Climate Maladaptation and the Commons: Groundwater Management in India*

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Abstract

India is the world's largest groundwater user, with 90% used for agriculture. Groundwater, however, is a common pool resource, generating a tragedy of the commons that threatens agricultural sustainability. We develop a parsimonious model to show how a popular policy intervention — subsidizing efficient irrigation technology — can exacerbate distortions away from socially optimal groundwater extraction. We test the model's predictions by leveraging geophysical variation in extraction externalities and a $1.35 billion program subsidizing efficient irrigation. Consistent with the model's predictions, the policy's impact depends on the severity of extraction externalities: extraction falls 9.2% in low-externality areas but rises 11.0% in high-externality areas. Low-externality farmers maintain cultivation using less groundwater, while high-externality farmers cultivate more intensively. Finally, the program causes climate-adaptive responses in low-externality areas – reducing extraction during normal rainfall and increasing it during droughts – but the opposite pattern in high-externality areas, consistent with climate maladaptation. Our findings illustrate that the same common pool conditions that typically justify an intervention may also determine its welfare implications.

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1 Introduction

The Green Revolution transformed Indian agriculture, driving a ten-fold increase in groundwater irrigation between the 1960s and 2010s as farmers met the increased water requirements of expanded cropping (Mukherji, 2022). This irrigation boom underpinned sharp gains in agricultural yields and food security, but also positioned India as the world's largest groundwater user, which has led a modern depletion crisis: in much of Western India, groundwater extraction now exceeds natural recharge, driving water tables deeper (CGWB, 2022). As water tables fall, groundwater becomes more costly to extract (Ryan, 2022, Manring, 2013), diminishing farmers' access to a key input and compromising their ability to bear climate shocks.

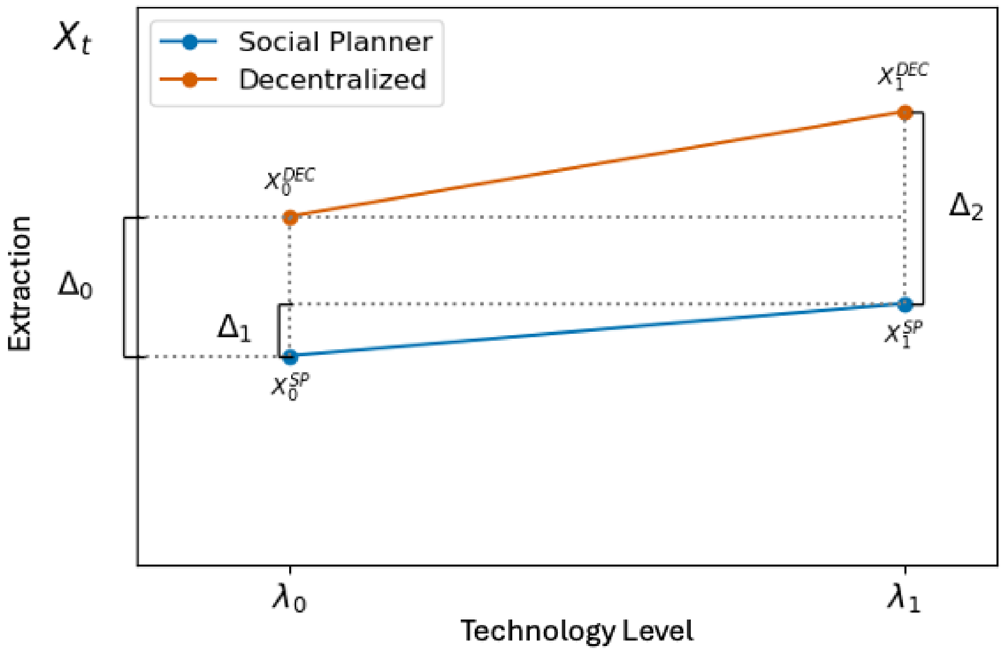
In response, policymakers have promoted micro-irrigation subsidies as a conservation solution. In contrast with traditional irrigation methods, micro-irrigation technologies deliver groundwater more precisely to the plant root, achieving more targeted and consistent soil moisture. These systems can significantly reduce water requirements for the same agricultural output (Narayanamoorthy, 2004). In developing contexts such as India, where weak institutions may preclude more classic solutions to the tragedy of the commons – such as Pigouvian taxation or Coasean bargaining – micro-irrigation improvements represent a institutionally feasible, politically palatable path for intervention. Policymakers commonly promote these technologies as providing "more crop per drop" under the expectation that, if farmers can achieve the same – or better – output with less groundwater, total extraction may fall. However, economic intuition reveals an opposing force: increasing the marginal productivity of groundwater increases the incentive to extract it, and thus farmers may extract *more* groundwater – the classic rebound effect identified by Jevons (1865), in which efficiency improvements paradoxically increase total resource use.

In this paper we show how the severity of extraction externalities – the very distortion that warrants intervention in common pool resources – plays a central role in determining whether technology ameliorates or exacerbates groundwater extraction and its possible welfare consequences. Three questions guide our analysis. First, does the impact of technology improvements on groundwater extraction depend on the severity of extraction externalities? Second, if technology improvements impact groundwater use, through what mechanisms do farmers adjust? Third, how does technology affect farmers' ability to cope with climate shocks through groundwater extraction? We provide both theoretical foundations and empirical evidence answering not only whether technology improvements may fail to conserve common pool resources but also why. The results reveal a fundamental tension: the areas where externalities are most severe are precisely where technology backfires, leading to *increased* groundwater extraction. Intuitively, efficient irrigation makes groundwater more productive today and more valuable tomorrow, but farmers in high-externality settings respond primarily to the former while discounting the latter.

To provide intuition and guide our subsequent empirical analysis, we develop a two-period model of groundwater extraction under common pool externalities and rainfall uncertainty. Groundwater depletion reflects a tragedy of the commons: farmers cannot exclude others from extraction, yet each farmer's pumping depletes the shared stock (Hardin, 1968), increasing future extraction costs for all (Gisser and Sanchez, 1980, Provencher and Burt, 1993, Negri, 1989). Because individual farmers maximize private rather than social welfare, extraction exceeds the social optimum. In our model, farmers share an aquifer and must decide how much groundwater to extract each period, given uncertainty about future rainfall. Crucially, farmers internalize only a fraction of their extraction's impact on future water availability, captured by parameter $\theta \in [0, 1]$ where higher values indicate more severe externalities. This manifests in the evolution of the water table. Extraction today lowers the water table – and, therefore, increases the cost of extraction – tomorrow. Since θ reflects the degree to which the aquifer is shared with other farmers, individual farmers only internalize $1 - \theta$ of how their extraction impacts the water table tomorrow. As $\theta \to 0$, the externality shrinks and the individual farmer's solution approaches the social planner's solution. However, as θ increases and the aquifer becomes more shared, each farmer internalizes less of how their actions affect the water table, distorting their behavior away from the social optimum.

This distortion plays a key role in each of the model's main predictions about how irrigation efficiency improvements interact with externalities. We capture irrigation efficiency as a parameter λ that scales how efficiently a marginal unit of water turns into agricultural output, and we therefore express improvements in irrigation efficiency as an increase in λ. From this setup, the model generates four main predictions, as visualized in Figure 1. First, the presence of externalities, $\theta > 0$, generates a wedge between individual and socially optimal extraction, visualized as Δ_0, consistent with overextraction in common-pool settings. Second, technology may increase or decrease total extraction, even for a social planner, depending on other model parameters. In Figure 1, we choose to depict this as an increase in socially optimal extraction, Δ_1, to emphasize that increased extraction *could* be a socially optimal response. Third, and most critically, there exists an externality threshold θ^* above which efficient irrigation *increases* the wedge between individual and socially optimal extraction, visualized as the increase $\Delta_2 - \Delta_0 > 0$, the additional technological "backfire" attributable to externalities. This additional technological "backfire" occurs because efficiency improvements increase the shadow value of groundwater – making it more valuable both today and in the future – but individual farmers respond to these higher returns without fully internalizing the social cost of depletion. Since farmers internalize only $1 - \theta$ of how their extraction impacts future groundwater availability, they increase extraction more than a social planner would in response to the same technology improvement. Fourth, comparative statics reveal that this wedge widens further as climate becomes more volatile, indicating that efficient irrigation may be climate maladaptive when externalities are severe.

Figure 1: Theoretical Technological Backfire



Note: This figure depicts how technology increased from λ_0 to λ_1 may impact individual (decentralized) and socially optimal groundwater extraction. Δ_0 shows the over-extraction at baseline due to the externality. Δ_1 shows the possible optimal increase in extraction due to more efficient irrigation, as in Jevons (1865). Δ_2 shows the new gap in extraction, which has increased from Δ_0. The increase in the wedge $\Delta_2 - \Delta_0 > 0$ represents the additional technological backfire due to externalities.

To test these predictions, we leverage policy-induced variation in irrigation efficiency improvements from India's Groundwater Management Scheme (In Hindi, *Atal Bhujal Yojana*; henceforth ABY). With a total budget of \$1.35 billion distributed across 227 subdistricts in seven states of Western India, ABY channels funds to local governments to augment existing schemes that subsidize groundwater conservation technologies. The program primarily subsidizes micro-irrigation technologies—systems that increase the marginal productivity of groundwater without altering the physical extraction process itself, analogous to increases in λ in our model. The ABY treatment period began in March 2020 and will continue through March 2026.

For variation in extraction externalities, we exploit geophysical characteristics of India's varied aquifer systems. Aquifers are underground formations of porous rock that store groundwater in interstitial spaces, much like a sponge. When a farmer extracts groundwater, pumping creates a cone of depression – the water table declines not only beneath the well but across a surrounding area. The spatial extent of this cone depends on aquifer transmissivity – a hydrological measure of how easily water flows laterally through the aquifer, determined by both rock permeability and aquifer thickness. Higher transmissivity creates wider cones, meaning more farmers are hydraulically connected and share the same effective groundwater source. This determines the severity of externalities: when more farmers share the same effective source of groundwater, each individual farmer's extraction represents a smaller fraction of total depletion, and thus each internalizes less of how their pumping affects future water availability. We construct an externality score based on transmissivity weighted by farming household density, serving as an empirical analogue to θ in our model, where higher values indicate more severe externalities. Intuitively, the externality score captures that the externality is determined not just by the spatial reach of depletion but also how many farmers are impacted by it.

We combine these two sources of variation using data from India's Central Groundwater Board (CGWB), which monitors groundwater depth at observation wells across nearly 6,000 subdistricts, satellite-based land use classifications from the Indian Space Research Organization (ISRO), and hydrogeological surveys of aquifer characteristics from India's Water Resources Information System (WRIS), harmonized spatially via the Population Census 2011 map of subdistrict boundaries.

Our main empirical strategy employs a triple difference-in-differences design: we test whether the impact of technology adoption through ABY depends on the severity of extraction externalities. This approach exploits a fundamental feature of our model: as $\theta \to 0$, the individual farmer's extraction decision converges to the social optimum. We operationalize this by splitting subdistricts at the median of our externality score, defining low-externality subdistricts where $\theta \leq \theta^{median}$ and high-externality subdistricts as those where $\theta > \theta^{median}$. Intuitively, in low-externality subdistricts, individuals internalize a greater share of how their extraction impacts shared groundwater availability, and therefore their incentives may more closely reflect socially optimal behavior. The differential response to ABY between high- and low-externality subdistricts, therefore, identifies whether technology widens the extraction wedge when externalities are severe. If, for example, technology causes farmers in high-externality subdistricts to extract more relative to those in low-externality subdistricts, this would be consistent with our key theoretical prediction: irrigation efficiency improvements exacerbate distortions away from socially optimal behavior when externalities are severe.

Our empirical findings are consistent with these theoretical predictions. Testing how irrigation efficiency improvement through ABY impacts total groundwater extraction, we find that, in aggregate, ABY appears to have had no effect on extraction – the difference-in-difference estimate is small and not statistically distinguishable from zero. However, this masks significant heterogeneity. For low externality subdistricts – where $\theta \leq \theta^{median}$ – ABY reduces total groundwater extraction by 9.2% ($p < 0.10$). However, in high externality subdistricts ($\theta > \theta^{median}$), total groundwater extraction *increases* by 11.0% ($p < 0.01$), a 20.2 percentage point swing representing a rebound effect of nearly 220%. These results align with two main theoretical predictions. First, that extraction falls in low-externality subdistricts but rises in high-externality subdistricts is consistent with the prediction that technology can – but may not necessarily – reduce groundwater extraction. Second, this result illustrates that technology widens the wedge between private and socially optimal extraction when externalities are severe enough; the 20.2 percentage point differential demonstrates that technology amplifies distortions away from the social optimum precisely where they are already more severe.

Next, we explore the mechanisms driving these extraction patterns. While data limitations preclude examining crop switching and yield responses at the subdistrict level, we can test whether farmers adjust their land use along two margins: extensive (sowing more land area) or intensive (cropping the same land more frequently within the same year). We find no evidence of extensive margin adjustment—sown area remains unchanged, consistent with sticky land markets and binding land constraints in rural India (Morris and Pandey, 2009). However, we observe significant intensive margin responses in high-externality subdistricts. These areas show a 2.4 percentage point increase in land under multi-cropping ($p < 0.10$), representing a 20% rise over the pre-treatment mean. This pattern suggests that when technology increases the marginal productivity of groundwater, farmers in high-externality areas respond by intensifying cultivation on existing plots rather than expanding cultivated area. Notably, low-externality subdistricts show no such intensification, indicating that conservation in these areas occurs through efficiency gains rather than reduced cropping intensity.

Finally, we examine outcomes on climate resilience. A core purpose of groundwater is to substitute for rainfall when it is insufficient for crop growth (Taraz, 2017). This implies that farmers who wish to smooth agricultural output across climate shocks will extract more groundwater when rainfall is low. In our data, farmers begin extracting significantly more groundwater when annual rainfall drops below approximately 600mm – at this threshold, extraction increases by about 10% relative to median rainfall years (1000mm). We use this empirically-derived threshold to examine how technology adoption impacts farmers' groundwater extraction when faced with a low rainfall shock. To the policymaker interested in climate adaptation, technology adoption would allow farmers to use less groundwater during periods of normal rainfall, thus allowing them to use more groundwater to substitute for rainfall when it is low. We find, again, that the impact of ABY on extraction patterns across rainfall shocks depends on the severity of externalities. In low-externality subdistricts, where ABY reduces overall extraction, the program generates the intended climate adaptation: ABY causes farmers to extract less during periods of normal rainfall and extract more during periods of low rainfall, preserving the groundwater buffer for when it is most needed. Strikingly, high-externality subdistricts exhibit the opposite treatment effect: ABY causes farmers to extract more when rainfall is normal and less when it is low. This pattern is consistent with our earlier finding that high-externality farmers respond to efficiency improvements by intensifying cultivation. By extracting more groundwater during normal rainfall years to support increased cultivation intensity, these farmers deplete the water table more severely, compromising their ability to extract during droughts when the buffer stock is most valuable. This result implies that when externalities are severe, irrigation efficiency improvements can be climate *mal*adaptive – the intervention intended to enhance farmers' resilience to climate volatility instead increases their exposure.

