solutions are needed that can be integrated into the existing cropping system.

This study examines a technological intervention—laser-assisted precision land levelling or laser land levelling (LLL)—as an alternative possible solution for addressing groundwater decline. LLL is a precision guide system used to level the land during the land preparation before the sowing of crops. The levelled land ensures uniform water distribution, which reduces water wastage (Lybbert et al., 2018). Existing studies show that adopting LLL leads to water savings of 25% at the farm level (Aryal et al., 2018b, 2020; Lybbert et al., 2018). The technology has been promoted since 2001 by the Consortium of International Agricultural Research Centers (CGIAR), including the International Rice Research Institute (IRRI) and the International Maize and Wheat Improvement Center (CIMMYT), in collaboration with the Indian Council of Agricultural Research (ICAR) and State Agricultural Universities in northwestern India (Aryal et al., 2018b). LLL can be easily integrated into the existing farming system, as land levelling is already a common practice in the region. Laser land leveller is an indivisible technology, i.e., unlike new seeds and fertilisers, the technology cannot be tested in small quantities and owning the technology is not economically viable for farmers with small landholdings (Lu et al., 2016). In response, farmers adopt LLL by renting in the technology from individual private service providers. Though there are no data on the number of service providers, the number of LLL machinery in Punjab and western Uttar Pradesh increased from less than 1,000 in 2003 to more than 90,000 in 2015 (Surendran-Padmaja et al., 2024). Parallelly, local designing, assembling, and manufacturing of LLL machinery emerged in the region (Paudel et al., 2023). As a result, approximately 80% of farmers in northwestern India had adopted this technology, with varying levels of frequency and intensity, as of 2021 (Surendran-Padmaja et al., 2024).

While several technologies have been proposed for groundwater conservation, their efficacy is often questioned, as water savings at the farm level may not translate into meaningful reductions at the groundwater or aquifer level. For example, Joseph et al. (2022) show that introducing water-saving drip irrigation does not change the groundwater depletion trends in northwestern India. Similarly, Fishman et al. (2023) show that introducing drip irrigation does not reduce the hours spent pumping irrigation water, as farmers switch to different crops and trade the surplus water. Pfeiffer and Lin (2014) have also noted that increasing water efficiency in crops may not reduce groundwater extraction as farmers shift to water-intensive crops or expand irrigated acreage. This phenomenon is recognised as the 'rebound effect' or Jevons paradox, where the increase in efficiency on resource use will generate an increase in consumption of the resources (Alcott, 2005). Rebound effects have already been observed, for example, in the case of agriculture and soil management technologies and policies (Paul et al., 2019; Wheeler et al., 2020).

To address the lack of studies going beyond the farm level and to consider potential rebound effects with respect to the widely popular LLL, we assess the effect of the technology on groundwater declines at the village level. Hence, we move from crop- or farm-level effectiveness to system-wide effectiveness, the technology's ability to reduce groundwater decline at scale, which is its intended goal. The study also makes two additional contributions to the literature. First, our study is unique in that it investigates a technology with a relatively high adoption rate in small-scale farming, which is uncommon due to typical barriers to technology adoption. This provides an opportunity to assess whether a technology that has reached its full adoption potential can have a measurable impact at larger scales. Second, the technology co-exists with other policy solutions, which allows us to compare it with other policy alternatives.

Our analysis primarily focuses on the causal estimate of the adoption of LLL technology on groundwater. We merge primary survey data collected from 291 Indian villages on technology adoption with spatial data on groundwater and precipitation. We leverage the variation in adoption timing across villages to estimate its impact. Our analysis shows that the adoption of LLL has reduced groundwater by 3.7 meters in the months, directly succeeding in the use of technology. Considering a groundwater decline of 20 m over study period from 2020-21 and an average reduction in groundwater decline of 3.7 meters, using the technology could have resulted in an 18% reduction in groundwater depletion. Our study hence suggests that LLL has a potential effect in saving groundwater. However, considering the intensity of the extraction rates, technology alone cannot solve the current decline in groundwater in northwestern India.

4.2 Data

We use three datasets for empirical analysis: (1) primary data collected through a village-level survey of key informants in the northwestern India in 2021 and 2023, (2) monthly weather (rainfall) data extracted from the Climate Hazards Center, University of California Santa Barbara-Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (CHIRPS, n.d.) (3) monthly groundwater level data collected by the Central Groundwater Board (CGWB) of Government of India. Groundwater level is the depth at which groundwater is found below the groundwater surface measured in meters (m).

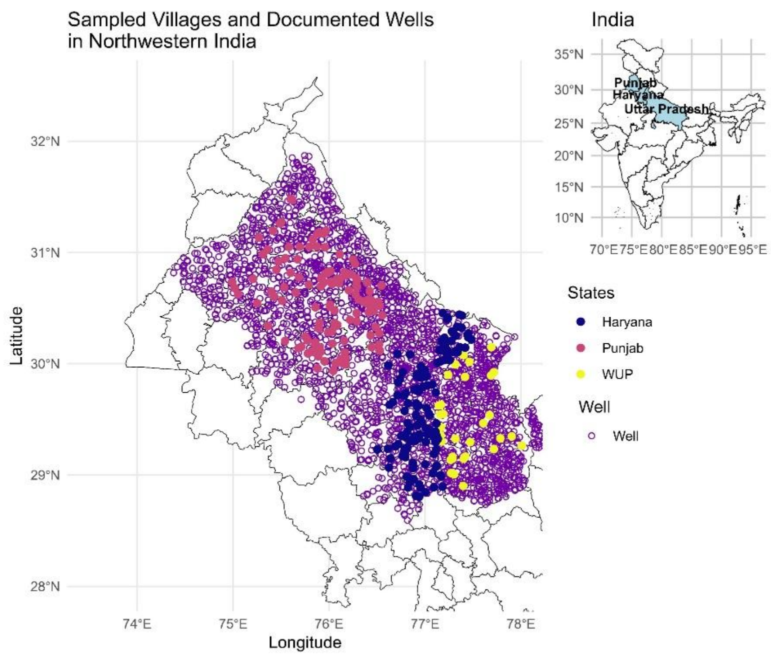


Figure 4.1: Study area villages in northwestern India

Note: In Punjab, Western Uttar Pradesh, and two districts of Haryana, the surveys were conducted in 2021-22 and 2022. In four districts of Haryana, the survey was conducted in 2022-23.

For the village-level survey, we collected data from 291 randomly selected villages across 17 districts in the northwestern Indian states of Punjab, Haryana, and Western Uttar Pradesh. These 17 districts, chosen from a total of 70, were purposively selected as they are key areas for rice-wheat cropping systems. The village sample is hence representative for the rice-wheat growing region of northwestern India. The data were collected using tablets with the Open Data Kit (ODK) software. We restructured the data from a cross-sectional form to a panel form for 2000 to 2021, with a new dummy variable equal to one for the years since the laser land leveller was first adopted in the village. We have shown a visual representation of the sampled villages in Figure 4.1. We use the village-level GPS coordinates collected during the survey to extract the rainfall data from the CHIRPS database.

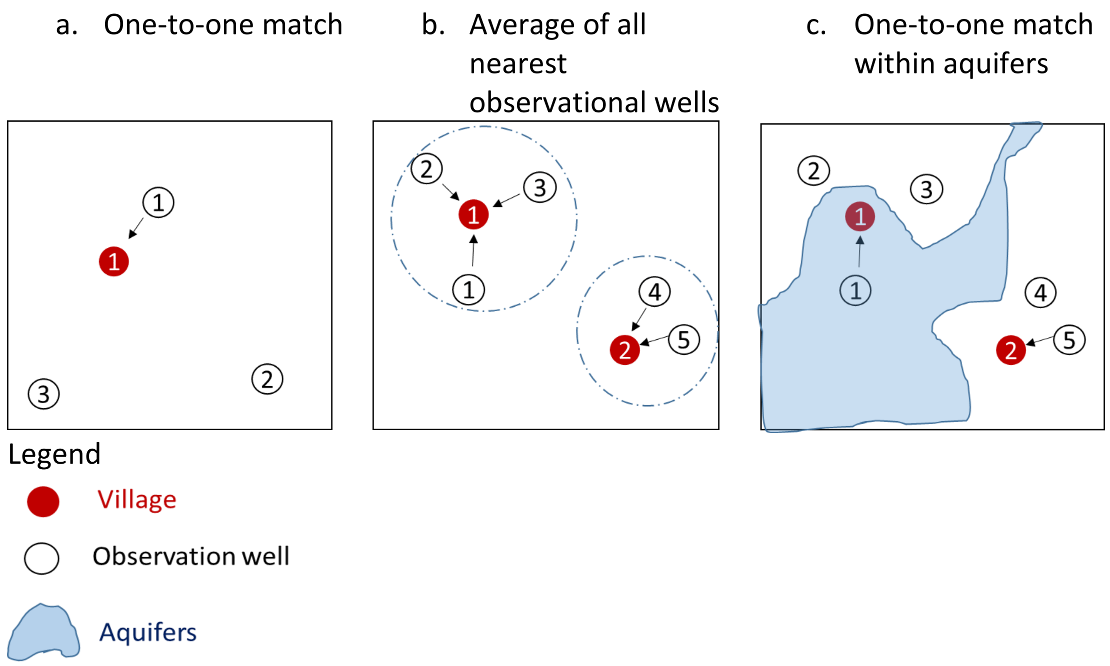


Figure 4.2: Different approaches of matching observation wells with sample villages

Since we do not have the village-level groundwater data, we used the groundwater level data recorded by the nearest observational well of CGWB as a proxy for the village-level groundwater level. We merged the village-level survey with groundwater level data using the GPS locations, matching the village with the nearest observation well (Figure 4.2a). We also use a sub-set of data matching the villages with the nearest observational well with two cut-off distances (15 km and 20 km). We used the geonear package in Stata software to merge the dataset based on the nearest GPS points (Picard, 2010). We dropped the observation wells where data were missing for all the months. We used different approaches of matching observational well with sample well for robustness (Figure 4.2). First, instead of matching the village with a single observational well (one-to-one match), we also estimated an average of the nearest observational wells by allocating the nearest observation wells to each village (Figure 4.2b). A single well observation could be biased due to the type of well and topography. Second, we also constrained the matching based on the same aquifers (Figure 4.2c). We used the aquifer shape files from CGWB to identify the aquifer where the village and observational well are situated.

In the groundwater level dataset, CGWB has been collecting monthly water table levels from roughly 3286 observation wells in the study region. The monthly observation is not frequent, i.e., data are unavailable for many months over the period, leading to missing data problems in the dataset. Previous studies assessing the effect of groundwater level using CGWB data have used an average of several months before and after the monsoon season as a pre-monsoon and post-monsoon (Gupta, 2023; Tripathi et al., 2016). Since the water table level is seasonal and fluctuates even between months, we use monthly data for the months of January, May, August, and November similar to Sekhri, (2012) from 2000 to 2021. Though the selection of months is based on data availability, these months coincide with the crop-growing season (Figure 4.3). The region's two main crop production systems are rice-wheat and sugarcane-wheat. LLL is mostly performed from April to May before planting rice in the rice-wheat production system and from March to April before planting sugarcane in the sugarcane-wheat production system. Rice is planted (transplanted) in early June and harvested in November, followed by wheat grown in November and harvested in March.

In the sugarcane-wheat production system, sugarcane is planted in May and after 9-10 months harvested the following January (Figure 4.3). This is followed by a ratoon sugarcane crop harvested in November. Subsequently, wheat is planted in November and harvested in February of the following year. The groundwater level in

May reflects the immediate impact of LLL on the initial irrigation stages, such as land preparation and puddling, for rice and sugarcane planting. The groundwater level in August, on the other hand, provides insight into the effect of LLL on rice irrigation and its subsequent impact on groundwater levels. Groundwater levels in November and January are expected to exhibit only a limited impact of LLL, as the effects of rainfall would likely have already diluted the technology's influence. These effects may even affect the data from August since the monsoon season in the region is starting in June.

a. Rice-Wheat production system b. Sugarcane-wheat production system

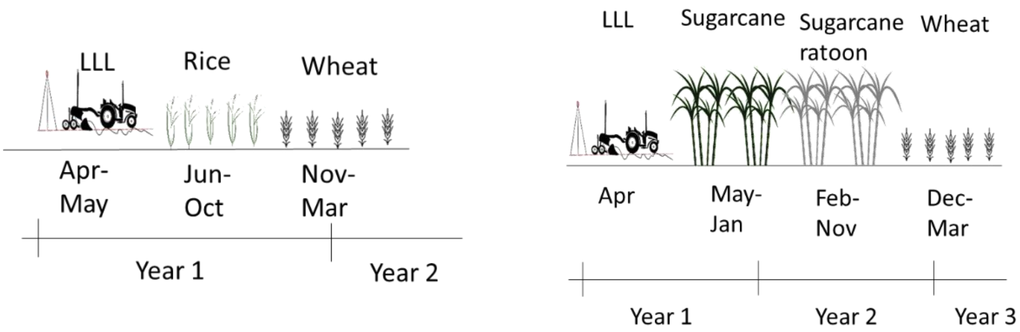


Figure 4.3: Major crop production systems in northwestern India

Using four different time points throughout the year also allows us to account for the mitigating effects of lateral groundwater flows on our estimates. Villages that overexploit their water resources may exhibit lower groundwater levels compared to neighbouring villages that adopt water-saving technologies. However, due to hydrological processes and the characteristics of aquifers in northwestern India, groundwater will eventually flow into the overexploited areas over time, restoring equilibrium. This process dilutes the observable impact of water-saving technologies on groundwater levels within the respective village over time and we expect more muted impacts for the months of November and January. Therefore, it is crucial to conduct measurements during different months throughout the year to capture these dynamics.

4.3 Estimation strategy

To estimate the impact of laser levelling technology on ground water table in a non-randomized experiment (observational data) setting, we control for factors likely to affect both treatment and outcome. We can hence first estimate the following basic Eq. 4.1:

$$W_{it} = \alpha_i + \beta D_{it} + \delta R_{it} + \emptyset P_{it} + u_i + e_{it} \qquad \text{Eq. 4.1}$$

Where, W_{it} is the groundwater level (depth in meters) for village *i* at time t. D_{it} is the dummy variable, which is one for every year since the LLL technology was adopted in the village. R_{it} is the total rainfall (mm) for the months preceding and including the month of observation of groundwater level, and P_{it} is a dummy variable capturing policy changes that affect irrigation patterns such as the introduction of the Punjab Preservation of Sub-soil Water Act in 2009 which bans sowing of rice before 10th June every year and the Haryana Preservation of Sub Soil Water Act in 2009 which prohibits sowing of nursery and transplanting of rice before notified dates. However, Punjab started implementing its law in 2006 by rationing the electricity (Sekhri, 2012). For Punjab, we designate the years after 2006 as the post-policy period, while for Haryana, the post-policy period begins with the years after 2009. β is the coefficient of interest showing the effect of adopting the LLL technology. u_i is the within-entity error term, e_{it} is the overall error term. For January, the treatment variable lagged by one year since the effect of adoption would be only visible the season after the technology was used (see Figure 4.3).

To reduce the potential bias from unobserved characteristics, the canonical difference-in-difference (DiD) model is a common standard if panel data are available. In the DiD approach, the treatment dummy interacts with a time dummy (pre-post), which can be extended to the two-way fixed effects (TWFE) model if additional unit or periods are added. However, if adoption did not happen in the same year but rather in a staggered manner, these models can be severely biased. Although previous studies have used TWFE for staggered adoption, recent literature has criticised this approach. Roth et al. (2023) have reviewed the shortcomings of using TWFE in such settings and summarised different alternative methods. The main criticisms of using canonical DiD are: i) in case of treatment effect heterogeneity (staggered treatment), the coefficients of the TWFE model might not accurately reflect the true treatment effect since one combines both comparisons of treated and not-yet-treated units (clean comparison) with comparisons of later-treated units and earlier-treated units (forbidden comparison) due to leads and lags, ii) in such cases the parallel trend assumption is also violated. Recent studies suggest several alternative approaches to the canonical DiD (Borusyak et al., 2024; Callaway & Sant'Anna, 2021; De Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun & Abraham, 2021).

We choose the approach of Callaway & Sant'Anna (2021), which allows us to examine the impact of LLL having only a binary treatment but a dynamic effect since the village area where the technology is adopted increases due to a staggered rollout of the technology. The approach also allows testing for conditional parallel trends and is flexible in aggregating the results with small-size cohorts. Callaway & Sant'Anna (2021) also assume in their staggered DiD approach that the treatment is irreversible and that there is negligible anticipation of treatment. The empirical model is denoted as Eq. 4.2:

$$W = \alpha_1^{g,t} + \alpha_2^{g,t}.G_g + \alpha_3^{g,t}.1\{T=t\} + \beta^{g,t}.\left(G_g * 1\{T=t\}\right) + \pi.X + \varepsilon^{g,t} \qquad \text{Eq. 4.2}$$

where W is the outcome of interest for a village in treatment group period g and time period t, where $t = 1, \dots \mathbb{T}$. G_g is a dummy variable equal to one if a unit is first treated in the period g. Treatment is determined when a village adopts the technology, $1\{T=t\}$ is a dummy variable equal to one if the village adopts the technology at time t. We compare 'not yet treated' villages with treated villages since all the villages become treated by 2021. The advantage of using this approach is that the treatment and control villages are comparable.

The average treatment effect is estimated with a conditional parallel trend based on a comparison of 'not-yet-treated' following a doubly robust method (Callaway & Sant'Anna, 2021). The group-time treatment effect is estimated by Eq. 4.3.

$$ATT(g,t) = \mathbb{E}[W_t(g) - W_t(0) | G_g = 1] \qquad \text{Eq. 4.3}$$

where ATT(*g,t*) is the expected difference between the outcome of interest for treated villages at time *t* and the counterfactual outcome at time *t*. Since we use 'not yet treated' as the control group (henceforth comparison group), the composition of the group changes over time. To interpret the coefficients, we summarize the aggregate group-time treatment effects into a single parameter as Eq. 4.4:

$$\theta_{gs}(g) = \frac{1}{\mathbb{T} - g + 1} \sum_{t=g}^{\mathbb{T}} ATT(g,t) \qquad \text{Eq. 4.4}$$

where $\theta_{gs}(g)$ is the aggregated group-specific effect for villages treated in period g for all post-treatment periods. The overall aggregation of treatment effects across all groups is estimated using Eq. 4.5.

$$\theta_{gs}^{o} = \sum_{g \epsilon \mathbb{G}}^{\mathbb{T}} \theta_{gs}(g) P(G = g | G \leq \mathbb{T}) \qquad \text{Eq. 4.5}$$

where θ_{gs}^{o} is the average effect of the adoption of LLL in the village. $P(G = g|G \leq \mathbb{T})$ is the weight giving preference to larger groups. Additionally, we again control for other confounding variables, such as rainfall and policy changes. The summary of variables used in the model is given in Appendix Table 6.9. Since study is a observational study, we henceforth refer treatment as post-adoption and control as pre-adoption.

The interpretation of our results depends on three assumptions. First, we assume a linear increase in the adoption rate, which becomes stable over time. This assumption would be violated if some village dis-adopts the technology. However, based on village survey data, we see that the adoption rates increased over time. The second assumption is regarding parallel trends; we assume that the post-adoption and comparison groups have the same trend in groundwater level during the pre-adoption period. We test for the difference in the groundwater level trend of the post-adoption and comparison group in the pre-adoption period. The third assumption is that there is no spill-over effect, i.e., the adoption of LLL in the post-adoption village does not result in changes in the groundwater level in the pre-adoption village. This is a strong assumption, as the effect could be bidirectional, especially if the post-adoption and pre-adoption villages are geographically close, so we might be underestimating the impact. Felbermayr et al., (2022) estimating the effect of weather anomalies, shows that spillover effects are very local and dissipate beyond the nearest region. We assume that the adoption of technology across villages happened in a diffusion pattern; the villages nearby are likely to be adopted in adjacent years. If this assumption holds true, the spill-over effect would be negligible. We tested this assumption by checking for spatial correlation between adoption years in adjacent villages using Moran's I coefficient (Deng et al., 2022).

4.4 Results and Discussion

4.4.1 Adoption and diffusion of laser land levelling in villages

Since the introduction of the LLL technology in 2001 in India (Aryal et al., 2018b), the adoption in villages has increased rapidly but in a staggered manner (Figure 4.4). The trends in the adoption of LLL over the period show that widespread adoption of the technology only happened 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 that targeted farmers, machinery operators, and also leaders of local cooperative societies could explain the wider technology adoption post-2010 (Surendran-Padmaja et al., 2024).

In general, the nature of technology and institutional innovations play a major role in technology diffusion. The laser LLL technology is accessed by most farmers from service providers who are farmers themselves in the same village or neighbouring village (Aryal et al., 2018b). This has contributed to the diffusion of the technology in villages in a staggered fashion (Figure 4.5).

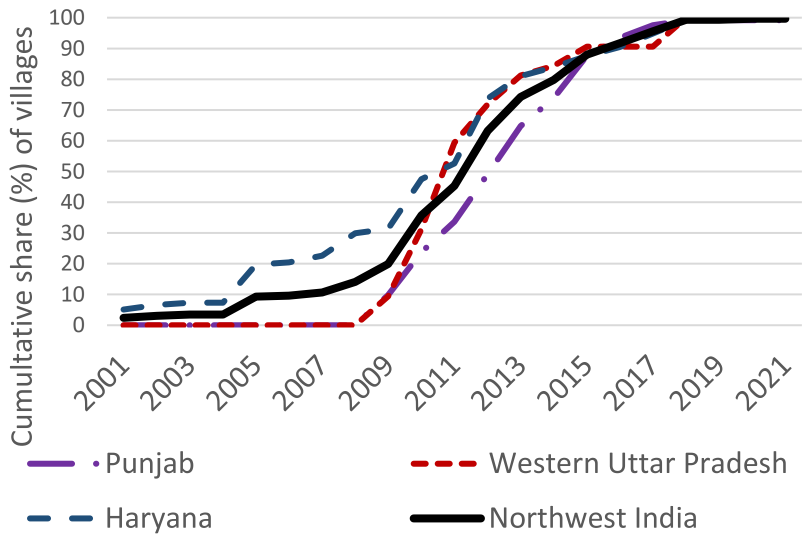


Figure 4.4: Cumulative share of adoption of laser land levelling in villages over the years in northwestern India

Note: We restructured the data from a cross-sectional form to a panel form for the years 2000 to 2021 based on key-informant survey, with a new dummy variable equal to one since the laser land leveller was first accessible in the village. WUP – western Uttar Pradesh.

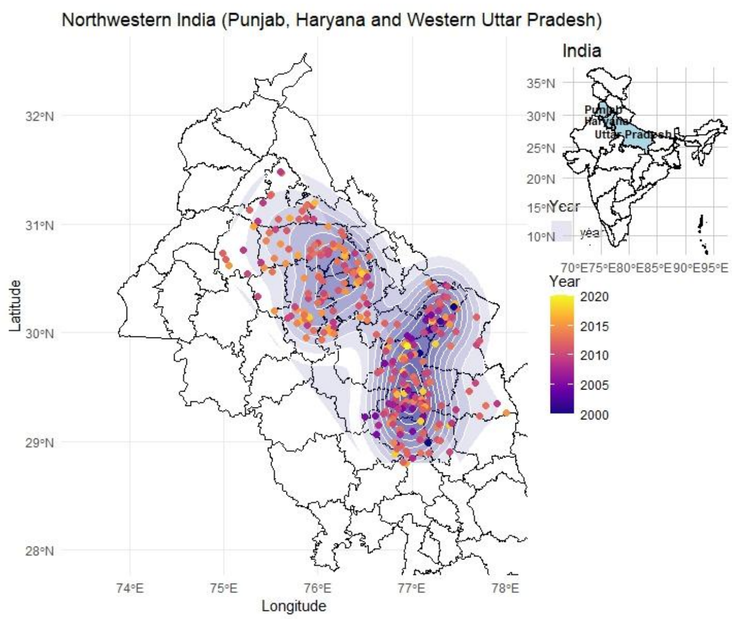


Figure 4.5: Diffusion of laser land levelling in villages in northwestern India

Note: The dots represent villages, and the colour gradient shows the year in which the technology was adopted in the village. The contours depict the diffusion pattern of technology by year. Moran's I values were significant at 1%, indicating that there is spatial autocorrelation between the village adoption years.

4.4.2 Trends in groundwater level

We visualised the trend in the groundwater level in our sample for different months, comparing villages that adopted LLL (post-adopted village) and villages that did not adopt by a particular year (pre-adopted village) (Figure 4.6). Overall, the depth of groundwater is increasing, depicting declining groundwater levels over time.

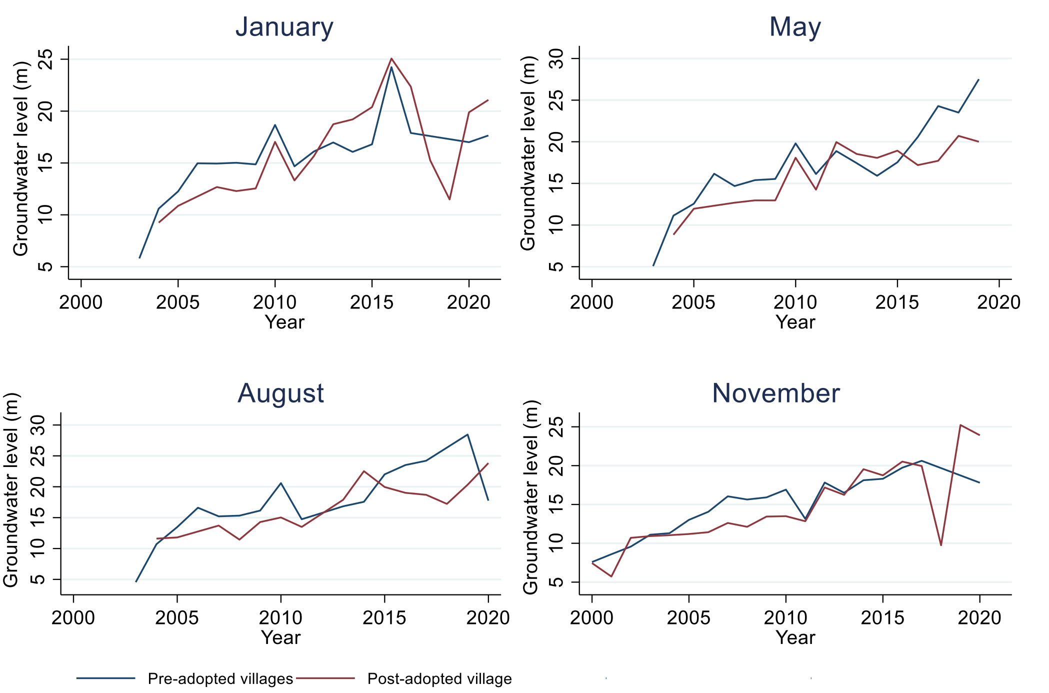


Figure 4.6: Trend in average groundwater level in the pre-adopted and post-adopted villages

Note: Data based on one-to-one matching of village and observational wells.