Our work contributes to three strands of literature. First, we build on the literature on how technology upgrading impacts natural resource management. A growing body of research documents that irrigation efficiency improvements often fail to lead to groundwater conservation. Studies from developed countries find that subsidized micro-irrigation technologies often do not reduce – and sometimes increase – groundwater extraction (Pfeiffer and Lin, 2014, Ward and Pulido-Velazquez, 2008, Berbel et al., 2015), while Grafton et al. (2018) synthesize evidence of this "irrigation efficiency paradox" across multiple settings. In developing countries, similar patterns emerge: farmers adopt water-efficient technologies but expand irrigated area or switch to water-intensive crops, offsetting conservation gains (Fishman, 2018, Birkenholtz, 2017). These studies focus on documenting how efficiency improvements backfire through various farmer responses. By contrast, we focus on *why*: the fundamental conditions that mediate how individuals respond to technology. The severity of extraction externalities varies across aquifers based on hydrogeological characteristics (Edwards, 2016, Brozović, Sunding, and Zilberman, 2010), with recent work showing that extraction decisions can be strategic complements or substitutes depending on these conditions (Koch and Nax, 2022). Furthermore, where recent work has largely explored farmers ability to pump groundwater (Ryan, 2022, Sekhri, 2014, Blakeslee, Fishman, and Srinivasan, 2020), we study whether and how it can be conserved. We show both theoretically and empirically that whether technology improvements lead to groundwater conservation depends principally on the severity of extraction externalities – the distortions that justify intervention may also undermine its effectiveness.

Second, we advance a growing literature on natural resource extraction and climate adaptation. Groundwater serves as a critical buffer stock that allows farmers to substitute for rainfall when it is insufficient for crop growth, smoothing agricultural production across climate shocks (Fishman, 2018, Taraz, 2017, Blakeslee, Fishman, and Srinivasan, 2020). Evidence on whether efficiency-enhancing technologies help farmers cope with climate variability remains mixed across different contexts (Kurukulasuriya and Mendelsohn, 2008, Di Falco, Veronesi, and Yesuf, 2011, Lobell et al., 2014, Perry, Yu, and Tack, 2020, Taylor, 2023). We identify the severity of extraction externalities as the key factor determining these divergent outcomes. As climate variability intensifies globally (Burke, Hsiang, and Miguel, 2015, Schlenker and Roberts, 2009) and aquifers transition from abundance to scarcity (Famiglietti, 2014, Jasechko and Perrone, 2021), our findings reveal that the effectiveness of technology improvements in building agricultural resilience depends critically on addressing the underlying extraction externalities.

Third, we contribute to the robust literature on managing common pool resources and designing policy instruments to alleviate the tragedy of the commons (Gordon, 1954, Ostrom, 1990). Theoretical solutions include Pigouvian taxes (Pigou, 1920), cap-and-trade systems (Montgomery, 1972), property rights that enable Coasean bargaining (Coase, 1960, Demsetz, 1967), and community-based management (Ostrom, 1990, Wade, 1988). However, these approaches may be infeasible in developing contexts due to weak institutional capacity, political constraints on taxation, or high transaction costs (Jack, 2013, Ostrom, 2009, Edwards, Ayres, and Libecap, 2018). Technology subsidies offer an attractive alternative: they are politically palatable, require neither coordination among users nor monitoring of individual extraction, and could theoretically reduce total extraction if farmers need less water to achieve the same production (Fischer, 2003, Khanna, Isik, and Zilberman, 2002). Our work demonstrates that the success of even these institutionally-light interventions depends on the conditions that generate over-extraction. This highlights a broader principle for common pool resource management: understanding the severity of the commons problem is prerequisite to designing effective solutions.

The rest of the paper proceeds as follows. Section 2 provides institutional background on groundwater use in India, Section 3 presents a conceptual framework of groundwater use and externalities, Section 4 details our data, Section 5 contains our empirical strategy and results, and, lastly, Section 6 concludes.

2 Institutional Background

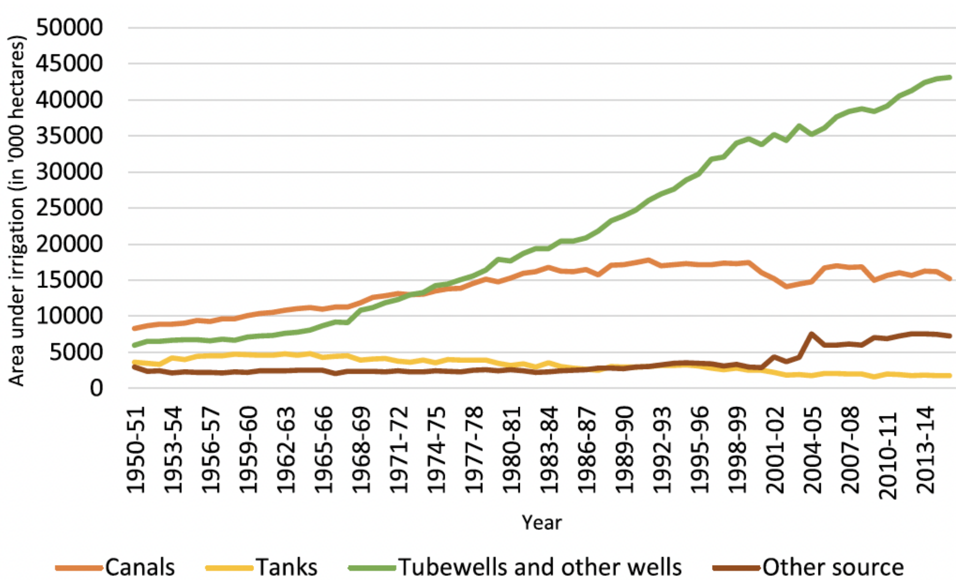
While India has a long agricultural history, the salience of groundwater depletion is relatively recent. In this section, we explain both institutional and physical factors that have governed and continue to govern how individuals use groundwater. Then, we detail a recent government scheme intended to mitigate groundwater depletion.

2.1 Groundwater and the Tragedy of the Commons

2.1.1 Groundwater Depletion in India

India's agricultural transformation over the past half-century is inextricably linked to groundwater exploitation. The Green Revolution, through its introduction of water-intensive high-yield crop varieties, enabled dramatic expansion in cropping intensity and sown area. While crops may receive water input from rainfall, the expansion in cropping necessitated expanding access to water from other sources to meet the increased water demand for agriculture. The majority of that demand has been met by increased access to groundwater. Figure 2 illustrates this progression: the area irrigated by tubewells and other wells – instruments through which farmers extract groundwater – increased ten-fold by 2014, while the area irrigated by surface water sources remained relatively stable (Mukherji, 2022). Today, India extracts more groundwater than the United States and China, the second and third largest groundwater users, combined.

Figure 2: Total Area Under Irrigation (Mukherji, 2022)

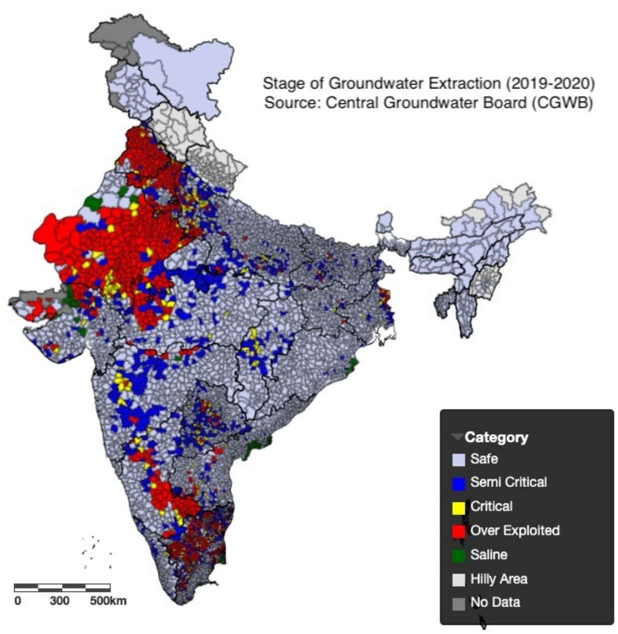


Groundwater access enabled farmers to cultivate water-intensive crops year-round, doubling and tripling yields in many regions (Sekhri, 2014). Unlike surface water systems that require extensive infrastructure and collective management, groundwater offered farmers autonomous control over irrigation timing—critical for responding to rainfall variability and maximizing returns to complementary inputs like fertilizers and pesticides (Pingali et al., 2019).

However, groundwater is a common pool resource, which can give rise to depletion as a consequence of externalities. Individual farmers extract groundwater, impacting the water availability of others around them. In the absence of regulation, farmers will extract according to their private interests, ignoring the economic costs imposed on others. This leads to a tragedy of the commons in which the wedge between privately and socially optimal extraction can lead to depletion of the shared resource.

Figure 3 illustrates the severity of the resulting crisis: approximately 50% of subdistricts in Western India now extract groundwater beyond natural recharge rates, with many classified as "over-exploited" or "critical" by the Central Ground Water Board (CGWB, 2022). The problem is particularly acute in the Indo-Gangetic plain, where water tables have declined by 3-4 cm annually since 2000 (Rodell, Velicogna, and Famiglietti, 2009). This depletion substantially increases extraction costs – deeper wells require more energy for pumping and, if the water table falls below the reach of the well, more expensive drilling equipment (Blakeslee, Fishman, and Srinivasan, 2020, Ryan, 2022, Manring, 2013).

Figure 3: Spatial Distribution of Water-Stressed Districts



The timing of the depletion crisis coincides with increasing climate variability. Extreme rainfall events have become more frequent and spatially variable across India, with the distribution of rainfall becoming increasingly uneven both within and across seasons (Fishman, 2016, Fishman, Devineni, and Raman, 2015). Increasingly variable monsoon patterns have reduced yields in staple food crops in the regions that cultivate them most intensely (Auffhammer, Ramanathan, and Vincent, 2012). Groundwater is a buffer stock, allowing farmers to substitute for insufficient rainfall and smooth agricultural production across droughts (Fishman, Devineni, and Raman, 2015, Taraz, 2017). As aquifers deplete, this buffering capacity weakens, threatening agricultural output (Blakeslee, Fishman, and Srinivasan, 2020).

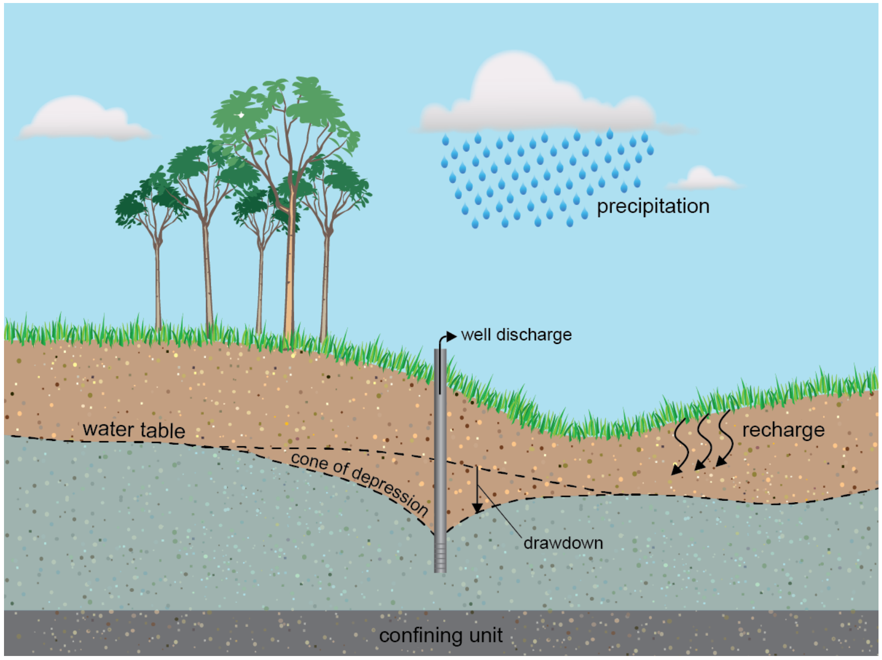
2.1.2 Aquifers and Externalities

Groundwater extraction externalities arise from the physical characteristics of aquifers, the subterranean structures which store groundwater. Aquifers consist of porous geological formation – fractured rock, sandstone, or alluvial deposits – that store water in interstitial spaces, much like a sponge. When a farmer extracts groundwater through a well, it does not uniformly lower the water table but rather creates a "cone of depression", illustrated in Figure 4. This cone represents the three-dimensional region where water levels decline due to extraction, with the deepest point at the well itself and gradually recovering to the static water level at distance.

In hydrogeological terms, the cone's radius depends on the aquifer's transmissivity – the product of hydraulic conductivity (how easily water flows through the medium) and aquifer thickness. Extraction in higher transmissivity aquifers creates wider cones of depression relative to lower transmissivity aquifers. These cones vary dramatically in scale: in low-transmissivity, hard rock aquifers, the radius can be as narrow as 200-500 meters (Machiwal et al., 2016), while in high-transmissivity alluvial aquifers, it can extend up to 5 kilometers (Michael et al., 2017). While, over time, water equilibrates over space, flattening the curvature of the cone, the spatial extent of the cone determines the spatial extent of water table depletion, particularly under continuous irrigation. Following extraction, water redistributes spatially within the aquifer, flattening the cone and spreading depletion over a broader area. Natural recharge occurs seasonally during monsoon months (Bhanja et al., 2019), but in Western India where extraction exceeds recharge (CGWB, 2022), water table declines persist across seasons and years[1].

[1]The cone of depression mainly occurs in unconfined aquifers, in which the water surface is able to fall freely due to gravity. However, whether or not an aquifer is confined impacts how groundwater pumping propagates spatially and hydraulically through an aquifer system. We discuss confinement conceptually and empirically in more depth in Appendix Section A.1.

Figure 4: Groundwater Extraction and the Cone of Depression

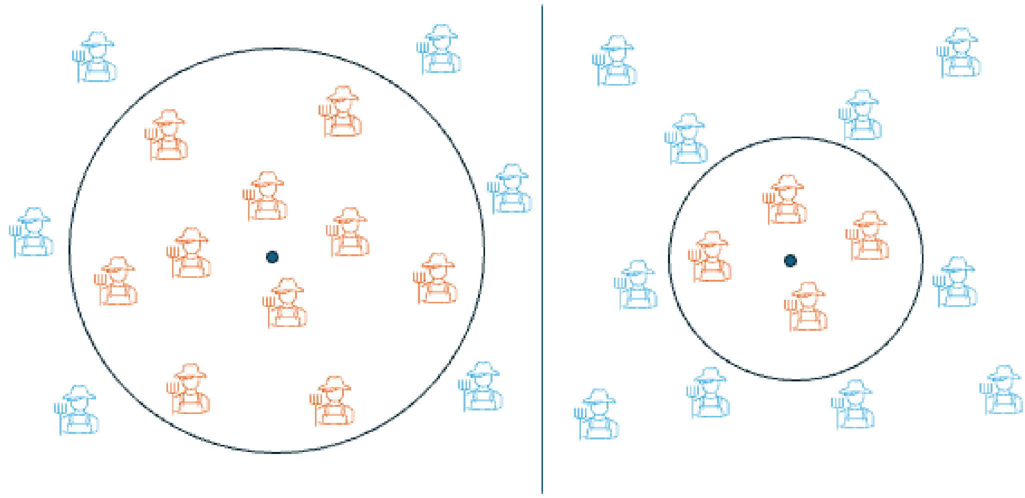


Source: Tara Gross, United States Geological Survey (USGS)

The externality arises because farmers within the cone are hydraulically connected – one farmer's extraction lowers water levels for others in the cone's reach. Higher-transmissivity aquifers generate wider cones of depression. As a consequence, given the same spatial distribution of farmers, an individual's extraction lowers the water table for a greater number of surrounding farmers.