For the month of November, the average groundwater level in 2000 was 6.5 meters, which increased to 14 meters by 2021 in the pre-adopted villages. This suggests that from 2001 to 2021, the groundwater levels in the research region were declining at a rate of one meter per year. This estimate is lower compared to the estimates from other studies (MacAllister et al., 2022; Shekhar et al., 2020). However, it is important to note that groundwater depletion is not uniform across the region. Joshi et al. (2021) analysed the groundwater depletion of northwestern India from 1974 to 2010 and demonstrated that depletion rates varied significantly across different areas and are found to be correlated with use of submersible pump, alluvial deposition architecture, and canals. However, comparing the average groundwater levels in treated and no-yet treated villages using the mean of the reference year should be interpreted with caution. For example, the effect of laser land leveling on groundwater levels may take several years to materialize after initial adoption since village-wide adoption is likely to stretch across several years, diluting the observable trends shown in Figure 4.6.

4.4.3 Effect of village-level adoption of laser land levelling on groundwater

We estimate the village-level adoption of LLL on groundwater levels using the staggered DiD approach of Callaway & Sant'Anna (2021) (Table 4.1). We estimate the effect separately for different months, controlling for rainfall and policy factors. The estimates using the staggered DiD approach using a regression estimator show negative and statistically significant effects on groundwater decline in May. On average, the groundwater decline in the villages during the month of May, where the technology was adopted over a period of time, was reduced by 3.7 meters (Panel A). This is expected since May is immediately after LLL and the crops grown, both rice and wheat, have a higher water usage during this period. We find a similar estimate in case of the sub-sample of data with cut-off distance between village and observational well as 15 km and 20 km distance. These cut-offs were used to retain both a reasonable number of observational wells to run regressions for the different regions as well as exclude distant wells. Restricting the distance to below 15 km yielded an insufficient number of observations. For the month of August, the coefficient is negative but statistically insignificant in the case with no cut-off distance. However, we find a significant reduction of the groundwater decline in water levels in the sub-sample data with cut-off distance between village and observational well of 15 km and 20 km distance (Panel B & C).

As expected, the months of November and January show no significant effects, likely because the impact of rainfall and the soil's hydrological processes may have diluted the technology's impact. Since both post-adoption and pre-adoption village wells are in the same aquifer, water lateral flow happens between the post-adoption and pre-adoption village wells in the inter-year period. Wang et al. (2020) show that in deep aquifers, the groundwater lateral flow could replenish groundwater depression cones caused by over-exploitation.

Table 4.1: Effect of laser land levelling on groundwater level

	(1) January	(2) May	(3) August	(4) November
Panel A: Without cut-off distance				
Laser land levelling	0.887	-3.729***	-2.449	0.030
	(0.758)	(1.134)	(1.542)	(0.780)
Rainfall	Yes	Yes	Yes	Yes
Policy dummies	Yes	Yes	Yes	Yes
Observations	1603	2473	1565	3838
Panel B: Distance between village and observation well (cut-off 20 km)				
Laser land levelling	1.145	-3.878***	-3.106*	-0.272
	(0.812)	(1.061)	(1.669)	(0. .766)
Rainfall	Yes	Yes	Yes	Yes
Policy dummies	Yes	Yes	Yes	Yes
Observations	1426	2282	1406	3571
Panel C: Distance between village and observation well (cut-off 15 km)				
Laser land levelling	0.777	-4.019***	-3.899**	-0.479
	(0.869)	(1.033)	(1.740)	(0.733)
Rainfall	Yes	Yes	Yes	Yes
Policy dummies	Yes	Yes	Yes	Yes
Observations	1298	2142	1295	3368

Note: The observation unit is a village. The outcome variable is village level groundwater level. The estimates are from staggered DiD model using outcome regression estimator based on ordinary least squares. The estimates are group averages with conditional parallel trend assumptions and have not yet been treated as a control. Estimated using csdid package in stata. The outcome variable is village level groundwater level. Units that were always treated are omitted. The estimates are based on one-to-one matching of village and observation wells (Figure 4.2a). *** shows significance at 1%, ** shows significance at 5%, and * shows significance at 10%.

Similarly, Zeng et al. (2016) show that the offset of the over-exploited region by recharge through groundwater lateral flow is higher in plains compared to mountains. Joshi et al. (2018) show that aquifers in northwestern India are characterised as thick and plain with distinct lateral flows and argue that these recharge processes should be integrated in groundwater management plans. Overall, these lateral flows are an important component of groundwater recharge in the same aquifer (de Graff, 2022; Joshi et al., 2018; Wang et al., 2020; Zeng et al., 2016) and increasing the time gap between groundwater level measurement and the post-adoption through LLL could attenuate the observable impact over time. It has to be noted that the inter-year and seasonal effect on water level as a result of technology use is yet to be explored, as authors note that seasonality plays an important role in the groundwater table in the region (Tripathi et al., 2016).

4.4.4 Robustness and sensitivity checks

We consider a couple of issues that could affect our estimates and grouped them into four major categories: i) selection of observation wells, ii) recall bias, iii) missing data, and iii) parallel trends.

Selection of observation wells

As outlined in the methodology section (Figure 4.2b, Figure 4.2c), we did two additional estimations. First, apart from one-to-one matching, where we selected one observational well nearest to the village, we took an average of a number of wells in the proximity of the village. This is done to avoid the bias of generalizing the groundwater level based on single-well observation. However, the challenge with selecting a cluster of observational wells near the village is that multiple villages could share the same wells. To address this issue, we clustered the observational wells to villages so that the wells were mutually exclusive for villages, and the average of the wells was estimated. The second challenge is that wells located far from villages could be included in the calculation of the average, potentially distorting the results. Unlike in Table 4.1, where one-to-one matching is used, we instead matched the average groundwater depth from multiple wells near each village with village-level adoption data for Table 4.2 (see Figure 4.2). In addition, we again use a distance cut-off of 15 km and 20 km between the village and observational wells. The results show that with a 15 km cut-off distance, we observe a significant reduction of 1.7 m in May and 1.8 m in November. While these results align with our previous findings, we note the absence of significant results for a 20 km cut-off distance. This discrepancy may arise from biasing the groundwater level estimates for villages with nearby wells by including wells located too far from the village.

We further estimated the effect by selecting the one nearest well and defining that this well had to be exclusive for the respective village. We again find a statistically significant groundwater savings to an extent of 3 m in May (Appendix Table 6.10). Due to the reduced number of observations resulting from the strict selection criteria for observation wells, these results should be interpreted with caution. However, these robustness checks confirm that our estimation for the month of May is robust to alternative approaches.

Table 4.2: Effect of LLL on groundwater with average values for observation well data

	(1) January	(2) May	(3) August	(4) November
Panel A: Distance between village and observation well (<20 km)				
Laser land levelling	-0.839	0.119	0.423	-0.420
	(0.732)	(0.663)	(0.700)	(0.558)
Rainfall	Yes	Yes	Yes	Yes
Policy dummies	Yes	Yes	Yes	Yes
Observations	787	1140	798	1895
Panel B: Distance between village and observation well (<15 km)				
Laser land levelling	1.388	-1.707^{***}	0.216	-1.891^{***}
	(0.898)	(0.560)	(0.685)	(0.679)
Rainfall	Yes	Yes	Yes	Yes
Policy dummies	Yes	Yes	Yes	Yes
Observations	666	1006	691	1085

Note: The observation unit is a village. The outcome variable is village level groundwater level. The estimates are from staggered DiD model using outcome regression estimator based on ordinary least squares. The estimates are group averages with conditional parallel trend assumptions and have not yet been treated as a control. Estimated using csdid package in stata. Units that were always treated are omitted. *** shows significance at 1%, ** shows significance at 5%, and * shows significance at 10%.

In a second robustness check, we constrained the matching of the village and observational well within the aquifer using a map of aquifers within the region. Using the one-to-one matching approach, we found that 85% of the villages and observation wells were located within the same aquifers. To estimate the effects within aquifers, we utilised the average observation well data within a 15 km cut-off, focusing on villages and observation wells matched within the same aquifers (Table 4.3). For the month of May, the estimates closely align with the previous results presented in Table 4.2, Panel C. We find, however, a statistically significant positive effect for the month of January (2.5 m), which we cannot explain. However, we note that for the month of January, any meaningful results are unlikely since the effect of LLL is likely to be diluted by hydrological processes in the soil and the monsoon season. We also suggest that reverse causality—where larger annual groundwater declines trigger LLL adoption—could have produced this specific result. In general, our model could involve reverse causality, with greater groundwater declines leading to LLL adoption as a response. However, this would imply a consistent positive relationship between LLL adoption and groundwater decline, which our analysis does not support. Overall, reverse causality would only dampen the negative effect observed across most specifications for the key month of May.

Table 4.3: Effect of LLL on groundwater with 15 km cut-off distance matching within-aquifer

	(1) January	(2) May	(3) August	(4) November
Laser land levelling	2.485**	-1.474**	-0.117	0.675
	(0.999)	(0.552)	(0.729)	(0.688)
Rainfall	Yes	Yes	Yes	Yes
Policy dummies	Yes	Yes	Yes	Yes
Observations	549	872	603	1470

Note: The observation unit is a village. The outcome variable is village level groundwater level. The estimates are from staggered DiD model using outcome regression estimator based on ordinary least squares. The estimates are group averages with conditional parallel trend assumptions and have not yet been treated as a control. Estimated using csdid package in stata. Units that were always treated are omitted. The estimates are based on Table 4.2. Panel C: Distance between village and observation well (<15 km). *** shows significance at 1%, ** shows significance at 5%, and * shows significance at 10%.

Recall bias

The data on the first year of LLL adoption at the village level was collected using a key informant survey from each village. Beegle et al. (2012) and Wollburg et al. (2021) have discussed potential issues and reliability of recall data with long time intervals. To test if respondents provide consistent answers, we collected data from three key informants in each village in Haryana and western Uttar Pradesh on the first year LLL was adopted in the village. We used the Kruskal-Wallis equality-of-populations rank to test for differences in responses between the key informants (Appendix Table 6.11). The test shows that there is no statistically significant difference in the responses of key informants in Haryana and western Uttar Pradesh, which suggests that our data are not suffering from individual recall bias.

Missing data

One issue with the panel data used in this analysis is the presence of missing values in the observational well data. Appendix Table 6.12 gives the extent of missing data calculated as the share of missing data in the total data points for 291 villages for 21 years (6338 data points). The missing data vary across the months, with the highest share missing for August (61%) and the lowest for November (30%).

Table 4.4: Effect of LLL on groundwater with imputation of missing groundwater data

	(1) January	(2) May	(3) August	(4) November
Panel A: Imputing missing data with district-level values				
Laser land levelling	0.983	-2.264*	-2.915**	-0.078
	(0.632)	(1.84)	(1.141)	(0.791)
Rainfall	Yes	Yes	Yes	Yes
Policy dummies	Yes	Yes	Yes	Yes
Observations	3337	3760	3487	4521
Panel B: Imputing missing data with district-level values and moving average				
Laser land levelling	-2.425***	-3.878***	-3.953***	-1.691***
	(0.457)	(0.588)	(0.615)	(0.556)
Rainfall	Yes	Yes	Yes	Yes
Policy dummies	Yes	Yes	Yes	Yes
Observations	4484	4578	4471	5287
Panel C: Imputing missing data with district-level values (cut-off 15km)				
Laser land levelling	0.652	-2.474***	-3.700***	-0.644
	(0.677)	(1.038)	(1.093)	(0.769)
Rainfall	Yes	Yes	Yes	Yes
Policy dummies	Yes	Yes	Yes	Yes
Observations	2830	3560	3009	3936
Panel D: Imputing missing data with district-level values and moving average (cut-off 15km)				
Laser land levelling	-2.571***	-3.960***	-4.130***	-1.900***
	(0.492)	(0.592)	(0.630)	(0.571)
Rainfall	Yes	Yes	Yes	Yes
Policy dummies	Yes	Yes	Yes	Yes
Observations	3813	4258	3837	4588

Note: The observation unit is a village. The outcome variable is village level groundwater level. The estimates are from staggered DiD model using outcome regression estimator based on ordinary least squares. The estimates are group averages with conditional parallel trend assumption and have not yet been treated as a control. Estimated using csdid package in stata. The estimates are based on one-to-one matching of village and observation wells (Figure 4.2a). *** shows significance at 1%, ** shows significance at 5%, and * shows significance at 10%.

To account for the missing data, we imputed missing value using two approaches; first, we imputed the missing value with district-level average values provided by CGWB. Even with the imputed, the share of missing data was 20-30% (Appendix Table 6.13). We further took a moving average of district-level imputed value, reducing the share of missing data to 2-14% across the four different months. We estimated the effect of the adoption of LLL at the groundwater level using a staggered DiD model using two datasets: one with imputed values based on district-level data only and another with additional imputed values using a moving average approach (Table 4.4). The estimate again confirms our previous models. For Panel B, we even had significant effects across all four months. However, we caution that using a moving average is not ideal for a DiD setting. Additionally, the values for November and January remain smaller compared to those for May and August, supporting our assumption that the impact of LLL is most reliably assessed for May and, to some extent, for August. We conduct an additional robustness check using a cut-off of 15km for the imputed data in Panel C & D that confirms our previous findings.