Figure 5 visualizes the cone of depression from above: a single extraction point in a high-transmissivity aquifer affects farmers (orange) across a large radius, while the same extraction in a low-transmissivity aquifer affects only those within a smaller radius. This leads to two related consequences. First, since individual farmers extract groundwater according to their own private costs rather than the costs borne by others within their radius, they may over-extract relative to what is socially optimal. Second, because farmers within in the same radius may extract simultaneously, and the water table declines as a result of aggregate extraction, those on higher-transmissivity aquifers may attribute a smaller share of water table decline to their own extraction. When the relationship between individual extraction and total depletion is diluted, incentives to conserve groundwater diminish – reducing extraction today has less assumed impact on future water availability.

Figure 5: Externalities and Spatial Reach of the Cone of Depression



Note: This figure visualizes a top-down view of two cones of depression generated from a single point of extraction (blue dot). The distribution of individuals is identical between the left and right panels. Orange individuals represent those who are impacted by extraction and blue individuals represent those who are not.

2.2 Policy: The Groundwater Management Scheme (*Atal Bhujal Yojana*)

Given the challenges of directly regulating groundwater extraction in India – infeasibility of monitoring millions of dispersed wells, political resistance to pricing, and weak property rights and collective management institutions – policymakers have favored technology-based interventions. In India, there is significant room for improvement in irrigation efficiency. While 67% of all sown land is irrigated, only 11% of sown land is irrigated under efficient micro-irrigation technologies.

India's Groundwater Management Scheme (in Hindi, *Atal Bhujal Yojana*, abbreviated as ABY), launched in 2020, represents the country's largest groundwater conservation program, with a total budget of $1.35 billion over five years, spread across 227 subdistricts in seven states[2] of Western India, which account for approximately 25% of the area experiencing groundwater depletion (World Bank, 2024).

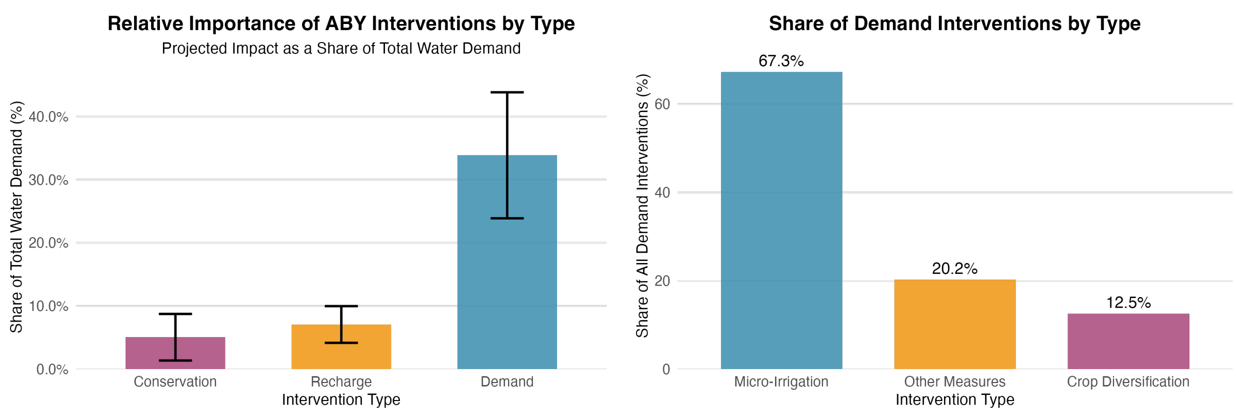
ABY is a cash infusion scheme, supplementing funding for existing programs intended to improve the sustainability of groundwater use. Broadly, these programs impact groundwater demand – how individual use of groundwater – and groundwater supply – how much groundwater is available to be extracted. In practical terms, the former primarily involves

[2]Gujarat, Haryana, Karnataka, Madhya Pradesh, Maharashtra, Rajasthan, and Uttar Pradesh.

subsidizing upgrades from traditional irrigation systems to micro-irrigation systems. The latter involves structures that improve groundwater recharge from rainfall, such as injection wells, and groundwater storage, such as ponds and percolation tanks.

In principle, therefore, ABY could subsidize a wide range of interventions impact groundwater use and availability. However, we show in Figure 6 that, in practice, ABY primarily subsidized micro-irrigation upgrading. The left panel shows the projected impact of demand-side versus supply-side interventions on groundwater depletion, as estimated by village councils in their budget proposals. Demand-side interventions—those targeting water use efficiency—account for approximately three times the projected reduction in groundwater extraction compared to supply-side interventions focused on recharge and storage.The right panel reveals that these demand-side interventions consist predominantly of micro-irrigation upgrades: "per drop more crop" technologies that increase the marginal productivity of extracted groundwater water but do not impact its ability to be extracted. Importantly, this emphasis on micro-irrigation reflects institutional constraints rather than deliberate prioritization – ABY channels funding through existing agricultural schemes, limiting village councils to interventions already available through state programs.

Figure 6: Breakdown of Interventions Funded by ABY



Note: We generate both figures using data from Water Security Plans (WSPs) generated at the village council (*gram panchayat*) level. The left panel reports the projected reduction in total groundwater use as a share of baseline total groundwater use, as derived by the village councils themselves. The right panel disaggregates the interventions affected groundwater use by type.

According to program documents (Department of Water Resources and Ganga Rejuvenation, 2023), ABY targeted subdistricts where groundwater extraction exceeded 70% of natural recharge—the water-stressed areas shown in Figure 3. However, because ABY operated by infusing cash into existing schemes, final selection also depended on administrative capacity – some water-stressed subdistricts were excluded due to implementation constraints, while others below the 70% threshold were included based on institutional readiness. The final selection of 227 subdistricts was announced on December 25, 2019, with program implementation beginning in early 2020.

ABY's theory of change posits that irrigation efficiency improvements will reduce groundwater extraction while maintaining agricultural productivity. Micro-irrigation technologies can reduce water requirement by up to 84% compared to traditional irrigation methods while maintaining or improving yields (Narayanamoorthy, 2004). If these efficiency gains unambiguously induce farmers to use less water to achieve the same output, total extraction will fall – the logic underpinning the projected impacts shown in Figure 6. However, whether farmers use efficiency gains to reduce extraction or to expand production remains an empirical question. The next section develops a conceptual framework for understanding why farmers may or may not conserve groundwater when irrigation efficiency improves.

3 Conceptual Framework of Groundwater Use, Technology, and Externalities

To understand how technology upgrading may impact groundwater extraction and welfare, we develop a two-period model of groundwater use with extraction externalities and stochastic rainfall. The purpose of this model is two-fold. First, it provides an understanding of how the presence of externalities mediates farmers' extraction choices before and after a technology upgrade. Second, it provides foundational intuition for the empirical analysis in Section 5.

3.1 Setup

Consider a continuum of farmers indexed by $i \in [0, 1]$ who share an aquifer. Each farmer begins with an initial depth to water $d_i(1) = D(1)$, where all farmers face the same initial depth. Farmers make extraction decisions over two periods under rainfall uncertainty.

Rainfall follows a binary distribution:

$$R(t) = \begin{cases} R_H & \text{with probability } p \\ R_L & \text{with probability } 1 - p \end{cases}$$

where $R_H > R_L$, representing normal rainfall and low rainfall, respectively. Rainfall serves two purposes. It recharges the aquifer, raising the water table and reducing the depth to water $D(2)$, and it contributes to soil moisture for crop production. The timing of choices is as follows:

1. **Period 1:** Given initial rainfall $R(1)$ depth $D(1)$, each farmer chooses groundwater extraction $x_i(1)$, determining agricultural yield and lowering the water table.

2. Rainfall $R(2) \in \{R_H, RL\}$ is realized, partially recharging the aquifer and providing soil moisture for crops.

3. **Period 2:** Given realized rainfall and updated depth $D(2)$, each farmer chooses extraction $x_i(2)$.

Though farmers choose extraction in both periods, we focus primarily on first-period extraction, which determines water availability and, therefore, yield in period 2. In other words, $x_i(1)$ will illustrate how farmers balance consumption intertemporally.

3.1.1 Technology and Production

Agricultural yield is a concave function of soil moisture $z_i(t)$:

$$y_i(t) = \log(z_i(t)) \tag{1}$$

Where total soil moisture is the sum of extracted groundwater and rainfall:

$$z_i(t) = \boldsymbol{\lambda} x_i(t) + \rho R(t) \tag{2}$$

The technology parameter $\lambda > 0$ represents irrigation efficiency – the marginal productivity of groundwater in generating effective soil moisture and, therefore, yield. This technology parameter is central to our analysis, as it represents the parameter impacted by upgrading from traditional irrigation to micro-irrigation. The parameter ρ represents the share of rainfall that feeds the crops, with the remaining portion $(1 - \rho)$draining into the ground and recharging the aquifer.

3.1.2 Extraction Costs

Following the empirical literature on groundwater extraction costs (Manring, 2013, Ryan, 2022), we model extraction costs as linear in depth:

$$\psi(x_i(t), D(t)) = x_i(t) \cdot D(t) \tag{3}$$

This specification reflects the physical costs associated with pumping from deeper water tables: as the water table becomes deeper, the distance over which a given quantity of groundwater must be lifted increases[3]. As a consequence, more extraction imposes higher costs.

3.1.3 Consumption and Utility

Farmers' consumption equals agricultural output net of extraction costs:

$$c_i(t) = y_i(t) - \psi(x_i(t)) = \log(\lambda x_i(t) + \rho R(t)) - x_i(t) \cdot D(t) \tag{4}$$

Utility is a function of consumption and CRRA: $u(c) = \frac{c^{1-\gamma}-1}{1-\gamma}$.

3.2 Externalities and Groundwater Depletion

As detailed in Section 2.1.2, shared access to groundwater generates extraction externalities: when one farmer extracts groundwater, it impacts the water table for others around them. We capture this in an externality parameter θ that describes the degree to which one farmer's extraction depletes the water table for others who share the aquifer, illustrated in Figure 5. From period 1 to period 2, the depth to water changes as a result of the individual farmer's extraction $x_i(t)$, others' extraction $X(t)$, and rainfall, a portion $(1-\rho)$ of which recharges the aquifer. The evolution of the depth to water as a function of an individual farmer's extraction is therefore:

$$d_i(t) - d_i(t-1) = \boldsymbol{(1-\theta)}\, x_i(t) + \boldsymbol{\theta}\, X(t) - (1-\rho)\, R(t). \tag{5}$$

This equation captures a relationship that is central to our model. The externality generates an intertemporal distortion in the the individual farmer's perception of how their own extraction impacts their future costs. In the extreme case where $\theta = 1$, for example, the farmer will optimize their extraction as if the water table evolves independently of their own extraction. That is, for larger θ, the farmer internalizes less of how their individual extraction impacts the shared water table, which evolves as a result of the extraction decisions of *all*farmers who share it:

[3]The linear setup captures costs in three cases. In India, electricity is often subsidized or free, and it may additionally be rationed. In the case where electricity costs are positive, the cost function reflects that the pump will have to run longer for a given quantity of groundwater to be extracted from a greater depth. In the case where electricity is free, we assume it is rationed. When the water table is deeper, the increased time required to pump the same quantity of groundwater leads to a lower quantity of extracted groundwater than could have been extracted within a given time limit if the water table was higher. In the case where electricity is neither priced nor rationed, extraction costs arise when the water table drops below the reach of well, requiring the farmer to drill deeper at their own expense. In this case, the cost is "lumpy". However, we posit that the linear extraction cost in our model simply smooths over these lumpier costs, as we do not impose limits on depth. In general, the results of this model do not require strong assumptions about the functional form of extraction costs, only that they are monotonically rising with extraction.

Aggregating across all farmers reveals why this creates an intertemporal distortion. The shared water table evolves according to total extraction $X(t)$, yet when $\theta > 0$ fail to internalize how their own extraction contributes to this aggregate depletion. Since extraction costs are increasing in depth, farmers undervalue how their current extraction raises future production costs. This wedge between individual perception and collective reality is the mechanism through which technology can generate climate maladaptation.

$$D(t) - D(t-1) = \int_i [(\mathbf{1} - \boldsymbol{\theta}) x_i(t) + \boldsymbol{\theta} X(t)] di - (1-\rho) R(t) \tag{6}$$

$$= X(t) - (1-) R(t) \tag{7}$$

This formulation illustrates how externalities impact individual behavior. As $\theta \to 0$, an individual farmer's own extraction impacts a greater share of the change in depth to water and, therefore, their future cost of extraction. As $\theta \to 1$, the farmer takes more of the change in water depth between periods as given. In other words, θ governs the degree to which farmers internalize how their individual extraction impacts the future depth of the water table and, since extraction costs are increasing in depth, the costs associated with agricultural production.

3.3 Optimization and Equilibrium Conditions

Decentralized (Farmer's) Problem: Each farmer chooses extraction $\{x_i(1), x_i(2); R\}$ to maximize expected utility:

$$\max_{\{x_i(t)\}} \quad \sum_{t=1}^{2} \beta^{t-1} \mathbb{E}_R \big[u(c_i(t)) \big]$$

subject to

$$d_i(t) - d_i(t-1) = (1-\theta)\, x_i(t) + \theta\, X(t) - (1-\rho)\, R(t),$$
$$c_i(1) = \log(\lambda x_i(1) + \rho R_1) \; - \; x_i(1) \cdot D(1),$$
$$c_i(2) = \log(\lambda x_i(2) + \rho R) \; - \; x_i(2) \cdot D(2).$$

Social Planner's Problem: The social planner solves an identical problem, but aggregates over all farmers, choosing $\{x_i(1), x_i(2)\}_{i \in [0,1]}$ to maximize:

$$\max_{\{x_i(t)\}} \sum_{t=1}^{2} \beta^{t-1} \int_0^1 \mathbb{E}_R\big[u(c_i(t))\big]\, di$$

subject to:

$$\begin{aligned} D(t) - D(t-1) &= \int_i [(1-\theta)x_i(t-1) + \theta X(t-1) - (1-\rho)R(t)]\, di \\ &= X(t-1) - (1-\rho)R(t) \end{aligned}$$

where:

$$\begin{aligned} X(t) &= \int_0^1 x_i(t)\, di, \\ c_i(1) &= \log(\lambda x_i(1) + \rho R(1)) - x_i(1) \cdot D(1), \\ c_i(2) &= \log(\lambda x_i(2) + \rho R(2)) - x_i(2) \cdot D(2). \end{aligned}$$

The social planner, in aggregating overall farmers, fully internalizes the externality. In other words, the social planner understands exactly how aggregate extraction will impact the water table across periods. By contrast, the individual only maps $(1-\theta)$ of their own extraction to period 2 depth to water. This difference generates key differences in first order conditions:

Social Planner's Euler Equation:

$$\frac{\lambda}{\lambda X^*_{SP}(1) + \rho R_1} - D(1) = \beta \mathbb{E}_R \left[\frac{u'(C_{SP}(2;R))}{u'(C_{SP}(1))} \cdot X^*_{SP}(2;R) \right] \tag{8}$$

Decentralized (Farmer's) Euler Equation:

$$\frac{\lambda}{\lambda X^*_{DE}(1) + \rho R_1} - D(1) = \beta \boldsymbol{(1-\theta)}\, \mathbb{E}_R \left[\frac{u'(C_{DE}(2;R))}{u'(C_{DE}(1))} \cdot X^*_{DE}(2;R) \right] \tag{9}$$

In equilibrium, equates the net marginal benefit of extraction in period 1 (LHS) with the discounted net marginal benefit of extraction in period 2 (RHS). The critical difference appears in the externality factor $(1-\theta)$ the on the right-hand side of the farmer's Euler. This term captures the fundamental distortion: individual farmers discount the future shadow value of extraction by the externality parameter, reducing the individual's incentive to conserve groundwater in period 1 for later extraction in period 2.