Parallel trends

LLL, once introduced in the village, spread over the total cultivated area in the village. So, the effect of the adoption of LLL on groundwater in our village-level models is likely to increase after first initial adoption over time, eventually stabilizing once the adoption reaches its full potential. To visualise this dynamic effect, effects over time, we present event-study plots (Figure 4.7). We use a dataset with imputed values based on district level data to have sufficient data points and a cut-off of 15km to avoid using observation wells which are too far away from the surveyed villages (Table 4.4, Panel C). The x-axis is the length of the period of adoption, where negative values are periods before the adoption of technology and positive values after the adoption. The y-axis depicts the effect size, i.e., the average treatment effect of the treated (ATT). The y-axis values closer to zero and non-significant indicate that the parallel-trend assumption is fulfilled. The negative y-values after the zero-period of adoption show the effect of technology adoption on groundwater decline. The figure shows that the effects are growing over time for the months of May and August. This suggests that over time, the effects of technology adoption are becoming more pronounced. This trend is reasonable because, as LLL is initially introduced in a village, the proportion of land that has been levelled—and thus contributes to groundwater savings—gradually increases. As more farmers adopt the technology and implement it across larger areas, the cumulative impact on groundwater conservation becomes more significant.

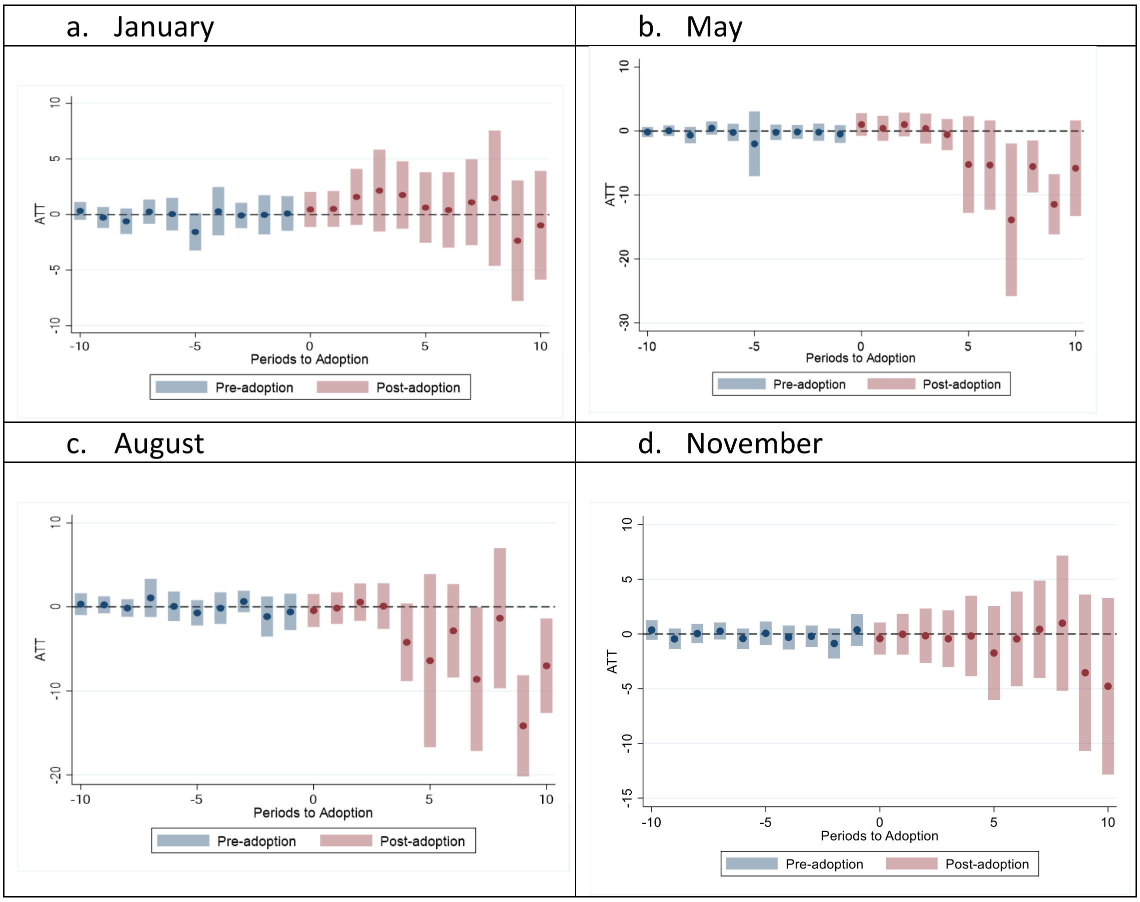


Figure 4.7: Event-study plot to test parallel pre-adoption trends

Note: The x-axis is the length of the technology introduction, where negative values are periods before the adoption of technology and positive values after the adoption. The y-axis depicts the effect size, i.e., the average treatment effect on the treated (ATT). The dark points in the graph are estimated ATT values, and the boxes are confidence intervals at 95%. The blue colour represents the pre-adoption period, and the red colour represents the post-adoption period.

4.5 Conclusion

In this study, we investigate the impact of LLL, a technology-driven approach to address the rapid groundwater decline in northwestern India. We analyse how the village-level adoption of LLL impacted groundwater levels proxied by observational well data. Our estimates show that the adoption of LLL led to a significant decrease in groundwater decline in May, the month following the use of technology, ranging from 1.4 to 4 m, while our preferred model suggests 3.7 m. This suggests that the adoption of LLL has led to reduction in the water pumped for irrigation. Based on this average treatment effect, adopting the technology could have resulted in up to 20% reduction in groundwater depletion based on a decline of 20 m in groundwater levels over the study period, while more conservative estimates suggest a reduction by 7%. Multiple robustness checks confirm the direction and significance of the effect. We do not observe a consistent effect of technology use in the successive months, particularly November and January. This could suggest increased water usage in the months following May, potentially in response to LLL. However, this pattern has not been documented in any previous studies. We therefore assume that the null effects observed, particularly in November and January, result from monsoon rains and hydrological processes that dilute the immediate impact of the technology. In particular lateral flows below the surface, where groundwater is moving to overexploited areas from regions under less pressure, can over extended time gaps between groundwater measurement and LLL attenuate observable impacts in one village, though the seasonal effects on water levels remain underexplored. Overall, our analysis suggests that LLL has successfully reduced groundwater decline in the region at larger scales.

The effect of LLL on groundwater savings is in particular notable comparing it to the often ineffective efforts documented in literature for other policies and technology solutions in the region. Sekhri (2012) shows that the regulation for delaying rice transplantation in Punjab and Haryana resulted even in an increase in groundwater decline. Sekhri (2012) argues that farmers might have responded to the policy by increasing the irrigation after mid-June transplanting. This result is similar to a recent study by Kishore et al. (2024) which show a similar adverse effect due to a government policy delaying rice transplanting where significant expansion of the area under rice and the extraction capacity of pumps post-policy implementation lead to increased water extraction. These policies were hence mostly ineffective since farmers did not reduce their overall irrigation but only delayed irrigation or changed other cropping practices to maximise their returns from farming. LLL, however, achieved significant reductions in groundwater decline since, by design, it saves the groundwater required for irrigation. Our results suggest that technologies and policies aimed at reducing the groundwater decline should focus on directly changing the behaviour of the farmers with respect to irrigation.

LLL was only effective since it was widely adopted by most farmers in the region. The energy costs for pumping groundwater are small, and farmers would have little incentive to adopt a technology that only saves energy costs. However, the technology also has other important co-benefits. Studies documented a significant increase in yield and income (Lybbert et al., 2018), while others noted that the aesthetic appeal of levelled fields further motivated adoption (Surendran-Padmaja & Parlasca, 2024). This suggests that within a market where farmers have little incentive to save irrigation water, aligning other benefits with saving groundwater is essential. Our findings highlight that LLL could be an important technology for different regions to address groundwater challenges, even in settings where the economic costs of using additional irrigation water are low.

However, in northwestern India, the extent to which water is saved using LLL technology is not enough to stop or reverse the decline of groundwater. The estimated current rate of groundwater decline in the region is higher than the estimated savings by LLL. Since the adoption rates are at their potential maximum, there is little scope to increase the benefits of the adoption of technology. Our study shows that, at best, technology could slow down the decline. It is, hence, pivotal to develop other technology—and policy-based solutions to address the decline in groundwater. Specifically, policies that raise the energy costs of groundwater use for irrigation, coupled with measures to offset the potential negative impacts on farmers' incomes, could encourage more sustainable resource use. While the intensive cropping systems in northwestern India have played a key role in ensuring the country's food security, their high resource intensity is now threatening both future food production and environmental sustainability in the long term. This study highlights how technological solutions can contribute to more sustainable agricultural systems.

Chapter 5 : General conclusion

5.1 Summary of the dissertation

The Green Revolution significantly increased the productivity of food crops and ensured food security in developing countries through the intensification of agricultural production systems. However, this intensification has led to negative environmental consequences, such as groundwater depletion, which threatens the sustainability of agricultural production systems. Additionally, existing agricultural production systems are becoming unsustainable due to rising food demand and groundwater exploitation. To meet future food needs, transitioning to more sustainable agricultural production systems that fulfil food and nutritional needs while minimizing negative environmental impacts is essential. There are technology and policy-based solutions that could help improve existing systems. This dissertation focuses on northwestern India, one of the world's highest intensified agricultural production systems with alarming groundwater depletion rates. We studied the adoption and impact of laser land leveling (LLL) technology, a technology-based solution that reduces water use for irrigation adopted in northwestern India.

In this dissertation, we explored three related research questions: 1) Why are farmers adopting LLL technology, 2) How were the farmers able to access the LLL technology, and 3) What is the effect of adopting LLL technology on groundwater levels? First, we analyzed how the perception of the individual farmer and the benefits designed by the technology developers influence the adoption of the technology. We collected primary quantitative survey data from 1021 farming households and conducted qualitative interviews in Punjab, India. We used a mixed method approach employing qualitative interviews and regression and a machine learning causal forest approach for quantitative analysis. The study finds that while LLL impacts yield and water savings less than expected, farmers' perceptions, electricity availability, and technology compatibility have encouraged widespread adoption.

Second, we investigated the role of private service providers in the adoption of LLL. Using plot-level data from 1661 households across 84 villages in Punjab and western Uttar Pradesh, we estimated the relationship between the number of service providers and the adoption of LLL, controlling for farm, household, and other contextual factors. The study particularly focused on the heterogeneous effect of the service provision on farm and plot sizes. The results show that a larger number of service providers is associated with a higher rate of LLL adoption. However, the effect of service providers on adoption vary by farm and plot size and are larger for smaller farms/plots, thus enabling small plot owners and farmers to adopt the technology.

Next, we estimated the effect of the LLL adoption on village groundwater levels. We combined primary data from 291 villages on LLL adoption with groundwater data from 3286 observation wells and rainfall data for a period of 21 years (2000-21). We leveraged the variation in the adoption timing across the villages and employed a staggered difference-in-difference approach to estimate the impact of LLL adoption on groundwater. We find that the adoption of LLL has resulted in a decline in the groundwater level to an extent of 3.7 m in May, the month succeeding the use of the technology. The results suggest that LLL technology mitigates the groundwater decline in northwestern India.

5.2 Policy implications

Based on the findings from this dissertation, three specific policy points are recommended:

1. **Considering designed, perceived and co-benefits for LLL technology dissemination efforts**

In a conventional, linear technology dissemination framework, technologies are developed by researchers and transferred to farmers without any cross-learning. Our findings show that in the case of LLL technology adoption, beyond the benefits designed by the researchers, farmers realise new benefits (co-benefits) and perceive benefits based on their experience. Research and development institutions developing the technology should probe these co-benefits and understand farmers' perceptions of the technology. Investigating technology adoption in the later stages of adoption provides scope for a feedback loop and the co-creation of knowledge. Policies promoting LLL technologies in other regions and countries should first consider identifying unanticipated co-benefits and perceived benefits by farmers and then bundling them with benefits designed by the researchers to drive adoption.

2. **Promoting private service provider as an institutional mechanism for ensuring inclusive adoption of technology**

Traditionally, co-operatives and custom-hiring centres, a centralized model, are promoted as institutional mechanisms for adopting indivisible technologies like agricultural machinery. Our findings present a compelling case for promoting individual service providers to scale LLL technology adoption inclusively. A shift from the traditional, centralized model to a service-based, on-demand, flexible model could improve the access and affordability of technology for smallholders. Policies such as low-interest loans and grants could promote private individual service providers. This could also create a competitive rental market and foster smallholder-inclusive technological change.

3. **Laser land levelling as a solution for mitigating groundwater decline**

The adoption of LLL technology has led to a statistically significant reduction in the decline of groundwater in May, the month following the application of the technology. Unlike the existing regulatory policy on delayed rice transplantation, which inadvertently increases the groundwater decline, LLL likely changes the behaviour of farmers and reduces groundwater used for irrigation. Hence, policies focused on resource conservation must holistically address farmers' incentives, integrating economic, behavioural and environmental aspects. However, technology alone might not be enough to mitigate the decline of groundwater, so we emphasise the need for further research on water conservation policies and technologies for sustainable groundwater management in northwestern India. Promoting LLL slows the rapidly declining groundwater levels and thus ensures environmental sustainability.

5.3 Overall conclusion, limitations and further research needs

The study concludes that LLL adoption has reduced the extent of groundwater decline in northwestern India. This was possible due to wide adoption of the technology by the farmers in the region. Farmers adopted the technology because of its co-benefits, such as increased yield, positive perceptions about the benefits, constraints in electricity availability, compatibility of LLL with other technologies, and the aesthetic value associated with the levelling of farms. The demand for the technology was met with the emergence of new institutional mechanisms– individual private service providers, who facilitated higher accessibility, resulting in higher adoption among small plot owners and farmers. The adoption of LLL has reduced the decline of groundwater to the extent of 3.7 meters in May. However, the estimated groundwater saving rate due to the adoption of LLL is insufficient to stop or reverse the decline of groundwater in northwestern India. Hence, developing other technology- and policy-based solutions or combining both are necessary for managing the groundwater decline. The study demonstrates LLL as a technological solution for sustainable agricultural production and provides insights into technical and institutional support for promoting the technology.

The study has a few limitations and scope for further research. Chapter two and Chapter three rely on cross-sectional data, where the establishment of causality is difficult. So, we used regression models and claimed only association, not causation. For Chapter 2, there were challenges in accurately measuring irrigation hours, and future research could explore alternative measurement approaches. Further, the insights from qualitative data require further exploration to understand the role of technology development and extension institutions in shaping farmer perceptions. The results from Chapters two and three are context-specific to northwestern India, where factors like widespread tractor ownership facilitate LLL adoption and competitive rental markets; these dynamics may not apply in regions where tractor ownership is uncommon. Moreover, LLL's unique characteristics, such as its infrequent use and the tendency of machinery owners to rent it out, may limit the generalizability of findings to other technologies. Follow-up research across diverse regions and technologies is necessary to enhance the understanding of how indivisible technologies can be effectively adopted in small farm settings. In Chapter four, the effect of the adoption of LLL was only visible in May and not in other months. Though we argue that this could be due to the hydrological process, lateral flows of groundwater, wherein groundwater moves from a less exploited area to an overexploited area, these inter-seasonal effects are yet to be explored.

References

Abay, K. A., Barrett, C. B., Kilic, T., Moylan, H., Ilukor, J., & Vundru, W. D. (2023). Nonclassical measurement error and farmers' response to information treatment. *Journal of Development Economics*, *164*, 103136. https://doi.org/10.1016/j.jdeveco.2023.103136

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://doi.org/10.3368/le.90.1.26

Alcott, B. (2005). Jevons' paradox. *Ecological Economics*, *54*(1), 9–21. https://doi.org/10.1016/j.ecolecon.2005.03.020

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

American Psychological Association. (2020). *Publication manual of the American Psychological Association: The official guide to APA style* (7th ed.). American Psychological Association.

Aryal, J. P., Khatri-Chhetri, A., Sapkota, T. B., Rahut, D. B., & Erenstein, O. (2020). Adoption and economic impacts of laser land leveling in the irrigated rice-wheat system in Haryana, India using endogenous switching regression. *Natural Resources Forum*, *44*(3), 255–273. https://doi.org/10.1111/1477-8947.12197

Aryal, J. P., Rahut, D. B., Jat, M. L., Maharjan, S., & Erenstein, O. (2018a). 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., Rahut, D. B., Jat, M. L., Maharjan, S., & Erenstein, O. (2018b). 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., Sapkota, T. B., Jat, M. L., & Bishnoi, D. K. (2015). On-farm economic and environmental impact of zero-tillage wheat: A case of noth-western India. *Experimental Agriculture*, *51*(1), 1–16. https://doi.org/10.1017/S001447971400012X

Athey, S., & Imbens, G. (2016). Recursive partitioning for heterogeneous causal effects. *Proceedings of the National Academy of Sciences*, *113*(27), 7353–7360. https://doi.org/10.1073/pnas.1510489113

Athey, S., Tibshirani, J., & Wager, S. (2019). Generalized random forests. *The Annals of Statistics*, *47*(2). https://doi.org/10.1214/18-AOS1709

Barnes, A. P., Soto, I., Eory, V., Beck, B., Balafoutis, A., Sánchez, B., Vangeyte, J., Fountas, S., Van Der Wal, T., & Gómez-Barbero, M. (2019). Exploring the adoption of precision agricultural technologies: A cross regional study of EU farmers. *Land Use Policy*, *80*, 163–174. https://doi.org/10.1016/j.landusepol.2018.10.004

Baul, T., Karlan, D., Toyama, K., & Vasilaky, K. (2024). Improving smallholder agriculture via video-based group extension. *Journal of Development Economics*, *169*, 103267. https://doi.org/10.1016/j.jdeveco.2024.103267

Beegle, K., Carletto, C., & Himelein, K. (2012). Reliability of recall in agricultural data. *Journal of Development Economics*, *98*(1), 34–41. https://doi.org/10.1016/j.jdeveco.2011.09.005

Belton, B., Fang, P., & Reardon, T. (2024). Combine harvester outsourcing services and seasonal rural non-farm employment in Myanmar. *Applied Economic Perspectives and Policy*, aepp.13480. https://doi.org/10.1002/aepp.13480

Bhattarai, N., Pollack, A., Lobell, D. B., Fishman, R., Singh, B., Dar, A., & Jain, M. (2021). The impact of groundwater depletion on agricultural production in India. *Environmental Research Letters*, *16*(8), 085003. https://doi.org/10.1088/1748-9326/ac10de

Bjornlund, V., & Bjornlund, H. (2024). Reviewing the Green Revolution strategy in view of lessons from Mexico and India – Africa. *International Journal of Water*

Resources Development, 1–45. https://doi.org/10.1080/07900627.2024.2363954

Boretti, A., & Rosa, L. (2019). Reassessing the projections of the World Water Development Report. *Npj Clean Water*, *2*(1), 15. https://doi.org/10.1038/s41545-019-0039-9

Borusyak, K., Jaravel, X., & Spiess, J. (2024). Revisiting Event-Study Designs: Robust and Efficient Estimation. *Review of Economic Studies*, *91*(6), 3253–3285. https://doi.org/10.1093/restud/rdae007

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 51–71. https://doi.org/10.1023/A:1010933404324

Brown, B., Samaddar, A., Singh, K., Leipzig, A., Kumar, A., Kumar, P., Singh, D. K., Malik, R., Craufurd, P., Kumar, V., & McDonald, A. (2021). Understanding decision processes in becoming a fee-for-hire service provider: A case study on direct seeded rice in Bihar, India. *Journal of Rural Studies*, *87*, 254–266. https://doi.org/10.1016/j.jrurstud.2021.09.025

Burton, R. J. F. (2012). Understanding Farmers' Aesthetic Preference for Tidy Agricultural Landscapes: A Bourdieusian Perspective. *Landscape Research*, *37*(1), 51–71. https://doi.org/10.1080/01426397.2011.559311

Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-Differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001

CGIAR Research Program on Rice. (2019a). *Laser land leveling in Cambodia and Vietnam*. Reported in Rice Annual Report 2019. Innovations. https://hdl.handle.net/10568/122416

CGIAR Research Program on Rice. (2019b). *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/

Chakraborti, R., Davis, K. F., DeFries, R., Rao, N. D., Joseph, J., & Ghosh, S. (2023). Crop switching for water sustainability in India's food bowl yields co-benefits for food security and farmers' profits. *Nature Water*, *1*(10), 864–878. https://doi.org/10.1038/s44221-023-00135-z

Chakrabortty, R. K., Abdel-Basset, M., & Ali, A. M. (2023). A multi-criteria decision analysis model for selecting an optimum customer service chatbot under uncertainty. *Decision Analytics Journal*, *6*, 100168. https://doi.org/10.1016/j.dajour.2023.100168

Chatterjee, S., Lamba, R., & Zaveri, E. D. (2024). The role of farm subsidies in changing India's water footprint. *Nature Communications*, *15*(1), 8654. https://doi.org/10.1038/s41467-024-52858-6

Chen, J., Zhao, C., Jones, G., Yang, H., Li, Z., Yang, G., Chen, L., & Wu, Y. (2022). Effect and economic benefit of precision seeding and laser land leveling for winter wheat in the middle of China. *Artificial Intelligence in Agriculture*, *6*, 1–9. https://doi.org/10.1016/j.aiia.2021.11.003

Chernozhukov, V., Hansen, C., Kallus, N., Spindler, M., & Syrgkanis, V. (2024). *Applied causal inference powered by ML and AL*.

CHIRPS. (n.d.). *CHIRPS: Rainfall Estimates from Rain Gauge and Satellite Observations* [Dataset]. https://www.chc.ucsb.edu/data/chirps

Dalin, C., Wada, Y., Kastner, T., & Puma, M. J. (2017). Groundwater depletion embedded in international food trade. *Nature*, *543*(7647), 700–704. https://doi.org/10.1038/nature21403

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. (1996). The mechanization of reaping in the Ante-bellum Midwest. In H. Rosovksy (Ed.), *Industrialization in two Systems: Essays in honor of Alexander Gershenkron* (pp. 3–39). Wiley.

Davis, K. F., Chhatre, A., Rao, N. D., Singh, D., Ghosh-Jerath, S., Mridul, A., Poblete-Cazenave, M., Pradhan, N., & DeFries, R. (2019). Assessing the sustainability of post-Green Revolution cereals in India. *Proceedings of the National Academy of Sciences*, *116*(50), 25034–25041. https://doi.org/10.1073/pnas.1910935116

De Chaisemartin, C., & D'Haultfœuille, X. (2020). Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *American Economic Review*, *110*(9), 2964–2996. https://doi.org/10.1257/aer.20181169

de Graff, I. E. M. (2022). A model comparison assessing the importance of lateral groundwater flows at the global scale. *Environmental Research Letters*, *17*. https://doi.org/10.1088/1748-9326/ac50d2

DeFries, R., Fanzo, J., Remans, R., Palm, C., Wood, S., & Anderman, T. L. (2015). Metrics for land-scarce agriculture. *Science*, *349*(6245), 238–240. https://doi.org/10.1126/science.aaa5766

Deng, Y., Khan, S. U., Zhao, M., & Lu, Q. (2022). The spatiotemporal dynamic and spatial spillover effect of agricultural green technological progress in China. *Environmental Science and Pollution Research*, *29*, 27909–27923.

Dessart, F. J., Barreiro-Hurlé, 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

Devineni, N., Perveen, S., & Lall, U. (2022). Solving groundwater depletion in India while achieving food security. *Nature Communications*, *13*(1), 3374. https://doi.org/10.1038/s41467-022-31122-9

di Falco, S., Veronesi, M., & Tesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, *93*(3), 829–846. https://doi.org/10.1093/ajae/aar006

D'Souza, A., & Mishra, A. K. (2018). Adoption and Abandonment of Partial Conservation Technologies in Developing Economies: The Case of South Asia. *Land Use Policy*, *70*, 212–223. https://doi.org/10.1016/j.landusepol.2017.10.015

Emerick, K., De Janvry, A., Sadoulet, E., & Dar, M. H. (2016). Technological Innovations, Downside Risk, and the Modernization of Agriculture. *American Economic Review*, *106*(6), 1537–1561. https://doi.org/10.1257/aer.20150474

Esen, Ö., Yıldırım, D. Ç., & Yıldırım, S. (2024). A quantile regression approach to assess the impact of water-related environmental innovations on water stress. *Technological Forecasting and Social Change*, *203*, 123343. https://doi.org/10.1016/j.techfore.2024.123343

Evenson, R. E., & Gollin, D. (2003). Assessing the Impact of the Green Revolution, 1960 to 2000. *Science*, *300*(5620), 758–762. https://doi.org/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://doi.org/10.1086/451461

Felbermayr, G., Gröschl, J., Sanders, M., Schippers, V., & Steinwachs, T. (2022). The economic impact of weather anomalies. *World Development*, *151*, 105745. https://doi.org/10.1016/j.worlddev.2021.105745

Fetters, M. D., & Tajima, C. (2022). Joint Displays of Integrated Data Collection in Mixed Methods Research. *International Journal of Qualitative Methods*, *21*, 16094069221104564. https://doi.org/10.1177/16094069221104564

Fishman, R., Giné, X., & Jacoby, H. G. (2023). Efficient irrigation and water conservation: Evidence from South India. *Journal of Development Economics*, *162*, 103051. https://doi.org/10.1016/j.jdeveco.2023.103051

Fishman, R., Lall, U., Modi, V., & Parekh, N. (2016). Can Electricity Pricing Save India's Groundwater? Field Evidence from a Novel Policy Mechanism in Gujarat. *Journal of the Association of Environmental and Resource Economists*, *3*(4), 819–855. https://doi.org/10.1086/688496

Fuglie, K. O., & Kascak, C. A. (2001). Adoption and Diffusion of Natural-Resource-Conserving Agricultural Technology. *Review of Agricultural Economics*, *23*(2), 386–403. https://doi.org/10.1111/1467-9353.00068

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

Gollin, D., Hansen, C. W., & Wingender, A. M. (2021). Two Blades of Grass: The Impact of the Green Revolution. *Journal of Political Economy*, *129*(81), 2344–2384.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*(2), 254–277. https://doi.org/10.1016/j.jeconom.2021.03.014

Gosnell, H., Gill, N., & Voyer, M. (2019). Transformational adaptation on the farm: Processes of change and persistence in transitions to 'climate-smart' regenerative agriculture. *Global Environmental Change*, *59*, 101965. https://doi.org/10.1016/j.gloenvcha.2019.101965

Gulati, K., Lybbert, T. J., & Spielman, D. J. (2017, August 30). *Diffusing to Level Fields: Evolution of Laser Land Leveling Technology Markets in India*. Agricultural & Applied Economics Association Annual Meeting, Chicago, Illinois.