3.4 Why Technology May Exacerbate the Tragedy of the Commons

Equilibrium conditions generate three propositions that illustrate how technology upgrading impacts extraction in common pool settings and, importantly, illustrate why technology may not only increase groundwater extraction but exacerbate distortions away from social optima.

Proposition 1 (Tragedy of the Commons): *For any $\theta > 0$, farmers over-extract relative to the social optimum:*

$$\Delta(\lambda) = X(1)^{DE}(\lambda) - X(1)^{SP}(\lambda) > 0$$

This proposition establishes the fundamental tragedy of the commons in our setting. The wedge between individual and socially optimal extraction arises directly from the Euler equations: farmers discount the shadow value of groundwater –the water not extracted in period 1 – by $(1 - \theta)$. In equilibrium, farmers must extract more in period 1 to equate the left-hand and right-hand sides of their Euler equation. Since the marginal benefit of extraction is diminishing, this higher extraction level $X^{DE}(1)$ exceeds the social optimum $X^{SP}(1)$.

Proposition 2: *In the planner's solution, an increase in irrigation efficiency (λ) may lead to either an increase or a decrease in first-period extraction $X(1)$.*

Improved irrigation technology does not necessarily lead to water conservation, even under optimal management. Higher λ increases water's marginal productivity in both periods, creating opposing forces: immediate productivity gains incentivize higher period 1 extraction while increased future productivity encourages conservation. The sign of the change in optimal extraction depends on model parameters – risk aversion (γ), discount factor (β), and production function curvature – which determine the relative strength of these forces. If extraction increases, we observe Jevons' Paradox. If extraction decreases, conservation motives dominate.

Proposition 3: *There exists a threshold θ^* such that, for all $\theta > \theta^*$, the wedge between decentralized and planner's extraction increases with irrigation efficiency:*

$$\frac{\partial \Delta(\lambda)}{\partial \lambda} > 0$$

This proposition contains our central insight: technology can exacerbate distortions away from socially optimal behavior when externalities are severe. The mechanism operates through differential responses to productivity improvements. The social planner fully accounts for how extraction today affects future costs for all farmers sharing the aquifer. Individual farmers, internalizing only $(1-\theta)$ of how their extraction impacts future costs, underweight this intertemporal cost. Above threshold θ^*, this differential response causes the wedge between socially optimal and individual extraction to widen with technological improvement.

To build intuition, consider the case in which higher irrigation efficiency causes the social planner to reduce first period extraction.[4] As stated in Proposition 2, improved irrigation efficiency increases the marginal productivity of groundwater in both periods. This also increases the shadow value of conservation: the marginal unit of groundwater saved today is more valuable tomorrow. When this future productivity effect dominates—for example, under high risk aversion, strong patience, or severe climate risk—the planner responds by extracting less in period 1 to preserve groundwater for period 2.

The individual farmer faces a competing externality force that weakens the conservation incentive.[5] Since farmers only internalize share $(1-\theta)$ of how their extraction impacts the shared water table, the externality θ dampens the perceived ability of the individual farmer to turn period 1 conservation into period 2 extraction – "saving" a unit of extraction today only converts to a share $1-\theta$ of extraction tomorrow. As λ scales the intertemporal returns to extraction disproportionately between the social planner than the farmer, this dampening effect grows in magnitude: the individual farmer perceives a smaller increase in the returns to conservation than the social planner, widening the wedge between individual and socially optimal extraction when $\theta > \theta^*$.

3.5 Comparative Statics: Climate Maladaptation

Because our model incorporates stochastic rainfall, we are able to examine how welfare evolves under climate risk. In India, climate change projects to increase the variability of rainfall and extreme weather events, but not necessarily reduce the overall quantity of rainfall (Blakeslee, Fishman, and Srinivasan, 2020). We therefore derive two comparative statics that illustrate how the welfare gaps that arise in our propositions evolve as climate changes.

Comparative Static 1: *The wedge between individual and socially optimal extraction*

[4]Conceptually, the wedge can also increase if the social planner increases extraction and the individual farmer increases extraction more, as in Figure 1, or if the social planner reduces extraction and the individual farmer reduces extraction by less.

[5]There is also a "concavity force" that reinforces conservation. By Proposition 1, individual farmers over-extract in period 1 relative to the planner, operating on a flatter region of the marginal benefit curve. This raises period 2 costs and reduces period 2 extraction to a steeper region of the marginal benefit curve, reducing the cost of substituting period 1 extraction for period 2 extraction. However, this force is dominated by the externality force when $\theta > \theta^*$.

increases with drought probability $(1-p)$*:*

$$\frac{\partial \Delta}{\partial (1-p)} > 0$$

Due to risk aversion, higher drought probability increases the precautionary savings motive for both the social planner and the individual farmer. Both may, therefore, reduce extraction in period 1 to preserve groundwater for extraction in period 2. However, the equilibrium conditions lead to distortion: individual farmers discount the value of saving groundwater by $(1-\theta)$, and therefore will reduce their period 1 extract by less than the social planner, widening the welfare wedge.

Comparative Static 2: *The wedge between individual and socially optimal extraction increases with rainfall variance (mean-preserving spread):*

$$\frac{\partial \Delta}{\partial \mathrm{Var}(R)} > 0$$

A mean-preserving spread in rainfall increases the gap between high and low rainfall realizations, making drought states more relatively severe when they occur. As a result, the marginal value of groundwater in bad states increases. The social planner, recognizing this higher future marginal value, reduces period 1 extraction to preserve water for potential drought states. Individual farmers, internalizing only $(1-\theta)$ of how their extraction affects future water availability, respond less to the increased rainfall volatility. This differential response to extreme outcomes widens the extraction wedge.

These comparative statics demonstrate that extraction externalities determine whether technology conserves or depletes groundwater. Not only can technology amplify distortions away from the social optimum (Proposition 3), but these distortions grow as climate becomes more variable. The interaction between externalities, technology, and climate risk suggests that efficiency improvements may be particularly counterproductive in settings with both severe commons problems and increasing climate variability. In the next section, we turn to our empirical analysis to test whether these theoretical predictions bear out in practice.

4 Data

We begin by describing our empirical environment. Our analysis combines administrative groundwater records with remote sensing data, policy implementation records, and census information to construct a comprehensive panel dataset at the subdistrict level spanning 2016-2024. We detail the component pieces of this dataset and their characteristics below.

4.1 Central Groundwater Board (CGWB)

Data from the India's Central Groundwater Board (CGWB) provides us with data on annual total groundwater extraction in five waves: 2016-2017, 2019-2020, 2021-2022, 2022-2023, and 2023-2024. In addition to extraction (measured in hectare-meters[6]), the CGWB provides annual groundwater recharge from rainfall and other sources.

We primarily focus on groundwater extraction, which is measured by observing fluctuations in the water table at each measurement apparatus in a given subdistrict. The CGWB maintains a network of monitoring wells across India, with water levels measured four times per year (pre-monsoon, post-monsoon, and twice during the dry season). These water table fluctuations are then combined with aquifer-specific yield parameters to convert changes in water levels to volumetric extraction estimates (CGWB, 2022).

4.2 Water Resources Information System (WRIS)

From India's Water Resources Information System (WRIS), we obtain data on India's major aquifer systems as mapped by the National Water Informatics Centre (NWIC) in 2013. This hydrogeological assessment classifies India into 14 Principal aquifer systems and 42 Major aquifer systems. We extract aquifer characteristics including transmissivity (how easily water flows horizontally through the aquifer) and aquifer rock type (for example, alluvial or hard rock). We match each subdistrict to its underlying aquifer system based on spatial overlap.

4.3 ABY Program Data

We utilize administrative data and program documents from the Atal Bhujal Yojana for two purposes. First, we use program documents made public on the program website to identify the 227 subdistricts selected for treatment. These documents also detail the selection criteria, which we leverage for identification in our later analyses.

Second, we process the program's Water Security Plans (WSPs) to understand the mix of interventions undertaken, reported previously in Figure 6. As a requirement for receiving ABY funding, each gram panchayat –a village council administering a cluster of villages – was required to prepare a WSP detailing local hydrological characteristics and proposed interventions. These plans specify intervention types (such as drip irrigation), total groundwater use (in hectare-meters), projected reduction in groundwater use as a result of the intervention, and costs. Of the 8,223 gram panchayats treated under ABY, we obtained

[6] One hectare-meter (10,000,000 liters) is equivalent in volume to four Olympic swimming pools.

approximately 8,000 WSPs, of which roughly 6,000 were of sufficient quality to be processed. Because the WSPs are almost entirely image based – beyond figures, both text and tables are stored as images within each pdf – extracting from data from them is challenging. We build a script to process each file into markdown and then into CSV files for further cleaning and processing. The roughly 2,000 that were unable to be processed has sufficiently low image quality that data could not be reliably extracted from them.

4.4 Remote Sensing

We use several sources of remote sensing data to complement our traditional data sources.

Land Use (Bhuvan): We obtain annual land use classifications from the Indian Space Research Organization's Bhuvan platform at 56-meter spatial resolution for 2016-2019 and 2021-2024 (data are unavailable for 2020). The dataset provides binary land use classifications for each pixel. We aggregate these data to the subdistrict level and derive two measures of agricultural intensity: (1) percentage net sown area, calculated as the fraction of subdistrict area under cultivation in any season in a given year, and (2) percentage of multi-cropped area, calculated as the share of subdistrict area cropped across multiple agricultural seasons within the year.

Precipitation (CHIRPS): We obtain daily precipitation data from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset at 0.05° spatial resolution (approximately 5.5 km). We aggregate these data to the subdistrict level by taking spatial averages across pixels within each subdistrict boundary. From the daily precipitation series, we construct seasonal and annual rainfall variables to measure responses to climate variability.

4.5 The SHRUG

The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG), developed by Asher et al. (2021), is an open-access repository that harmonizes multiple Indian administrative datasets using consistent geographic identifiers based on the 2011 Population Census. We employ SHRUG data for two purposes. First, we use SHRUG's subdistrict shapefiles to spatially aggregate our remote sensing data and to geocode subdistrict identifiers in the CGWB groundwater data, allowing us to link entirety of our data sources together. Second, we use cross-sectional subdistrict characteristics from the 2020 Mission Antyodaya survey, a government census of rural infrastructure and amenities. These data include agricultural infrastructure, development facilities, and demographic characteristics.

5 Empirical Analysis

5.1 Constructing the Externality Score

Our conceptual framework demonstrates that the impacts of technology improvements that increase the marginal product of groundwater λ depend on the severity of the externality θ. While ABY, India's Groundwater Management Scheme, provides us with empirical variation in λ, we leverage physical aquifer characteristics to generate exogenous variation in θ.

As discussed in Section 2.1.2, extraction externalities arise from the spatial reach of the cone of depression created when farmers pump groundwater. The lateral extent of this cone depends on aquifer transmissivity – the product of hydraulic conductivity and saturated thickness. Higher transmissivity thus generates more severe externalities: an individual's extraction impacts more farmers, yet the individual bears only a fraction of the aggregate cost.

Remote sensing data from India's Water Resources Information System (WRIS) provides us with the physical characteristics of India's Major Aquifer Systems[7], including transmissivity. Using transmissivity (Edwards, 2016, Brozović, Sunding, and Zilberman, 2010), we build an externality score that leverages the spatial extent of the externality weighted by density of farming households in a given subdistrict. This density is a fraction, calculated from 2020 Mission Antyodaya data accessed via the SHRUG. The numerator is defined as the total number of households primarily engaged in farming, and the denominator is the total number of all households in a given subdistrict. Intuitively, the larger the number of farming households within a given spatial reach, the more severe the externalities. Formally, for subdistrict i, we define the externality score θ_i:

$$\theta_i = \text{Transmissivity}_i \times \left(\frac{\text{Farming Households}}{\text{Total Households}}\right)_i \tag{10}$$

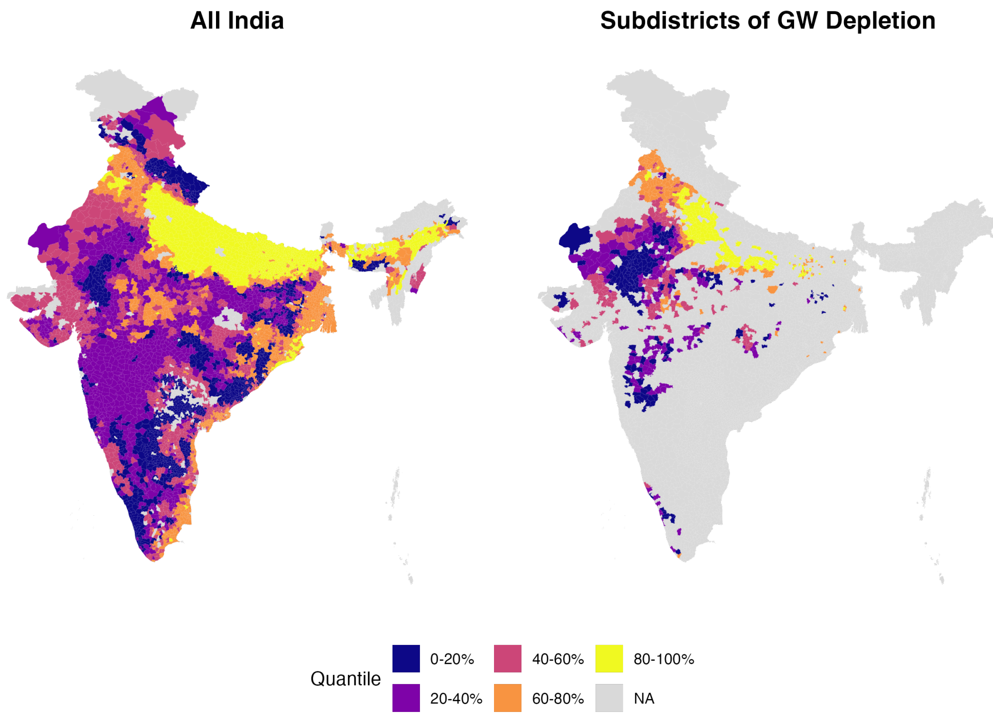
The externality score θ_i provides an ordering of externality severity across subdistricts that corresponds to the theoretical externality parameter θ in our model, where higher values indicate that farmers internalize a smaller fraction of their extraction's impact on the water table because they are more hydraulically connected to other farmers in the surrounding area[8]. Figure 7 plots the quintiles of this externality score both across the entirety of India

[7] We provide a map of the spatial boundaries of these major aquifers as well as their principal rock type in Appendix Figure 13.