Gupta, D. (2023). Free power, irrigation, and groundwater depletion: Impact of farm electricity policy of Punjab, India. *Agricultural Economics*, *54*(4), 515–541. https://doi.org/10.1111/agec.12773

Hasan, M. F., Smith, R., Vajedian, S., Pommerenke, R., & Majumdar, S. (2023). Global land subsidence mapping reveals widespread loss of aquifer storage capacity. *Nature Communications*, *14*(1), 6180. https://doi.org/10.1038/s41467-023-41933-z

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., Krupnik, T. J., Krishna, V., Uddin, Md. N., Aryal, J. P., Srivastava, A. K., Kumar, S., Shahzad, M. F., Bhatt, R., Gardezi, M., Bahinipati, C. S., Nazu, S. B., Ghimire, R., Anik, A. R., Sapkota, T. B., Ghosh, M., Subedi, R., Sardar, A., Uddin, K. M. Z., … Jain, M. (2024). Overcoming barriers to climate-smart agriculture in

South Asia. *Nature Climate Change*, *14*(2), 111–113. 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. (2021a). Groundwater depletion will reduce cropping intensity in India. *Science Advances*, *7*(9), eabd2849. https://doi.org/10.1126/sciadv.abd2849

Jain, M., Fishman, R., Mondal, P., Galford, G. L., Bhattarai, N., Naeem, S., Lall, U., Balwinder-Singh, & DeFries, R. S. (2021b). Groundwater depletion will reduce cropping intensity in India. *Science Advances*, *7*(9), eabd2849. https://doi.org/10.1126/sciadv.abd2849

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 7 New Delhi, India: Rice-Wheat Consortium for the Indo-Gangetic Plains. pp 48.

Jat, M. L., Gathala, M. K., Ladha, J. K., Saharawat, Y. S., Jat, A. S., Kumar, V., Sharma, S. K., Kumar, V., & Gupta, R. (2009). Evaluation of precision land leveling and double zero-till systems in the rice–wheat rotation: Water use, productivity, profitability and soil physical properties. *Soil and Tillage Research*, *105*(1), 112–121. https://doi.org/10.1016/j.still.2009.06.003

Jat, M. L., Singh, Y., Gill, G., Sidhu, H. S., Aryal, J. P., Stirling, C., & Gerard, B. (2015). Laser-Assisted Precision Land Leveling Impacts in Irrigated Intensive Production Systems of South Asia. In R. Lal & B. A. Stewart (Eds.), *Soil-Specific Farming* (0 ed., pp. 338–367). CRC Press. https://doi.org/10.1201/b18759-17

Jodhka, S. S. (2021). Why are the farmers of Punjab protesting? *The Journal of Peasant Studies*, *48*(7), 1356–1370. https://doi.org/10.1080/03066150.2021.1990047

Jones-Garcia, E., & Krishna, V. V. (2021). Farmer adoption of sustainable intensification technologies in the maize systems of the Global South. A review. *Agronomy for Sustainable Development*, *41*(1), 8. https://doi.org/10.1007/s13593-020-00658-9

Joseph, J., Scheidegger, J. M., Jackson, C. R., Barik, B., & Ghosh, S. (2022). Is flood to drip irrigation a solution to groundwater depletion in the Indo-Gangetic plain? *Environmental Research Letters*, *17*(10), 104002. https://doi.org/10.1088/1748-9326/ac8f5d

Joshi, S. K., Rai, S. P., Sinha, R., Gupta, S., Densmore, A. L., Rawat, Y. S., & Shekhar, S. (2018). Tracing groundwater recharge sources in the northwestern Indian alluvial aquifer using water isotopes (δ18O, δ2H and 3H). *Journal of Hydrology*, *559*, 835–847. https://doi.org/10.1016/j.jhydrol.2018.02.056

Kamau, H., Roman, S., & Biber-Freudenberger, L. (2023). Nearly half of the world is suitable for diversified farming for sustainable intensification. *Communications Earth & Environment*, *4*(1), 446. https://doi.org/10.1038/s43247-023-01062-3

Keil, A., Krishnapriya, P. P., Mitra, A., Jat, M. L., Sidhu, H. S., Krishna, V. V., & Shyamsundar, P. (2021). Changing agricultural stubble burning practices in the Indo-Gangetic plains: Is the Happy Seeder a profitable alternative? *International Journal of Agricultural Sustainability*, *19*(2), 128–151. https://doi.org/10.1080/14735903.2020.1834277

Keil, A., Mitra, A., Srivastava, A. K., & McDonald, A. (2019). Social inclusion increases with time for zero-tillage wheat in the Eastern Indo-Gangetic Plains. *World Development*, *123*, 104582. https://doi.org/10.1016/j.worlddev.2019.06.006

Kishore, P., Roy, D., Birthal, P. S., & Srivastava, S. K. (2024). *Regulation, and Policy Response to Groundwater Preservation in India.* Policy Paper 43, ICAR-National Institute of Agricultural Economics and Policy Research (NIAP), New Delhi.

Knapp, T., Kovacs, K., Huang, Q., Henry, C., Nayga, R., Popp, J., & Dixon, B. (2018). Willingness to pay for irrigation water when groundwater is scarce. *Agricultural Water Management*, *195*, 133–141. https://doi.org/10.1016/j.agwat.2017.10.013

Krishna, V. V., Aravalath, L. M., & Vikraman, S. (2019). Does caste determine farmer access to quality information? *PLOS ONE*, *14*(1), e0210721. https://doi.org/10.1371/journal.pone.0210721

Krishna, V. 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

Krishna, V. V., & Mkondiwa, M. (2023). Economics of Crop Residue Management. *Annual Review of Resource Economics*, *15*(1), 19–39. https://doi.org/10.1146/annurev-resource-101422-090019

Kumar Joshi, S., Gupta, S., Sinha, R., Logan Densmore, A., Prakash Rai, S., Shekhar, S., Mason, P. J., & Dijk, W. M. V. (2021). Strongly heterogeneous patterns of groundwater depletion in Northwestern India. *Journal of Hydrology*, *598*, 126492. https://doi.org/10.1016/j.jhydrol.2021.126492

Kumar, M. D., Bassi, N., & Verma, M. S. (2022). Direct delivery of electricity subsidy to farmers in Punjab: Will it help conserve groundwater? *International Journal of Water Resources Development*, *38*(2), 306–321. https://doi.org/10.1080/07900627.2021.1899900

Kuzma, S., Bierkens, M. F. P., Lakshman, S., Luo, T., Saccoccia, L., Sutanudjaja, E. H., & Van Beek, R. (2023). *Aqueduct 4.0: Updated Decision-Relevant Global Water Risk Indicators*. Technical Note. Washington, DC: World Resources Institute. doi.org/10.46830/ writn.23.00061

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

Lewbel, A. (2019). The Identification Zoo: Meanings of Identification in Econometrics. *Journal of Economic Literature*, *57*(4), 835–903. https://doi.org/10.1257/jel.20171348

Lu, L., Reardon, T., & Zilberman, D. (2016). Supply Chain Design and Adoption of Indivisible Technology. *American Journal of Agricultural Economics*, *98*(5), 1419–1431. https://doi.org/10.1093/ajae/aaw076

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://doi.org/10.1086/695284

MacAllister, D. J., Krishan, G., Basharat, M., Cuba, D., & MacDonald, A. M. (2022). A century of groundwater accumulation in Pakistan and northwest India. *Nature Geoscience*, *15*(5), 390–396. https://doi.org/10.1038/s41561-022-00926-1

Michler, J. D., Tjernström, E., Verkaart, S., & Mausch, K. (2019). Money Matters: The Role of Yields and Profits in Agricultural Technology Adoption. *American Journal of Agricultural Economics*, *101*(3), 710–731. https://doi.org/10.1093/ajae/aay050

Mishra, A. K., Khanal, A. R., & Pede, V. O. (2017). Is direct seeded rice a boon for economic performance? Empirical evidence from India. *Food Policy*, *73*, 10–18. https://doi.org/10.1016/j.foodpol.2017.08.021

Mitra, A., Balasubramanya, S., & Brouwer, R. (2023). Can cash incentives modify groundwater pumping behaviors? Evidence from an experiment in Punjab. *American Journal of Agricultural Economics*, *105*(3), 861–887. https://doi.org/10.1111/ajae.12340

Mottaleb, K. A. (2018). Perception and adoption of a new agricultural technology: Evidence from a developing country. *Technology in Society*, *55*, 126–135. https://doi.org/10.1016/j.techsoc.2018.07.007

Mottaleb, K. A., Krupnik, T. J., Keil, A., & Erenstein, O. (2019). Understanding clients, providers and the institutional dimensions of irrigation services in developing countries: A study of water markets in Bangladesh. *Agricultural Water Management*, *222*, 242–253. https://doi.org/10.1016/j.agwat.2019.05.038

Mulungu, K., Abro, Z. A., Muriithi, W. B., Kassie, M., Kidoido, M., Sevgan, S., Mohamed, S., Tanga, C., & Khamis, F. (2024). One size does not fit all: Heterogeneous economic impact of integrated pest management practices for mango fruit flies in Kenya—a machine learning approach. *Journal of Agricultural Economics*, *75*(1), 261–279. https://doi.org/10.1111/1477-9552.12550

Nakasone, E., Porter, M., Maredia, M. K., Jones, A., & Tschirely, D. (2024). A mixed methods assessment of technical and financial assistance to small- and medium-sized enterprises in Kenya's food sector. *Applied Economic Perspectives and Policy*, *2024*, 4. https://doi.org/10.1002/aepp.13264

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 leveling for sustainable rice production: Case studies in Cambodia, Thailand, Philippines, Vietnam, and India. *Precision Agriculture*, *23*(5), 1633–1652. https://doi.org/10.1007/s11119-022-09900-8

Ogundari, K., & Bolarinwa, O. D. (2018). Impact of agricultural innovation adoption: A meta-analysis. *Australian Journal of Agricultural and Resource Economics*, *62*(2), 217–236. https://doi.org/10.1111/1467-8489.12247

Okello, J., Zhou, Y., Barker, I., & Schulte-Geldermann, E. (2019). Motivations and Mental Models Associated with Smallholder Farmers' Adoption of Improved Agricultural Technology: Evidence from Use of Quality Seed Potato in Kenya. *The European Journal of Development Research*, *31*(2), 271–292. https://doi.org/10.1057/s41287-018-0152-5

Okorie, I. E., Afuecheta, E., & Nadarajah, S. (2023). Time series and power law analysis of crop yield in some east African countries. *PLOS ONE*, *18*(6), e0287011. https://doi.org/10.1371/journal.pone.0287011

Pal, B. D., Kapoor, S., Saroj, S., Jat, M. L., Kumar, Y., & Anantha, K. H. (2022). Adoption of climate-smart agriculture technology in drought-prone area of India – implications on farmers' livelihoods. *Journal of Agribusiness in Developing and Emerging Economies*, *12*(5), 824–848. https://doi.org/10.1108/JADEE-01-2021-0033

Pannell, D. (2007, June). *Influences on Technology Adoption in Different Phases.* Pannell Discussions #103. http://www.pannelldiscussions.net/2007/06/103-influences-on-technology-adoption-in-different-phases/.

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

Paul, C., Techen, A.-K., Robinson, J. S., & Helming, K. (2019). Rebound effects in agricultural land and soil management: Review and analytical framework. *Journal of Cleaner Production*, *227*, 1054–1067. https://doi.org/10.1016/j.jclepro.2019.04.115

Perez, N., Singh, V., Ringler, C., Xie, H., Zhu, T., Sutanudjaja, E. H., & Villholth, K. G. (2024). Ending groundwater overdraft without affecting food security. *Nature Sustainability*, *7*(8), 1007–1017. https://doi.org/10.1038/s41893-024-01376-w

Pfeiffer, L., & Lin, C.-Y. C. (2014). Does efficient irrigation technology lead to reduced groundwater extraction? Empirical evidence. *Journal of Environmental Economics and Management*, *67*(2), 189–208. https://doi.org/10.1016/j.jeem.2013.12.002

Picard, R. (2010). *GEONEAR: Stata module to find nearest neighbors using geodetic distances* [Computer software]. Boston College Department of Economics.

Pingali, P. L. (2012). Green Revolution: Impacts, limits, and the path ahead. *Proceedings of the National Academy of Sciences*, *109*(31), 12302–12308. https://doi.org/10.1073/pnas.0912953109

Roger, E. M. (2003). *Diffusion of Innovations* (5th ed.). Simon & Schuster International.

Roth, J., Sant'Anna, P. H. C., Bilinski, A., & Poe, J. (2023). What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics*, *235*(2), 2218–2244. https://doi.org/10.1016/j.jeconom.2023.03.008

Ruzzante, S., Labarta, 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

Saldana, J. M. (2015). *The coding manual for qualitative researchers* (3rd ed.). SAGE Publications.

Sarkar, A., & Das, A. (2014). Groundwater irrigation-electricity-crop diversification nexus in Punjab: Trends, turning points, and policy initiatives. *Economic and Political Weekly*, *49*(52), 64–73.

Sayre, S. S., & Taraz, V. (2019). Groundwater depletion in India: Social losses from costly well deepening. *Journal of Environmental Economics and Management*, *93*, 85–100. https://doi.org/10.1016/j.jeem.2018.11.002

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

Sekhri, S. (2012). *Sustaining Groundwater: Role of Policy Reforms in Promoting Conservation in India*. India Policy Forum.