[8] In Appendix section A.1, we discuss how other aquifer characteristics, such as confinement, may impact how the externality is measured and therefore how subdistricts are ordered in terms of externality severity. In Appendix section A.2, we construct an alternative externality score that incorporates these considerations and show that the ordering is preserved.

and across subdistricts most severely depleting their groundwater resources, as plotted in Figure 3. Notably, the range of distribution of the externality score is similar in both panels.

Figure 7: Spatial Distribution of the Externality Score



Note: Both panels plot quintiles of the externality score. The left panel plots the spatial distribution of the externality score for all subdistricts for which data is available. The right panel plots the spatial distribution of the externality score for subdistrict that, in 2019-2020, extracted groundwater beyond its natural rate of recharge, as noted in Figure 3.

For our main analysis, we partition subdistricts based on the median externality score within our sample, classifying them as high-externality $\theta_i^{high} = \mathbb{1}\{\theta_i > \theta^{median}\}$ or low-externality $\theta_i^{low} = \mathbb{1}\{\theta_i \leq \theta^{median}\}$. This binary classification simplifies the interpretation of our later empirical results[9].

5.2 Identification Strategy

5.2.1 Base Specification: Difference-in-Differences

To study the impact of ABY on outcomes of interest, we employ a difference-in-differences design, written as follows:

[9] Our results are qualitatively similar when using the full scale of the externality score.

$$Y_{it} = \alpha_i + \delta_t + \beta(Post_t \times ABY_i) + \epsilon_{it} \quad (11)$$

Where Y_{it} denotes the outcome of interest for subdistrict i in year t; α_i represents subdistrict fixed effects that absorb time-invariant differences between subdistricts; δ_t represents year fixed effect that absorb trends over time that do not vary by subdistrict; $ABY_i = 1$ if a subdistrict received ABY, $ABY_i = 0$ otherwise; and $Post_t = 1$ if $t \geq 2020$, as ABY implementation began in early 2020. The coefficient β captures the average treatment effect on the treated. Event studies are defined analogously, with year specific indicator variable in place of $Post_t$. Because treatment was assigned on December 25, 2019, and treatment began in March 2020 for all subdistricts. Treatment timing is therefore uniform across subdistricts, not staggered.

The validity of our estimates requires addressing potential selection bias arising from non-random treatment assignment. As discussed in Section 2.2, ABY explicitly targeted subdistricts exceeding a groundwater extraction-to-recharge ratio of 70%. Furthermore, because ABY is a cash infusion scheme – it channels funds into existing schemes targeting groundwater conservation – program administrators needed to select on subdistricts with sufficient administrative capacity. Selection into ABY was not random, and we address these concerns in two steps.

We address these selection concerns in two steps.

First, we trim our analysis sample to subdistricts exceeding an extraction-to-recharge ratio of 70%, prior to treatment. This assuages concerns that treatment and control subdistricts may have been on different depletion paths prior to the program and therefore, in potential outcomes, would have been on different trends of depletion in the absence of the program. Of the 819 subdistrict in India that sit above the threshold, less than 200 received ABY. There are two primary explanations for this. First, ABY was only implemented in certain districts of seven states where the density of subdistricts experience groundwater depletion was highest. However, there were many subdistricts outside of those areas experiencing similar levels of groundwater stress but may have not been selected purely due to budgetary constraints. In practice, subdistricts above the 70% could be excluded from treatment if they did not have sufficient administrative capacity, and subdistricts below the threshold may have been included if they had sufficient administrative capacity and if farmers reported the experience of groundwater stress.

We therefore address selection on secondary criteria concerning administrative capacity and farmers' experience of groundwater stress. Though program documents do not detail exactly what characteristics program administrators selected on, we can infer necessary facilities from how ABY was implemented in practice and match them to covariates in our data. We detail these covariates in Appendix Section E, and use them to generate entropy balancing weights (Hainmueller, 2012), which reweight units our treatment and control groups to minimize imbalance. In all specifications, we employ these entropy balancing weights and limit our sample to the region of common support of those weights between treatment and control groups.[10] Conditional on these procedures, we argue that treatment and control units would have evolved on parallel outcome trends in the absence of treatment.

5.2.2 Heterogeneity: Triple Differences

To understand how the impact of ABY differs by the severity of extraction externalities, we employ the following triple-differences specification:

$$Y_{it} = \alpha_i + \delta_t + \beta_1(Post_t \times ABY_i) + \beta_2(Post_t \times ABY_i \times \theta_i^{high}) + \beta_3(Post_t \times \theta_i^{high}) + \epsilon_{it} \quad (12)$$

Where $\theta_i^{high} = \mathbb{1}\{\theta_i > \theta^{median}\}$ indicates whether a subdistrict is above the median externality score. The coefficient β_1 captures the treatment effect in low-externality subdistricts; $\beta_1 + \beta_2$ captures the treatment effect in high-externality subdistricts; β_2, therefore, captures the additional differential effect for high-externality subdistricts, while β_3 absorbs the time trend for high-externality subdistricts[11].

The key identifying assumption of triple-difference design is parallel gaps: absent treatment, the *difference* in outcomes between high- and low-externality subdistricts would have followed parallel trends between treatment and control. A central concern is that high- and low-externality subdistricts may have already been adapting to groundwater scarcity at different rates, since, theoretically, over-extraction due to the presence of externalities may have made the need for adaptation more salient. However, we argue that the parallel gaps assumption is likely to hold for two reasons.[12] First, as discussed in Section 2.1.1, the groundwater depletion crisis in India is relatively recent, limiting the scope for adaptation to have already occurred differentially. Second, smallholder farmers are typically poor, limiting their ability to invest in micro-irrigation and adaptive technologies on their own.[13] Rather, these farmer are more likely to adopt these technologies through government subsidies and programs. By

[10]We retain 799 out of 819 units restricting to common support.

[11]Formally, there is also another linear term $\beta_4(ABY_i \times \theta_i^{high})$, however, because it is cross-sectional, it is absorbed by the subdistrict fixed effect α_i.

[12]A third argument involves inspecting pre-trends in the triple-difference coefficient across outcomes. We report these event studies in Appendix Section B. While these provide suggestive evidence that the parallel gaps assumption is likely to hold, it is still possible to violate this assumption in potential outcomes, hence we weight our discussion towards such arguments.

[13]We do not directly have data on plot size. However, we calculate from 2020 subdistrict data from Mission Antyodaya that the average cultivated area per farming household is 1.7 hectares in our sample, below the threshold for a smallholder farm, which is two hectares.

construction, ABY funds many such programs. If high-externality subdistricts were more likely to receive these programs, the externality score should be correlated with treatment. However, we find that, conditional on district fixed effects, high externality subdistricts were only 0.8% more likely to receive ABY than low-externality subdistricts. We provide additional comparisons of the characteristics of high- and low-externality subdistricts in Appendix Section D, noting that that the parallel gaps assumption restricts only differences in relative trends, not levels.

With these assumptions in mind, it is important to understand why heterogeneity by the externality score is useful. In our model, the only difference between the decentralized (farmer's) and the social planner's equilibrium conditions is the intertemporal distortion $(1-\theta)$, the factor by which the individual farmer discounts how much their extraction contributes to overall groundwater depletion and, therefore, the future costs of extraction. As $\theta \to 0$, however, the decentralized equilibrium converges to the social planner's equilibrium. In other words, when externalities are minimal, the individual farmer is closer to being the *de facto* social planner, and the wedge between individual and socially optimal behavior shrinks. Our empirical externality score θ_i allows us to proxy for this wedge. Treatment through ABY represents an increase in our technology parameter λ. The triple-difference coefficient β_2 reports the difference in treatment effects between high- and low-externality subdistricts, representing how the wedge $\frac{\partial \Delta}{\partial \lambda} = \frac{\partial \theta^{high}}{\partial \lambda} - \frac{\partial \theta^{low}}{\partial \lambda}$ grows or shrinks in response to technology upgrading.

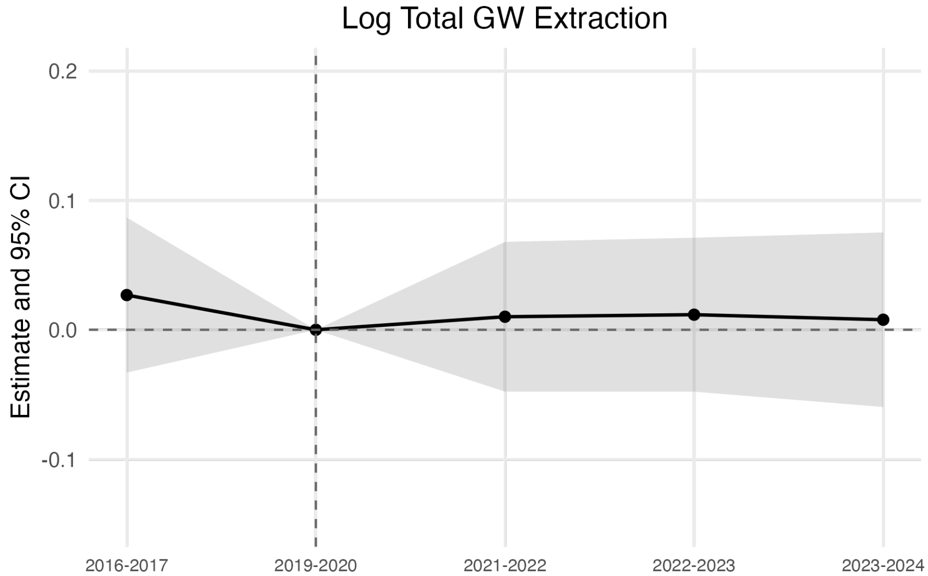
5.3 Impacts on Extraction

We begin by examining the treatment effect of ABY on our key outcome, total groundwater extraction. Figure 8 presents an event study corresponding to the base difference-in-difference specification in Section 5.2.1. The post-treatment coefficients are neither economically large – the 2022-2023 coefficient carries the highest magnitude, 1.16%, and we can rule out overall effect sizes larger approximately 6% in absolute value – nor statistically significant. At face value, this results implies that micro-irrigation upgrading through ABY had no effect on how much groundwater farmers extract.

However, when we examine how impacts differ by the externality score, we uncover that this aggregate effect masks significant heterogeneity. Figure 9 reports the treatment effect for low-externality (in blue) and high-externality[14] (in orange) subdistricts using event study analogue of the triple-differences specification in Section 5.2.2.

[14] Note that the orange coefficients represent the treatment effect $\beta_1 + \beta_2$. The difference between the orange and blue points is therefore the triple-difference coefficient β_2. We include event study plots of β_2 in Appendix Section B.

Figure 8: Aggregate Impact of ABY on Total Groundwater Extraction



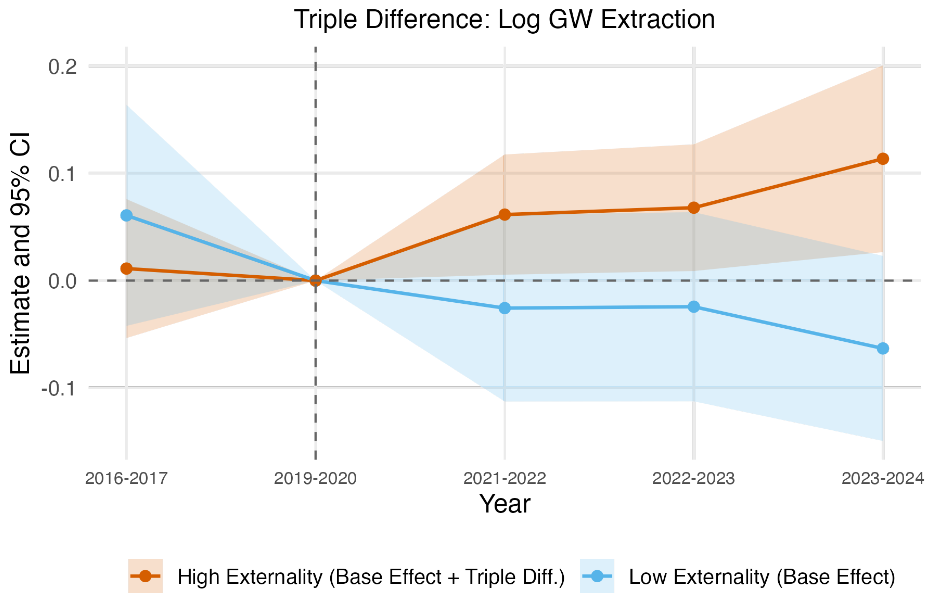
Note: This figure reports event study coefficients for the analogue to the difference-in-differences specification from Equation 11. Black dots represent point estimates, and the ribbon reports the 95% confidence interval of each point estimate. The y-axis outcome is log total extraction and should thus be interpreted as percentage changes. The x-axis reports the year range, as reported in the CGWB data. Note that, for readability, we do not plot the time scale proportionally.

he heterogeneous treatment effects in Figure 9 reveal a sharp divergence consistent with our theoretical predictions. In Table 5.4, we report the triple-differences estimates to understand the total treatment effects. These reveal that, for low-externality subdistricts, ABY appears to have successfully induced farmers to extract less groundwater, a reduction of 9.2% ($p < 0.10$) overall. The opposite holds for high-externality subdistricts, which extract 11.0% ($p < 0.01$) *more* groundwater as a result of treatment. This implies a total difference in treatment effects of 20.2%, over twice the magnitude of the treatment effect in low-externality subdistricts. This implies that the presence of severe externalities not only nullifies the conservation effect that ABY has at baseline but reverses it, resulting in an average treatment effect of zero.

This result provides us with empirical evidence for the theoretical result derived in Proposition 3 of our model: when externalities are sufficiently severe $\theta > \theta^*$, technology upgrading that increases the marginal product of extracted groundwater exacerbates the wedge between socially optimal and individual groundwater extraction. The sign reversal – greater conservation in low-externality areas versus greater depletion in high-externality areas – represents the starkest possible confirmation of this prediction[15]. Furthermore, the divergent

[15]Note that other, less stark results would still be consistent with Proposition 3. Consider, for example, the following result: low- and high-externality farmers both extract less as a result of ABY, but low-externality

Figure 9: Heterogeneous Impacts of ABY by Externality Severity



Note: This figure reports event study coefficients for the analogue to the difference-in-differences specification from Equation 12. Blue dots represent point estimates for the base effect, or the treatment effect for low-externality subdistricts, β_1, and orange dots report the treatment effect for high-externality subdistricts, $\beta_1 + \beta_2$. The separate difference-in-difference and triple-difference plots can be found in Appendix Section B. The ribbons report the 95% confidence interval of each point estimate. The y-axis outcome is log total extraction and should thus be interpreted as percentage changes.

results provide insight on Proposition 2, which states that whether irrigation efficiency improvements cause farmers to reduce or increase extraction is theoretically ambiguous, as it depends on other parameters of the model. That the treatment effects of high- and low-externality subdistricts take opposite signs implies that a key parameter determining the sign in Proposition 2 is the externality itself.

5.4 Impacts on Cultivation Intensity

Having established how ABY impacts farmers' choices of groundwater extraction, we now turn to mechanisms: how does technology upgrading impact how farmers use groundwater? Prior evidence suggests that irrigation technology can affect agricultural production decisions: enabling cultivation of water-intensive crops, expanding cultivated area, or cultivating the existing plots more frequently over the same year (multi-cropping) (Pfeiffer and Lin, 2014, Fishman, Giné, and Jacoby, 2023, Grafton et al., 2018). While data limitations preclude

farmer reduce their extraction by more than high-externality farmers. This would suggest that the wedge between socially optimal and individual extraction grows, but it does not imply that technology exacerbates depletion in high-externality subdistricts.

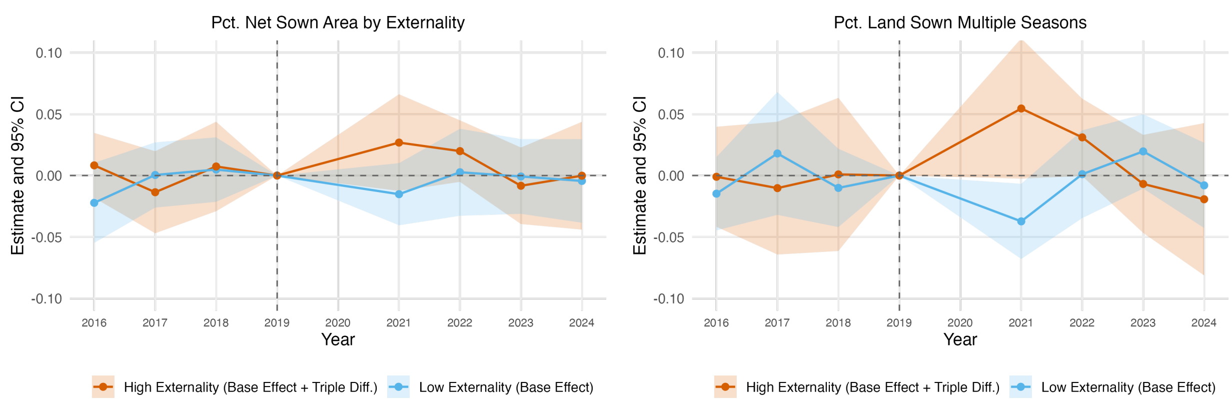
reliable analysis on agricultural yields or crop switching[16], we can explore land use adjustments along two observable margins:

1. **Extensive margin:** the percentage of land in a given subdistrict that is sown under any season during a given year (percentage of land net sown). For brevity in notation, we refer to this as net sown land.

2. **Intensive margin:** the percentage of land in a given subdistrict that is sown across multiple seasons within the same years. We refer to this as "multi-cultivated" area.

We report the results on these event studies in Figure 10 and we report the triple-difference coefficients in Table 5.4. The blue lines report the treatment effects for low-externality subdistricts. While the results on both net sown land and multi-cultivated area are both statistically indistinguishable from zero, they may, in context, suggest another margin of success for ABY. Previously, we observed that low-externality subdistricts extract less groundwater overall following ABY. The results on land use, therefore, suggest that farmers are able to maintain the same cultivation intensity while using less groundwater, consistent with the conservation objectives of ABY.

Figure 10: Heterogeneous Impact of ABY on Cultivation Intensity



Note: The left panel reports the percentage of land sown under any season. The right panel reports the percentage of land that is cropped over multiple seasons within the same year. In both cases, the units of the event study coefficients are percentage points

By contrast, we observe that high-externality subdistricts intensify their land use. While it does not appear that they significantly expand the area of cultivation, they do appear to

[16]Ground truth data on agricultural yields and crop-specific output is only available at the district-level for our sample period. A common alternative approach uses remote sensing data on vegetation. We include additional results on vegetation and a brief discussion of the concerns with using such data in Appendix Section C.

sow the same area over more seasons, consistent with prior literature showing that farmers exploit efficiency gains from micro-irrigation to increase production and total groundwater use. This effect is economically large, a 3.5pp difference from low-externality subdistricts and a 2.4pp total treatment effect on net, an effect size of approximately 10% relative to the pre-treatment, low-externality control mean. While this may be welfare-enhancing in the short-run, the effects appear short-lived, as land use patterns return to their pre-ABY levels in the later stages of our data, despite increased groundwater use persisting. This presents a puzzle that we explore through our further results.

The welfare implications of these patterns in high-externality subdistricts depend on the underlying mechanisms that cause land use patterns to revert despite persistently higher levels of groundwater utilization. One possible explanation is that farmers initially use multi-cropping to build liquidity to purchase the inputs for higher-value crop varieties. In this case, it is not obvious that farmers are worse off. However, recent literature shows that such adaptations are rare in the short run (Burlig, Preonas, and Woerman, 2021). A second explanation could be diminished water quality. As aquifers deplete, the quality of water often diminishes as total dissolved solids often settle lower in the aquifer. In this case, farmers may still extract more groundwater by volume, but the productivity of that water may be lower as water levels fall. Though our empirical environment precludes examination of either of these channels[17], we argue that it is unlikely that increased groundwater extraction and briefly intensified land use are indicative of welfare gains. More plausibly, the pattern could reflect unsustainable intensification that may have left farmers more exposed to climate shocks – a possibility we explore directly in the next section.

[17]While the CGWB has long-run, well-level data on both groundwater levels and groundwater quality, the wells are measured too sparsely across time and space to provide reliable insights on either over our 10-year sample period. ABY provides more frequent measurements of water quality for treated subdistricts but not control subdistricts.

Table 1: Triple-Differences Results: Groundwater Extraction and Land Use

	(1) Log(Total Extraction)	(2) Pct. Net Sown Area	(3) Pct. Area Multi-Cultivated
Post × ABY	-0.097*	-0.002	-0.011
	(0.053)	(0.010)	(0.015)
Post × ABY × High Ext.	0.207***	0.004	0.035*
	(0.065)	(0.014)	(0.021)
Subdistricts	776	776	776
Control Mean	9,103.68 (ha-m)	0.383	0.201
Coef. Units	% change	pp	pp

Notes: * p<0.10, ** p<0.05, *** p<0.01. Standard errors clustered at subdistrict level in parentheses. All regressions include subdistrict and year fixed effects and are weighted using entropy balancing weights. Control means are pre-treatment (2015-2019) means for low externality areas. Log total extraction, as measured by the CGWB, described the total groundwater extraction in a given subdistrict for any purpose. The percentage of land net sown reports the total area of land sown under any season within a given year. The percentage of multi-cultivated land reports the total area of land sown across multiple seasons within the same year. Both land use variables are contained in the Bhuvan Land Use data.

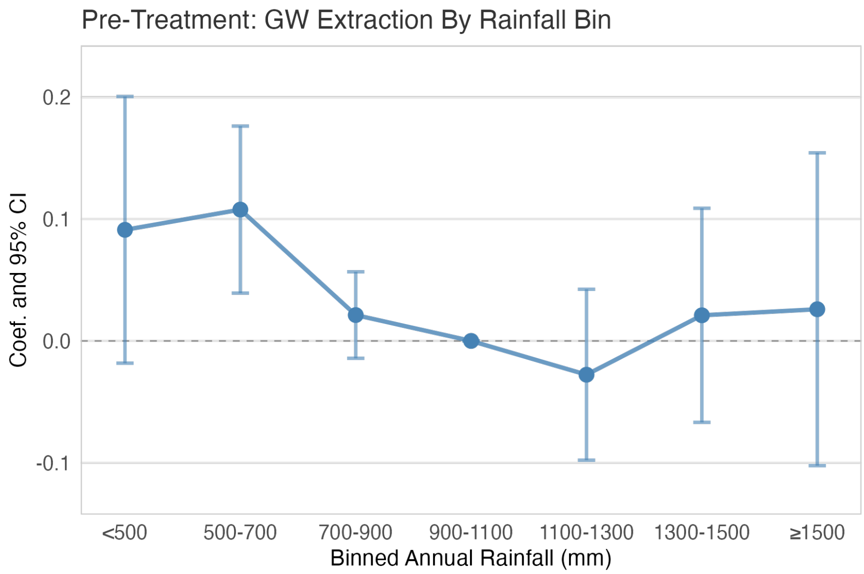
5.5 Climate (Mal)adaptation

Groundwater acts as a buffer stock for agricultural production, enabling farmers to smooth water input and hence agricultural output across climate shocks. When rainfall is insufficient for crop growth, farmers extract groundwater as a substitute, allowing them to maintain total water input despite weather variability (Fishman, Devineni, and Raman, 2015, Taraz, 2017). This smoothing mechanism becomes increasingly critical as climate change intensifies rainfall variability (Burke, Hsiang, and Miguel, 2015). In this section, we examine whether irrigation technology bolsters or undermines this climate-adaptive capacity.

First, we establish the baseline relationship between rainfall and extraction. The rainfall thresholds that trigger increased groundwater use may vary by crop (Schlenker and Roberts, 2009, Hogan and Schlenker, 2024), as water requirements may vary by plant. In the absence of crop-specific data, we empirically identify the relevant rainfall thresholds below which farmers extract more water by regressing pre-treatment extraction on rainfall bins. Figure 11 illustrates that farmers extract approximately 10% more groundwater once annual rainfall falls to 500-700mm relative to the median (900mm-1100mm).

We use this low rain threshold to examine how ABY affects farmers' ability to smooth total water input across rainfall shocks. Our specification adapts the triple-differences design

Figure 11: Extraction by Rainfall Bin, Pre-Treatment



Note: This figure reports log total groundwater extraction for a given subdistrict in a given bin of total annual rainfall. To avoid conflating these behaviors with treatment effects, we restrict our sample to 2016-2017 and 2019-2020 in the CGWB data, prior to ABY treatment. We include subdistrict and year fixed effects to absorb cross-sectional differences across subdistricts and country-wide trends that may correlate with rainfall, respectively. We use the 900-1100, rainfall bin as the reference bin, which is the median of the subdistricts in our analysis sample. All coefficients should therefore be interpreted and the percentage difference in extraction from approximately normal rainfall.

in Section 5.2.2 as follows, which we run separately for high-externality and low-externality subdistricts:

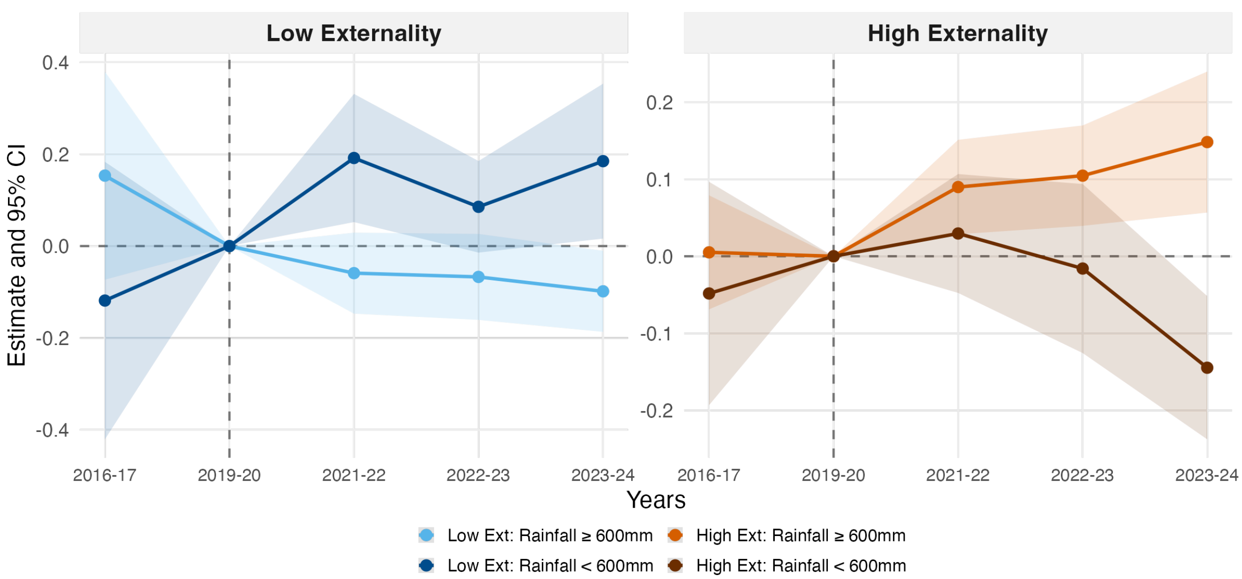
$$Y_{it} = \alpha_i + \delta_t + \beta_1(\text{Post}_t \times \text{ABY}_i) + \beta_2(\text{Post}_t \times \text{ABY}_i \times \text{LowRain}_{it}) + \beta_3\text{LowRain}_{it} + \epsilon_{it} \quad (13)$$

Where $LowRain_{it}$ is an an indicator for whether annual total rainfall in subdistrict i at time t was below a chosen threshold. For our main analysis, we choose 600mm, the midpoint of the bin identified in Figure 11. We run this regression separately for low- and high-externality subdistricts. As with the previous triple-differences design, we include subdistrict and year fixed effects and employ entropy balancing weights as described in Section 5.2.1 and Appendix Section E.

Identification in this design requires that the drought response differential between ABY and non-ABY subdistricts would have remained constant absent treatment. A key concern is that the composition of drought-affected areas changes from year to year as $LowRain_{it}$ varies. We therefore require two assumptions: (1) conditional on fixed effects, drought incidence is as-good-as-random and uncorrelated with treatment status, and (2) treatment itself does not affect the probability of experiencing drought. While recent literature suggests that large-scale irrigation can impact rainfall patterns (Braun and Schlenker, 2023), ABY affects only 227 subdistricts out of nearly 6,000 in India—too small a footprint to influence regional precipitation. Moreover, rainfall patterns are determined by monsoon systems operating at much larger spatial scales. We therefore argue that drought incidence remains exogenous to treatment, and thus our identifying assumptions are likely to hold.

We report the results of this specification in Figure 12[18]. The dark lines and point estimates represent the triple difference coefficients – the differential extraction response to low rain – while the lighter lines and point estimates represent the impact on extraction when rainfall is above the low rain threshold.

Figure 12: Impacts of ABY on Climate Smoothing



Note: This figure reports the event study coefficients analogous to the triple-differences specification in 13. The left panel reports coefficients for low-externality subdistricts, while the right panel reports coefficients for high-externality subdistrict. Darker dots are point estimates for subdistricts experiencing annual rainfall below 600mm, while lighter dots report point estimates for subdistricts experiencing rainfall at or above 600mm. In both panels, the outcome is log total groundwater extraction, and thus the y-axis should be interpreted as percentages. Ribbons report the 95% confidence interval of each point estimate.

In order to interpret these results, we return the intuition of the policymaker. In subsidizing more efficient micro-irrigation technology, ABY intended for farmers to conserve groundwater, replenishing water tables. Replenished water tables would bolster farmers' ability to adapt to climate shocks, as they are more able to smooth water input over periods of low rain. In the

[18]We include additional results on different thresholds in Appendix Section B, which exhibit similar patterns.

context of our regression, this would manifest as farmers reducing their extraction post-ABY during periods of normal rainfall (lighter lines) and either increasing or maintaining their extraction during periods of low rain (darker lines).

This is precisely the pattern we observe in the low-externality subdistricts in the left panel of Figure 12 – consistent with the climate adaptation intended by ABY policymakers. However, in the right panel, we observe the opposite pattern in high-externality subdistricts. Having established from Figure 9 that these subdistricts increase their total groundwater extraction, it appears that they do so by extracting more during periods of normal rainfall, compromising their ability to extract when rainfall is low. Furthermore, the decreasing trend in low-rain extraction may explain the land use patterns in Figure 10. Farmers' extraction during drought falls during the same periods when intensified land use recedes. It is plausible, therefore, that farmers are unable to sustain intensified land use due to increased susceptibility to climate shocks. Relative to low-externality subdistricts, it appears that technology is climate *mal*adaptive when externalities are severe.