Seo, K., Ryu, D., Eom, J., Jeon, T., Kim, J., Youm, K., Chen, J., & Wilson, C. R. (2023). Drift of Earth's Pole Confirms Groundwater Depletion as a Significant Contributor to Global Sea Level Rise 1993–2010. *Geophysical Research Letters*, *50*(12), e2023GL103509. https://doi.org/10.1029/2023GL103509

Shang, L., Heckelei, T., Gerullis, M. K., Börner, J., & Rasch, S. (2021). Adoption and diffusion of digital farming technologies—Integrating farm-level evidence and system interaction. *Agricultural Systems*, *190*, 103074. https://doi.org/10.1016/j.agsy.2021.103074

Sheikh, A. T., Mugera, A., Pandit, R., Burton, M., & Davies, S. (2022). The adoption of laser land leveler technology and its impact on groundwater use by irrigated farmland in Punjab, Pakistan. *Land Degradation & Development*, *33*(12), 2026–2038. https://doi.org/10.1002/ldr.4290

Shekhar, S., Kumar, S., Densmore, A. L., Van Dijk, W. M., Sinha, R., Kumar, M., Joshi, S. K., Rai, S. P., & Kumar, D. (2020). Modelling water levels of northwestern India in response to improved irrigation use efficiency. *Scientific Reports*, *10*(1), 13452. https://doi.org/10.1038/s41598-020-70416-0

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 S. Singh (Ed.), *Success Stories*. Coordinating Cell, AICRP on Farm Implements and Machinery, Central Institute of Agricultural Engineering, Nabi Bagh, Berasia Road, Bhopal-462 038, India.

Singh, K. (2009). Act to Save Groundwater in Punjab: Its Impact on Water Table, Electricity Subsidy and Environment. *Agricultural Economics Research Review*, *22*, 365–386.

Srivastava, S. K., Chand, R., Raju, S. S., Jain, R., Kingsly, I., Schdeva, J., Singh, J., & Kaur, A. P. (2015). Unsustainable groundwater use in Punjab agriculture: Insights from cost of cultivation survey. *Indian Journal of Agricultural Economics*, *70*(3), 365–378.

Stetter, C., Mennig, P., & Sauer, J. (2022). Using Machine Learning to Identify Heterogeneous Impacts of Agri-Environment Schemes in the EU: A Case Study. *European Review of Agricultural Economics*, *49*(4), 723–759. https://doi.org/10.1093/erae/jbab057

Storm, H., Baylis, K., & Heckelei, T. (2020). Machine learning in agricultural and applied economics. *European Review of Agricultural Economics*, *47*(3), 849–892. https://doi.org/10.1093/erae/jbz033

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, *225*(2), 175–199. https://doi.org/10.1016/j.jeconom.2020.09.006

Sunding, D., & Zilberman, D. (2001). Chapter 4 The agricultural innovation process: Research and technology adoption in a changing agricultural sector. In *Handbook of Agricultural Economics* (Vol. 1, pp. 207–261). Elsevier. https://doi.org/10.1016/S1574-0072(01)10007-1

Surendran-Padmaja, S., & Parlasca, M. C. (2024). *Perceived and designed benefits of resource conservation technologies: Insights from adoption of laser land levellers in India*.

Surendran-Padmaja, S., Parlasca, M. C., Qaim, M., & Krishna, V. V. (2024). *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.

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

UN. (2024). *Population*. https://www.un.org/en/global-issues/population

Van Dijk, M., Morley, T., Rau, M. L., & Saghai, Y. (2021). A meta-analysis of projected global food demand and population at risk of hunger for the period 2010–2050. *Nature Food*, *2*(7), 494–501. https://doi.org/10.1038/s43016-021-00322-9

Van Loon, J., Woltering, L., Krupnik, T. J., Baudron, F., Boa, M., & Govaerts, B. (2020). Scaling agricultural mechanization services in smallholder farming systems: 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 the Indo-Gangetic Plains. *Mitigation and Adaptation Strategies for Global Change*, *29*(5), 33. https://doi.org/10.1007/s11027-024-10127-3

Wada, Y., Wisser, D., & Bierkens, M. F. P. (2014). Global modeling of withdrawal, allocation and consumptive use of surface water and groundwater resources. *Earth System Dynamics*, *5*(1), 15–40. https://doi.org/10.5194/esd-5-15-2014

Wager, S., & Athey, S. (2018). Estimation and Inference of Heterogeneous Treatment Effects using Random Forests. *Journal of the American Statistical Association*, *113*(523), 1228–1242. https://doi.org/10.1080/01621459.2017.1319839

Wang, L., Xie, Z., Xie, J., Zeng, Y., Liu, S., Jia, B., Qin, P., Li, L., Wang, B., Yu, Y., Dong, L., Wang, Y., Li, R., Liu, B., & Chen, S. (2020). Implementation of Groundwater

Lateral Flow and Human Water Regulation in CAS-FGOALS-g3. *Journal of Geophysical Research: Atmospheres*, *125*(18), e2019JD032289. https://doi.org/10.1029/2019JD032289

Wang, T., Jin, H., Sieverding, H., Kumar, S., Miao, Y., Rao, X., Obembe, O., Mirzakhani Nafchi, A., Redfearn, D., & Cheye, S. (2023). Understanding farmer views of precision agriculture profitability in the U.S. Midwest. *Ecological Economics*, *213*, 107950. https://doi.org/10.1016/j.ecolecon.2023.107950

Weersink, A. (2018). The Growing Heterogeneity in the Farm Sector and Its Implications. *Canadian Journal of Agricultural Economics/Revue Canadienne d'agroeconomie*, *66*(1), 27–41. https://doi.org/10.1111/cjag.12163

Weersink, A., & Fulton, M. (2020). Limits to Profit Maximization as a Guide to Behavior Change. *Applied Economic Perspectives and Policy*, *42*(1), 67–79. https://doi.org/10.1002/aepp.13004

Wheeler, S. A., Carmody, E., Grafton, R. Q., Kingsford, R. T., & Zuo, A. (2020). The rebound effect on water extraction from subsidising irrigation infrastructure in Australia. *Resources, Conservation and Recycling*, *159*, 104755. https://doi.org/10.1016/j.resconrec.2020.104755

Wollburg, P., Tiberti, M., & Zezza, A. (2021). Recall length and measurement error in agricultural surveys. *Food Policy*, *100*, 102003. https://doi.org/10.1016/j.foodpol.2020.102003

Zabel, F., Delzeit, R., Schneider, J. M., Seppelt, R., Mauser, W., & Václavík, T. (2019). Global impacts of future cropland expansion and intensification on agricultural markets and biodiversity. *Nature Communications*, *10*(1), 2844. https://doi.org/10.1038/s41467-019-10775-z

Zeng, Y., Xie, Z., Yu, Y., Liu, S., Wang, L., Zou, J., Qin, P., & Jia, B. (2016). Effects of anthropogenic water regulation and groundwater lateral flow on land processes. *Journal of Advances in Modeling Earth Systems*, *8*(3), 1106–1131. https://doi.org/10.1002/2016MS000646

Chapter 6 Appendices

Appendix 1. Appendix to Chapter 2

Table 6.1: Details of experts of the qualitative interview

Respondent number	Respondent details
F1	The farmer is 40 years old and has cultivated rice and wheat crops on 22 hectares of land for the last 25 years. He rents LLL from other farmers/service providers.
F2	The farmer is 38 years old and has been cultivating rice and wheat crops on 15 hectares of land (7.5 ha of owned land and 7.5 hectares of leased land) for 20 years of farming. He rents LLL from his relative.
F3	The farmer is 35 years old and cultivates rice and wheat on 7.5 hectares of land. In 2016, he bought a laser land leveller without an agricultural subsidy and rented it to another farmer (service provider).
F4	The farmer is 30 years old and has cultivated rice and wheat crops on his 4 hectares of land. He brought a laser land leveller without an agricultural subsidy and rented it to another farmer. He rents the laser land leveller to two to three villages with a service area of 120 hectares.
F5	The farmer is 41 years old and has cultivated rice and wheat crops on 12 hectares (of which 3.6 hectares are leased land) for the last 20 years. He rents LLL from other farmers/service providers.
F6	The farmer is 28 years old and has cultivated rice and wheat crops on 4 hectares (of which 2 hectares are leased land) of land for the last 10 years. He rents LLL from other farmers/service providers.
F7	The farmer is 42 years old with 30 acres of land and has cultivated rice and wheat crops on 12 hectares (of which 8 hectares are leased land) for the last 20 years. He rents LLL from a cooperative.
F8	The farmer is 28 years old with 30 acres of land and has cultivated rice and wheat crops on 13 hectares (of which 8.8 hectares are leased land) for the last 20 years. In 2019, he brought a laser land leveller without subsidy and rented it to another farmer (service provider).

Table 6.2: Description of the variables used in the model

Variable name	**Description**
Village-specific variables (n = 52)	
Share of adopters	Share of laser leveller adopters in the village (minus the household) in the reference year (2020-21)
Groundwater level	Groundwater depth at the village level (meters)
Crop diversity – Kharif	Crop diversity in the Kharif season (Simpson index[#])
Crop diversity – Rabi	Crop diversity in the Rabi season (Simpson index[#])
Distance to district HQ	Distance from the village center to the district headquarters (km)
Household-specific variables (n = 1021)	
Age of HH	Age of the household head
Education of HH	Number of years of education of the household head
Non-marginalised caste	The household belongs to one of the non-marginalized castes (dummy)
Majority religion	The religion of the household is a major religion in the state (dummy)
Number of plots	The total number of plots cultivated by household
Total cultivated area	Area cultivated by the household (ha)
Total adult members in the household	Number of adult members in the household
Women share	Share of adult women in the total number of adults in the household
Non-farm employment	A household member is employed in non-farm activities (dummy)
Asset index	Asset index estimated from 20 agricultural productive items
Service providers in 2020-21	Number of service providers the household has access to in 2020-21
Discount on first use of LLL	The household received a subsidy for the first event of adoption (dummy)
Access to information from (dummy)	The household accessed information in the last 12 months (2020-21) (dummy) from the given source
Plot-specific variables (n =1664)	
Plot area	The area of the plot in hectares
Soil type	Soil type in the plot (dummy)
Soil erosion	The plot is affected by soil erosion (dummy)
Waterlogging	The plot is affected by waterlogging (dummy)
Soil fertility	Soil fertility status in the plots (farmer assessment; dummy)
Rice crop variety[$]	If the rice crop variety cultivated in the plot is *Pusa 44* (dummy)
Rice crop duration[$]	If the rice variety is a short duration (dummy)
Wheat crop variety[$]	If the rice crop variety cultivated in the plot is *HD 3086* (dummy)
Wheat nitrogen application[$]	Quantity of nitrogen fertiliser applied in the wheat plot (kg/ha)
Pump hp	Horsepower of the submersible pump used for irrigation

Table 6.3: Summary of outcomes variables by treatment

	Rice yield (kg/ha)	Rice irrigation (h/ha)	Wheat yield(kg/ha)	Wheat irrigation (h/ha)
Never	6950.74	422.50	4836.44	6.79
	(1047.07)	(146.16)	(678.99)	(3.20)
Before three years	7150.44	422.86	4944.89	6.66
	(1044.68)	(138.12)	(607.18)	(2.76)
Last three years	7167.06	428.36	4926.11	6.74
	(930.50)	(131.70)	(644.59)	(3.06)
2020-21	7226.35	400.26	4888.60	6.05
	(871.10)	(145.67)	(650.54)	(2.89)

Note: The figure in parenthesis are standard deviations

Table 6.4: Estimates from ordinary least square regression

Variables	Rice yield (kg/ha)	Rice irrigation (h/ha)	Wheat yield (kg/ha)	Wheat irrigation (h/ha)
Frequency of LLL				
Before three years	25.858	-0.380	21.877	-0.411
	(112.733)	(17.340)	(75.579)	(0.356)
Last three years	130.245	-0.472	-0.601	-0.196
	(87.049)	(13.390)	(59.029)	(0.278)
Last year (2020-21)	187.506**	-25.423*	-11.638	-0.351
	(86.476)	(13.261)	(58.223)	(0.273)
Household-level variables				
Age of HH	-1.672	-0.333	0.323	0.007
	(2.589)	(0.394)	(1.761)	(0.008)
Education of HH	-3.195	-1.270	9.553*	-0.033
	(7.399)	(1.140)	(5.039)	(0.024)
Non-marginalised caste	40.966	-24.084	128.289	-0.146
	(140.862)	(22.337)	(94.371)	(0.457)
Majority religion	-102.875	-4.572	-46.913	0.0911
	(155.780)	(24.285)	(103.637)	(0.495)
Total adult members in the household	8.902	-2.692	-13.554	-0.171***
	(20.788)	(3.167)	(14.074)	(0.066)
Women share	1.853	0.493	0.870	-0.001
	(1.992)	(0.305)	(1.349)	(0.006)
Non-farm employment	-87.268	18.621	-26.284	0.381
	(120.595	(18.329)	(81.720)	(0.386)
Asset index	53.693**	0.019	33.376**	-0.073
	(21.190)	(3.283)	(14.357)	(0.069)
Number of plots	35.998	6.689	-10.178	-0.871***
	(40.005)	(6.178)	(27.390)	(0.131)
Service provider number	-3.005	-0.708	19.064**	0.058
	(114.093)	(17.519)	(8.701)	(0.045)
Discount on first use of LLL	-383.607*	1.416	-271.157**	-0.107
	(206.924)	(32.470)	(140.126)	(0.715)