These divergent patterns in climate adaptation connect directly to our model. Both of our comparative statics, $\frac{\partial \Delta}{\partial (1-p)}$ and $\frac{\partial \Delta}{\partial \mathrm{Var}(R)}$, show that the extraction wedge between individual and socially optimal extraction widens with climate risk because the presence of externalities distort farmers' precautionary savings motive. Our empirical results are consistent with this prediction: technology upgrading in high-externality subdistricts not only increases total groundwater extraction but also compromises farmers' ability to smooth production over climate shocks. This climate maladaptation, through the lens of the model, implies unambiguous welfare losses – farmers face increased exposure to rainfall variability while simultaneously depleting the buffer stock needed to cope with it.

6 Conclusion and Policy Implications

In the classic tragedy of the commons, individuals acting in their own self-interest over-extract a common pool resource, leading to welfare losses for all who share it. A standard feature of the tragedy of the commons is the presence of negative externalities – costs imposed on others that are not internalized by the individual user. Typically, such distortions justify intervention to correct them. A natural policy response is to improve extraction efficiency, enabling users to obtain more output per unit of the resource extracted. In this paper, we argue that the conditions that typically justify an such an intervention in common pool settings may also mediate whether it ameliorates or exacerbates over-extraction.

Today, groundwater depletion in India reflects the quintessential tragedy of the commons. Exploiting physical variation in externalities and a multi-state groundwater management scheme, we show that technologies intended to reduce groundwater extraction may instead increase it if externalities are sufficiently severe. We find that subsidies for micro-irrigation – technologies that increase the marginal product of groundwater but do not impact the ability to extract it – reduce groundwater extraction where externalities are low by 9.2% but increase it by 11.0% where externalities are high. High-externality farmers appear to use the additional groundwater to sow the same land over more seasons within the same year. However, this appears unsustainable even in the short-run. Increased extraction appears to compromise their ability to smooth over rainfall shocks. Low-externality farmers, however, maintain the same cropping intensity with less groundwater input, and they are better able to buffer against rainfall variability. Interpreted through our theoretical framework, this suggests that the impact of technological interventions on common pool resource depletion and welfare may depend principally on the conditions that have led to depletion to begin with.

Our findings contribute to a growing recognition that efficiency improvements often fail to lead to conservation in common pool settings. While previous work primarily identifies how individuals adjust their resource use, we identify the structural conditions determining why these failures occur. Furthermore, we complement prior work identifying externalities as a central mediator in resource depletion, for example in fisheries (Squires and Vestergaard, 2013), by providing a theoretical framework that applies more generally to common pool resource use and elucidates the fundamental drivers of technological backfire in such settings.

The policy implications challenge conventional approaches to resource conservation in developing countries. In the developing world, institutions are seldom strong enough to implement the classic solutions to the tragedy of the commons, such as Pigouvian taxation and Coasean bargaining. To policymakers in these contexts, subsidizing irrigation efficiency improvements is one of the few interventions that is both institutionally feasible and politically palatable. While our empirical findings suggest that such interventions may be fundamentally risky, our theoretical framework allows us to consider other policy instruments that are both institutionally-light and lead to conservation. Interventions that directly impact the costs or returns to agricultural effort also impact incentives to extract the groundwater to sustain it. Under minor modifications to our model, one can show that an unconditional cash transfer, by substituting for the returns to cultivation, may not only lead to groundwater conservation but also shrink the wedge between individual and socially optimal extraction. When farmers supply their own labor – as is typical among Indian smallholders – cash transfers substitute for agricultural income without requiring water inputs, reducing extraction through both income and substitution effects[19]. As others have argued (Chatterjee, Lamba, and

[19]Consider augmenting the model with labor input L where production depends on both soil moisture

Zaveri, 2024), cash transfer programs, such as the 2018 PM-Kisan basic income scheme, or workfare programs, such as the 2005 Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS), may thus offer unintended conservation benefits. Though neither program explicitly targets groundwater conservation, both provide income alternatives that reduce farmers' dependence on agricultural production and, consequently, groundwater. This warrants a new avenue of future research; the policies that most successfully conserve groundwater may not be the policies that directly target it.

and labor: $y = f(z, L)$ with complementarity, and utility $U(C) - \phi(L)$ where $\phi(L)$ is convex (e.g., the same effort becomes more unpleasant as farmers fatigue). An unconditional transfer T enters additively: $U(y - x \cdot D + T) - \phi(L)$. While the income effect is ambiguous—the transfer reduces marginal utility of output but also relaxes budget constraints for extraction – the substitution effect dominates when labor has convex disutility. The transfer provides income without requiring the complementary labor and water inputs needed for agricultural production. Since cultivation requires both effort and irrigation, farmers reduce both labor and extraction when given alternative income. Moreover, because the individual over-extracts relative to the planner (discounting future costs by $(1 - \theta)$), this substitution effect is stronger for the individual farmer, thereby shrinking the extraction wedge.

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Main Appendix

A Additional Characteristics of Aquifers

A.1 Confined vs. Unconfined Aquifers

Aquifers differ not only in how easily water flows through them but also in how the water is stored. An **unconfined** aquifer is the simplest case: it sits near the surface, and its upper boundary of the structure is the water table itself. The pores within the soil or rock are partly filled with air and partly with water, and the water table rises and falls with rainfall or pumping. Because the surface of the aquifer is uncovered, the water is at normal atmospheric pressure. When farmers pump from such an aquifer, they physically lower the water table, draining the spaces between grains much like water leaving a sponge. These systems generally have high storage capacity – known as *specific yield* – because a relatively large share of their water can drain out under gravity.

A **confined** aquifer, by contrast, lies deeper underground, between layers of clay or rock that are less permeable. These confining layers trap the water so that it is completely saturated and under pressure. When a well penetrates this layer, water may even rise up the well – sometimes above the top of the aquifer – because it is released from that pressure. Pumping from a confined aquifer does not drain pore spaces; instead, it slightly reduces the internal pressure of the water storage structure and allows a very small amount of water to expand from compression of the rock–water system. This means confined aquifers have much smaller storage, or *storativity*, than unconfined ones: a small change in volume or pressure can affect water availability across a much larger area.

In between these two types are **semi-confined** aquifers, where thin, partially permeable layers allow slow vertical leakage between zones. Over short timescales they behave like confined systems, but over longer periods they gradually equilibrate like unconfined ones.

From an economic perspective, these physical differences shape how far one farmer's pumping affects others. In unconfined aquifers, where storage is large, the effects of pumping tend to remain more local, propagating through the cone of depression; in confined or semi-confined aquifers, where storage is small, a given unit of extraction causes a change in hydraulic pressure that can propagate over a wider area. Two distinct but related hydrogeological measures capture these mechanisms. *Specific yield* (S_y) denotes the fraction of an unconfined aquifer's volume that can drain under gravity as the water table declines, with typical values ranging from 0.01 to 0.30. *storativity* (S) is the broader storage coefficient, defined as the volume of water released per unit surface area of aquifer per unit decline in hydraulic head. In unconfined aquifers this reflects gravity drainage; in confined aquifers it reflects elastic compression of the rock-water system. In unconfined settings $S \approx S_y$; in confined settings S s much smaller (typically 0.00001 to 0.001) and reflects elastic compression of the rock-water system rather than drainage (Woessner and Poeter, 2020).

A.2 Robustness of the Externality Score

Our main analysis measures the severity of groundwater extraction externalities with aquifer *transmissivity* and local farmer density. Transmissivity (T_i) captures the lateral ease of flow—and thus the spatial reach of depletion—while farmer density scales how many users are potentially affected within that reach. For subdistrict i,

$$\theta_i \;=\; \text{Transmissivity}_i \times \left(\frac{\text{Farming Households}}{\text{Total Households}}\right)_i \tag{14}$$

While this measure abstracts from aquifer confinement, India's WRIS dataset reports confinement categories inconsistently across states. To the degree that WRIS does report confinement within aquifer boundaries, they are almost always unconfined. To verify that this simplification does not meaningfully affect our results, we construct an alternative, storage-adjusted variant that accounts for the aquifer's ability to release water. Specifically, we replace transmissivity with the ratio of transmissivity to specific yield ($S_{y,i}$), which serves as an observable proxy for aquifer storage:

$$\tilde{\theta}_i \;=\; \frac{\text{Transmissivity}_i}{\text{Specific Yield}_i} \times \left(\frac{\text{Farming Households}}{\text{Total Households}}\right)_i$$

Dividing by $S_{y,i}$ increases the score in aquifers with lower storage (more confined behavior), reflecting that a given extraction induces pressure changes that propagate farther through the aquifer.

Although this adjustment incorporates an additional hydrological mechanism, it yields an almost identical spatial ordering of subdistricts. The rank correlation between θ_i and $\tilde{\theta}_i$ is 0.982 (Kendall's τ = 0.895), indicating near-perfect concordance in the ordering of subdistricts. This stability arises because transmissivity and specific yield are strongly correlated ($\rho = 0.73$) – both are higher in coarse, permeable sediments – and transmissivity exhibits substantially greater relative variation across subdistricts. Moreover, 94 percent of subdistricts classified in the top decile of θ_i also appear in the top decile of $\tilde{\theta}_i$, implying that the identification of high-externality areas is effectively invariant to the inclusion of storage characteristics.

Furthermore, the WRIS-reported specific yield values in our data (range: 0.01-0.085, median: 0.037) fall within the unconfined range and are several orders of magnitude larger than confined aquifer storage coefficients, as we discussed in the previous section. This is consistent with WRIS confinement classifications, which report most aquifers in our study area as unconfined or semi-confined. This indicates that aquifers under consideration in our study are largely unconfined and, therefore, cone-of-depression dynamics appropriately characterize extraction externalities. Because of this and because the relative ordering of externality severity is unchanged, we proceed with the baseline transmissivity-weighted score in our main analysis.