Variables	Rice yield (kg/ha)	Rice irrigation (h/ha)	Wheat yield (kg/ha)	Wheat irrigation (h/ha)
Access to information from				
Government extension agency	-198.537***	-39.292***	-55.688	-0.310
	(72.948)	(11.151)	(49.516)	(0.233)
KVK	210.259***	-9.155	-17.724	-0.518**
	(74.114)	(11.337)	(50.412)	(0.235)
Progressive farmer	-87.145	-46.065***	14.022	0.257
	(63.650)	(9.711)	(43.098)	(0.203)
NGO	161.920*	8.135	13.101	0.759***
	(91.923)	(14.092)	(62.611)	(0.292)
Farmer collective	-56.888	48.076***	66.664	-0.254
	(67.741)	(10.341)	(45.832)	(0.214)
Input dealer	103.505	-42.255***	8.588	-0.332
	(63.490)	(9.687)	(43.154)	(0.203)
Plot-level characteristics				
Plot area	-16.040	-2.677	-4.630	0.266***
	(12.873)	(1.994)	(8.605)	(0.040)
Soil type [Loamy-Sandy] (reference: clay)	-103.260	8.962	-6.192	0.112
	(65.015)	(9.969)	(44.037)	(0.207)
Soil fertility (reference: low fertile)				
Medium fertile	482.066**	-50.852	-91.822	-0.749
	(229.191)	(38.688)	(157.745)	(0.810)
High fertile	582.560**	-23.195	-26.239	-0.062
	(228.167)	(38.539)	(157.643)	(0.810)
Soil erosion	16.197	-10.059	-45.999	1.097**
	(155.248)	(23.650)	(103.611)	(0.486)
Water logging	-44.689	13.806	-151.310**	0.287
	(93.964)	(14.446)	(63.293)	(0.302)
Crop variety	141.714**	-19.928**	-11.135	-0.236
	(65.693)	(9.989)	(44.406)	(0.210)
Crop duration	-340.493***	6.15888		
	(114.093)	(17.519)		
Nitrogen use			0.2538	0.005***
			(0.353)	(0.002)
Pump Hp		-0.70787		-0.041
		(1.182)		(0.025)

Variables	Rice yield (kg/ha)	Rice irrigation (h/ha)	Wheat yield (kg/ha)	Wheat irrigation (h/ha)
Village level characteristics				
Groundwater level	-4.008**	0.512**	-1.903**	-0.0004
	(1.569)	(0.244)	(1.068)	(0.005)
Crop diversity – Kharif	-485.089	-77.966	-27.528	-0.840
	(344.970)	(52.323)	(237.494)	(1.103)
Crop diversity – Rabi	615.250**	-39.095	268.333	-0.999
	(280.070)	(42.815)	(188.975)	(0.893)
Share of adopters	-2.024	0.203	-0.977	-0.006
	(1.944)	(0.298)	(1.334)	(0.006)
Distance to district HQ	0.838	-0.633	5.135**	0.032***
	(3.057)	(0.471)	(2.079)	(0.010)
Districts (reference: Patiala)				
Ludhiana	-193.703	68.746***	-489.547***	-0.086
	(117.966)	(18.743)	(99.492)	(0.477)
Patiala	234.025	-9.422	-569.833***	-1.115**
	(156.041)	(23.986)	(113.107)	(0.557)
Sangrur	642.607***	-8.228	-476.893***	-0.841**
	(145.846)	(22.793)	(75.116)	(0.353)
Model intercept	6718.620***	536.357***	5115.205***	9.127***
	(395.623)	(63.449)	(303.566)	(1.457)
R^2	0.155	0.143	0.123	0.182
Observations[$]	964	914	1001	925

Note: [$]Sub-sample from the largest plot in which the crop is cultivated. *** shows significance at 1%, ** shows significance at 5%, and * shows significance at 10%.

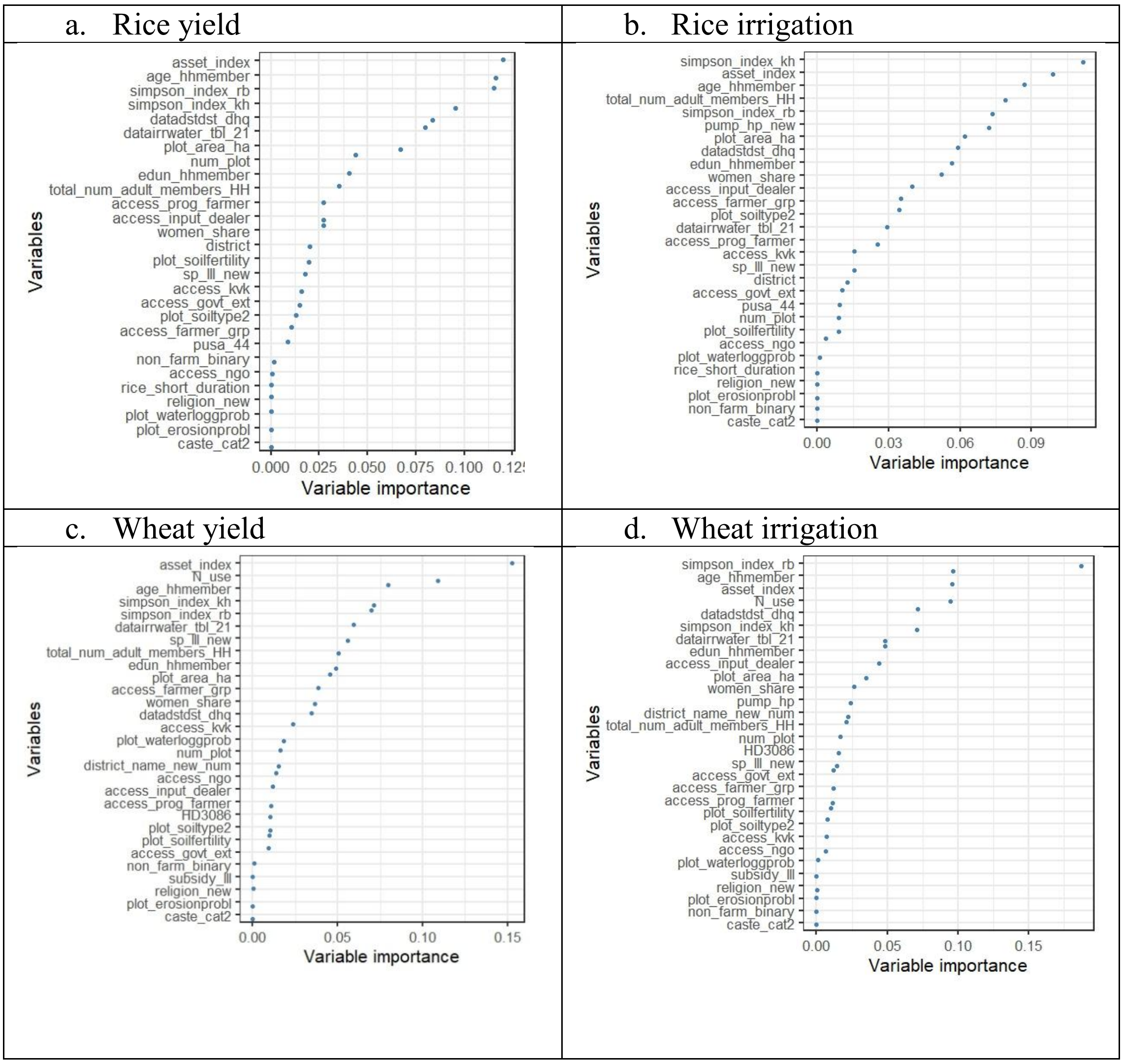


Figure 6.1: Variable importance plots from machine learning casual forest model

Note: Variable importance plots provide insights into the influential variable in estimating treatment effects; the higher the value, the more frequently the variable is used to split trees. Unlike OLS coefficients, which provide a single global effect estimate of each variable, variable importance plots capture non-linearity and interactions.

Appendix 2. Appendix to Chapter 3

Table 6.5: 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 only 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 6.6: 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
Private / Within village	62.50	58.55	65.06	57.19	26.74	26.49	39.47	34.18
Private / Outside village	29.51	32.64	25.9	34.69	70.35	73.51	55.26	59.49
Farmer co-operative	2.08	3.11	2.11	1.25	0.00	0.00	0.00	0.00
The 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 in current price)	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 6.7: 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$^{**\vert\#}$	0.032$^{*\vert\#\#\#}$
	(0.014)	(0.019)	(0.017)
Plot size	-0.015	2.E-04$^{\vert\#}$	
	(0.010)	(0.014)	
Plot size x Number of service providers (interaction)		-0.007$^{\#}$	
		(0.005)	
Farm size			-0.013$^{**\vert\#\#\#}$
			(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)			

	(1) Model 1	(2) Model 2	(3) Model 3
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 the sugarcane ratoon crop was grown in 2020/21 because levelling cannot be done before the sugarcane ratoon crop (436 plots).

Table 6.8: 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)

	(1) Model 1	(2) Model 2	(3) Model 3
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).

Appendix 3. Appendix to Chapter 4

Table 6.9: Summary of variables used in the model

Variable		Mean	Std. Dev.	Min	Max	Observations
Laser land levelling (1= Adopted, 0=not)	Overall	0.477	0.500	0.000	1.000	N = 6338
	Between		0.169	0.000	1.000	n = 291
	Within		0.470	-0.477	1.386	bar = 21.780
Outcome variable: Groundwater level (m)						
January	Overall	16.514	9.933	0.450	163.000	N = 2827
	Between		7.713	1.553	32.496	n = 291
	Within		6.226	-4.568	151.770	bar = 9.715
May	Overall	17.038	10.878	0.620	168.710	N = 3233
	Between		7.785	2.462	38.386	n = 291
	Within		7.575	-9.229	156.324	T = 11.11
August	Overall	17.301	12.809	0.130	171.920	N = 2455
	Between		9.115	1.094	51.126	n = 291
	Within		8.845	-11.851	158.709	bar = 8.436
November	Overall	15.059	10.669	0.400	196.000	N = 4452
	Between		7.008	1.541	30.625	n = 291
	Within		7.990	-10.043	185.844	T = 15.299
Rainfall in lagged months (cm)						
December (t-1) to January	Overall	37.9955	19.946	6.759	134.705	N = 6338
	Between		8.030	20.949	58.358	n = 291
	Within		18.2602	-2.961	114.342	bar = 21.780
February to May	Overall	84.941	47.217	19.858	330.022	N = 6338
	Between		15.529	48.921	125.438	n = 291
	Within		44.597	-5.807	291.383	bar = 21.780
June to August	Overall	435.983	266.997	77.948	1743.220	N = 6338
	Between		119.126	263.239	770.853	n = 291
	Within		239.360	-127.59	1409.599	bar = 21.780
September to November	Overall	158.34	113.626	21.580	628.870	N = 6338
	Between		32.3646	87.184	236.252	n = 291
	Within		108.994	-4.849	584.490	bar = 21.780

Variable		Mean	Std. Dev.	Min	Max	Observations
Policy dummies (1= period after policy implementation, 0=otherwise)	Overall	0.569	0.495	0.000	1.000	N = 6338
	Between		0.203	0.000	0.682	n = 291
	Within		0.454	-0.112	0.978	bar = 21.780
Distance to the nearest observation well (km)	Overall	6.901	5.872	0.026	44.784	N = 6338
	Between		4.098	0.403	23.904	n = 291
	Within		4.292	-11.384	41.175	bar = 21.780

Note: Based one-to-one matching of village and observation wells (Figure 4.2a). N = total number of observation, n= number of villages, bar = the overall mean of the variable combining both the within and between variation.

Table 6.10: Effect of LLL on groundwater using matching village with nearest observation wells with strict cut-off criteria

	(1) January	(2) May	(3) August	(4) November
Laser land levelling	-0.839	-3.600***	-0.397	-12.460***
	(0.529)	(1.972)	(0.743)	(3.084)
Rainfall	Yes	Yes	Yes	Yes
Policy	Yes	Yes	Yes	Yes
Observations	171	309	162	701

Note: The observation unit is a village. The estimates are group averages with conditional parallel trend assumption and not yet treated as control. Estimated using csdid package in stata. The estimates are group averages with conditional parallel trend assumptions and have not yet been treated as a control. Outcome regression estimator based on ordinary least squares. Unit that were always treated are omitted. The estimates are based on matching the village with the nearest observation wells, accounting for mutually exclusive wells, and dropping the observational well in which data is missing.

Table 6.11: Comparing responses of key informants

State	Chi-squared	Chi-squared with ties
Haryana	3.374	3.406
	(0.185)	(0.182)
Western Uttar Pradesh	1.495	1.544
	(0.473)	(0.462)

Note: Kruskal-Wallis equality-of-populations rank test. The figure in the parenthesis is in probability value (p-value).

Table 6.12: Share of missing data in observational well data

Groundwater data	**Missing**	**Observed**	**Total**	**Missing share**
January	3511	2827	6338	55.40
May	3105	3233	6338	48.99
August	3883	2455	6338	61.27
November	1886	4452	6338	29.76

Note: Based on the one-to-one matching dataset.

Table 6.13: Share of missing data after imputation

Groundwater data	**Observations after imputing with the district average**	**Missing share after imputing with the district average (%)**	**Observations after imputing with the district average and moving average**	**Missing share after imputing with the district average and moving average (%)**
January	4,442	30	5,544	13
May	4,604	27	5,683	10
August	4,400	31	5,426	14
November	5,028	21	6,239	1.6