B Additional Figures

Figure 13: Map: Major Aquifers of India with Rock Type

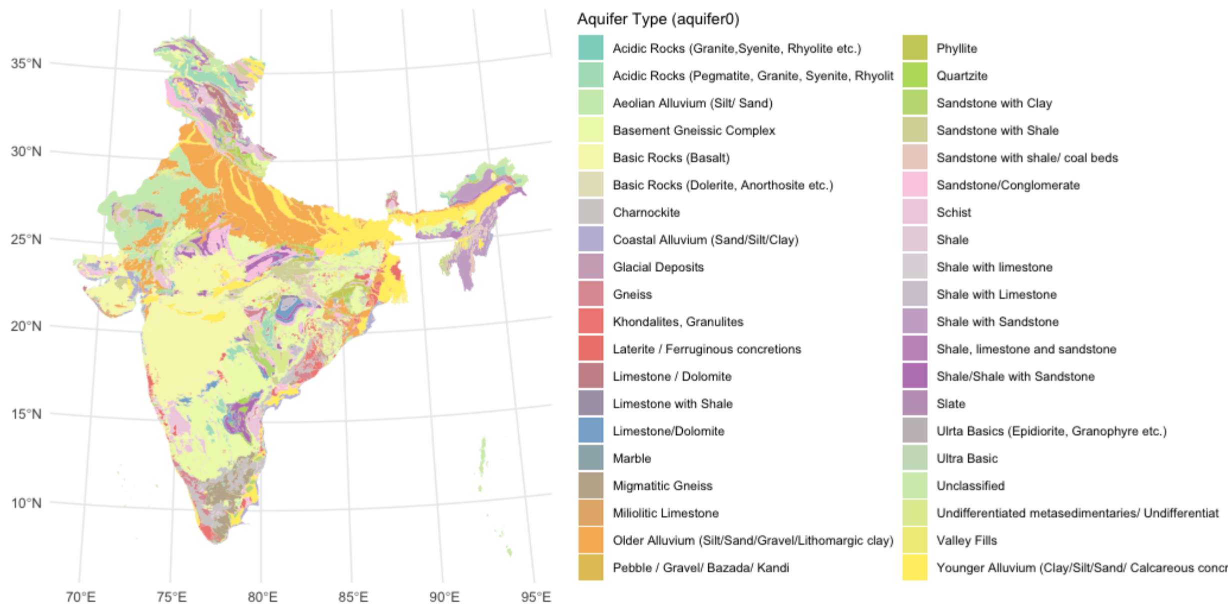


Figure 14: Triple Difference Coefficient, Groundwater Extraction

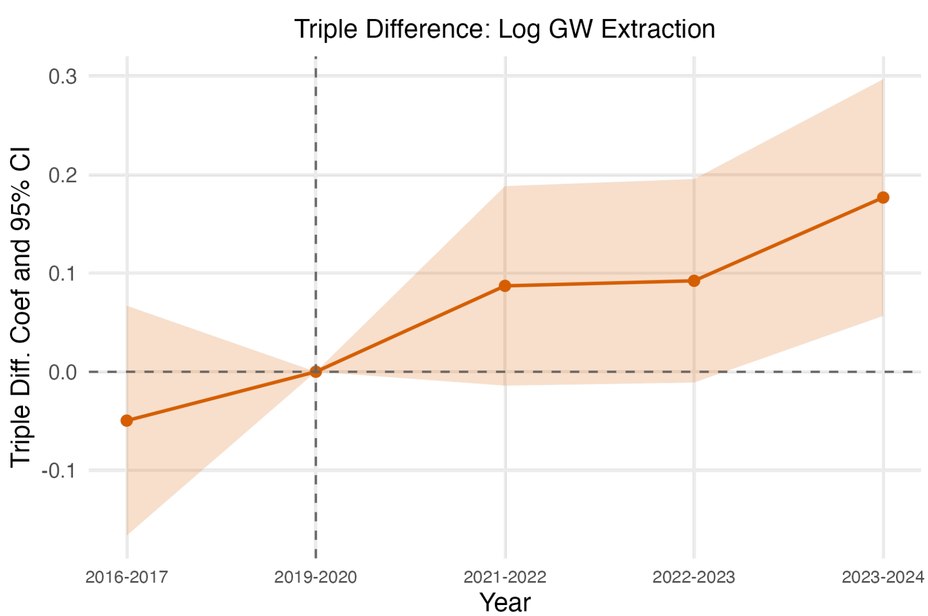


Figure 15: Base Event Study, Percentage of Land Net Sown

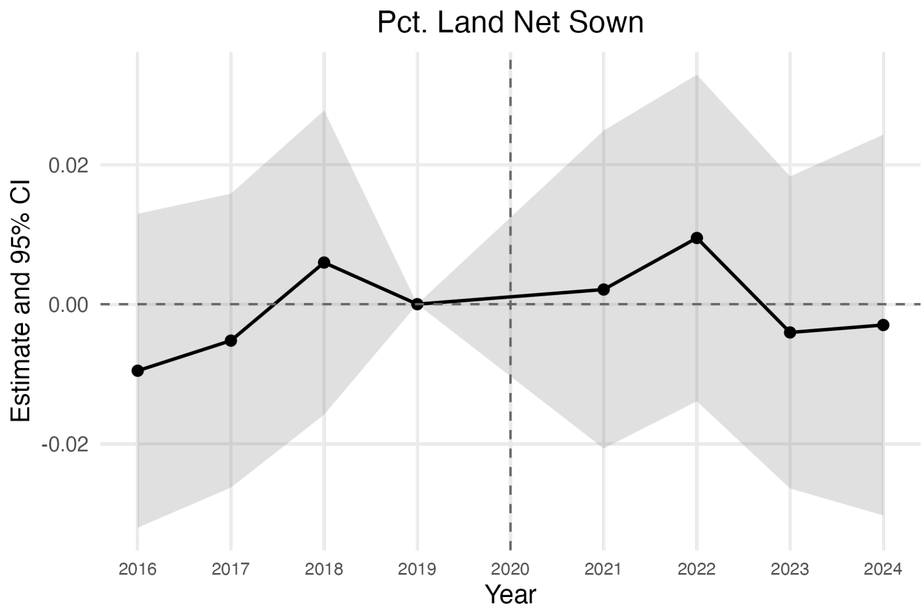


Figure 16: Triple Difference Coefficient, Percentage of Land Net Sown

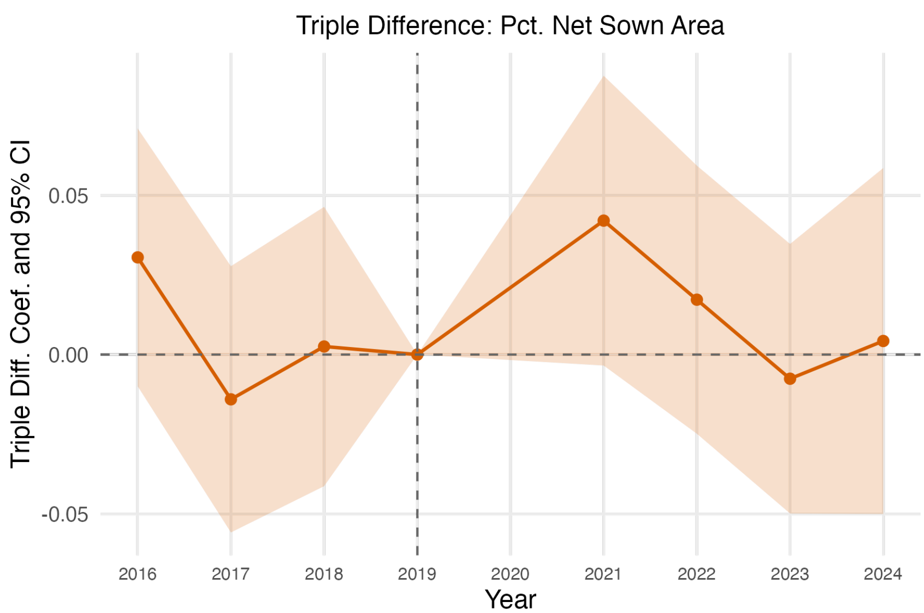


Figure 17: Base Event Study, Percentage of Multi-Cultivated Land

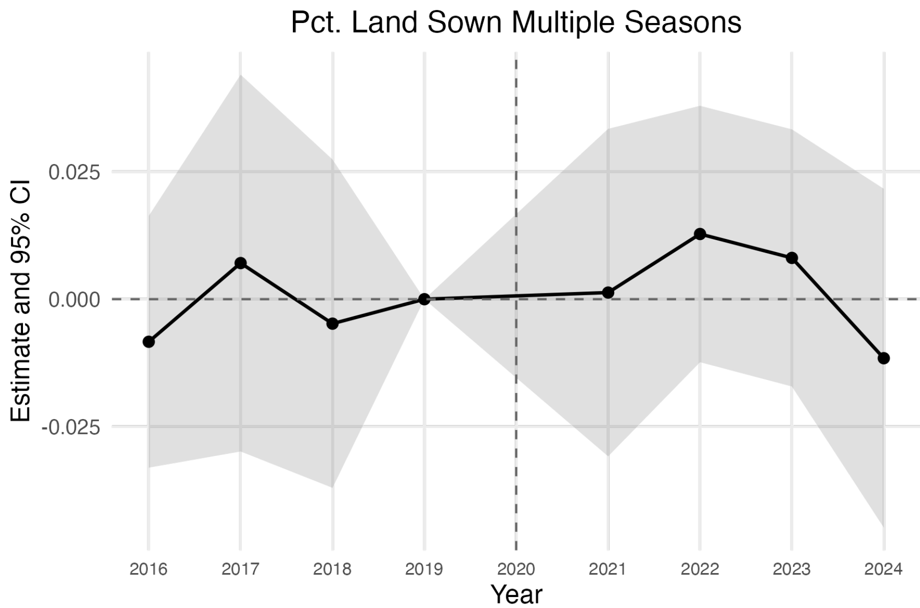


Figure 18: Triple Difference Coefficient, Percentage of Multi-Cultivated Land

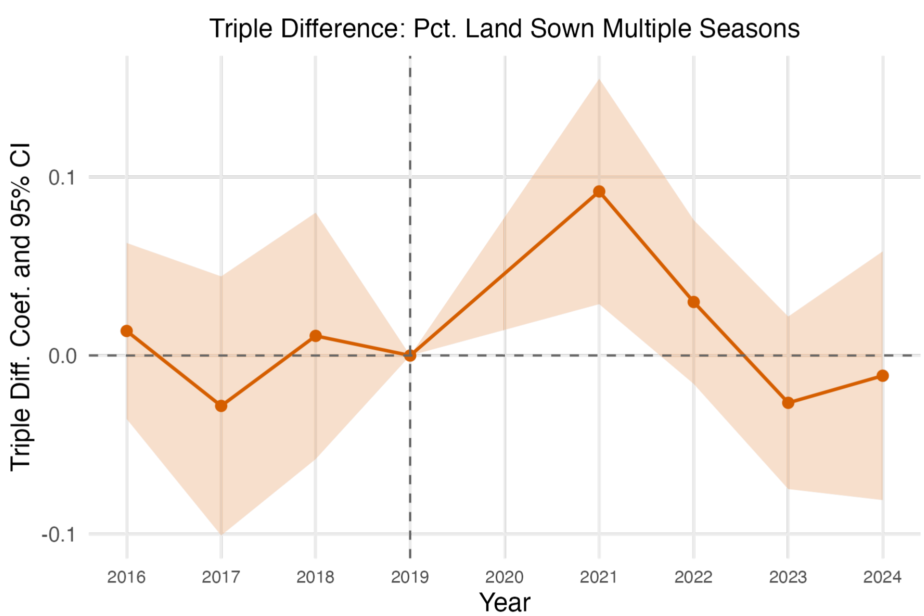


Figure 19: Extraction by Rainfall Bin, Pre-Treatment

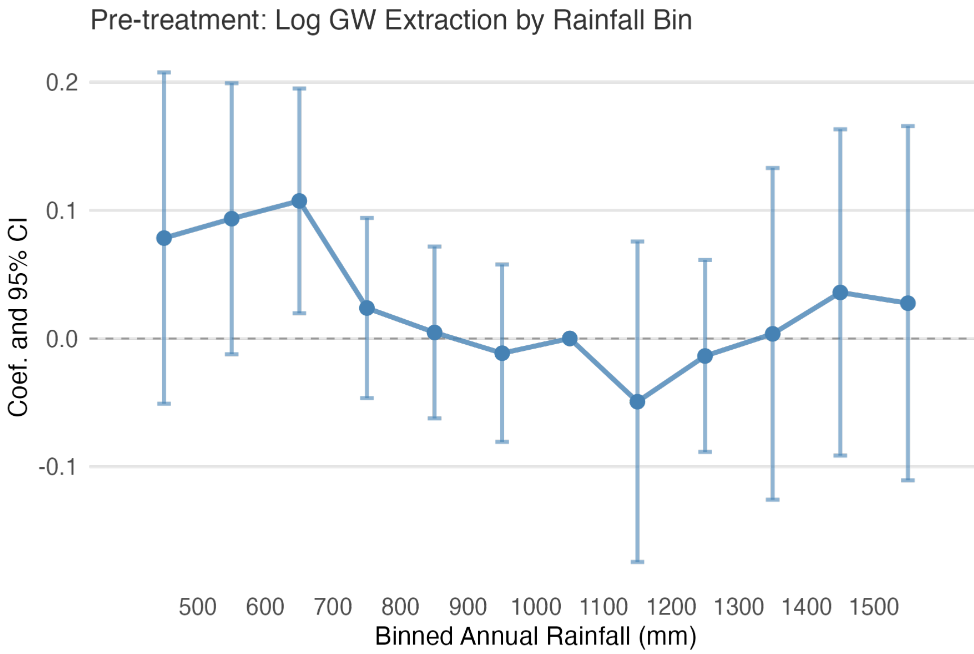


Figure 20: Impacts of ABY on Climate Smoothing (500mm)

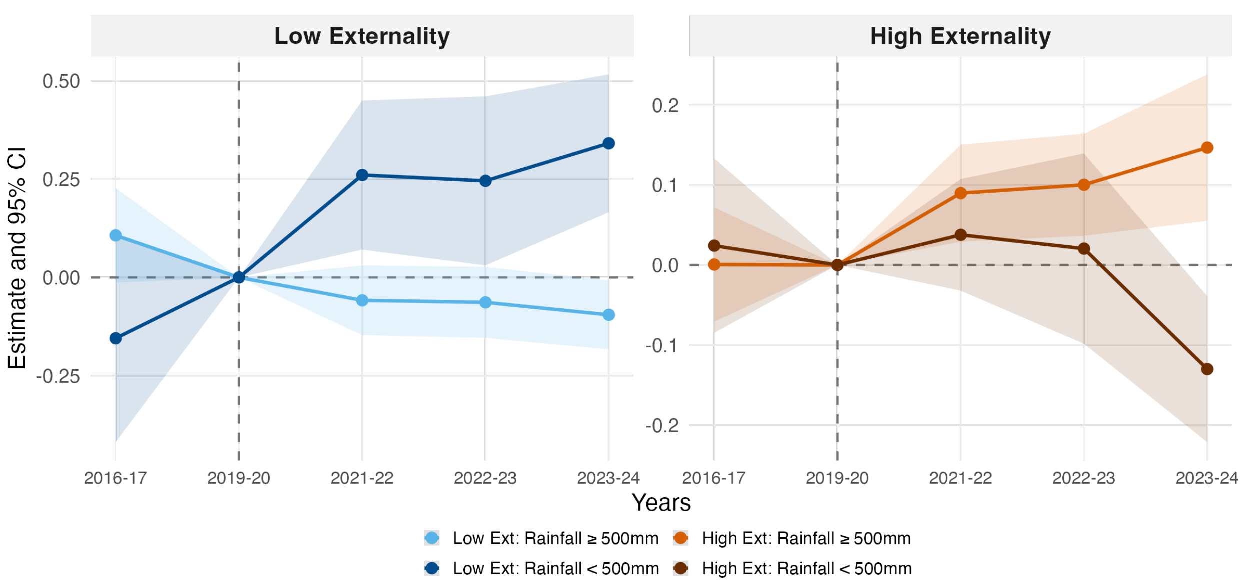
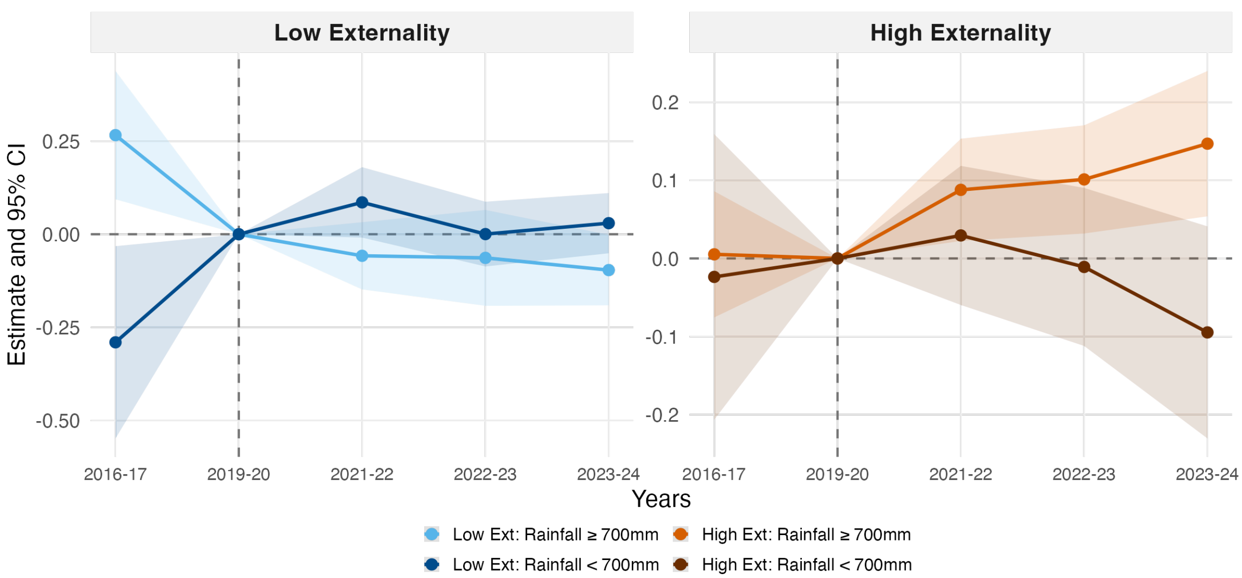


Figure 21: Impacts of ABY on Climate Smoothing (700mm)



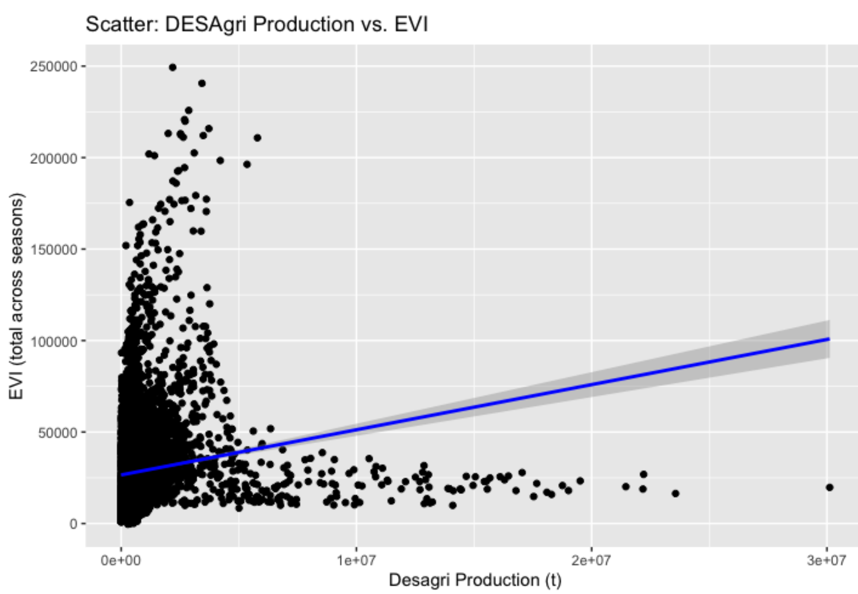
C Vegetation and Evapotranspiration

C.1 Vegetation

Ground-truth data on agricultural output at the subdistrict level are not publicly available in India for our sample period. We therefore use satellite-based vegetation indices from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS). Specifically, we employ the Enhanced Vegetation Index (EVI), which measures vegetation greenness based on reflected light in visible and near-infrared wavelengths. Following Asher and Novosad (2020), we construct a proxy for agricultural yield by subtracting mean EVI during the planting period from maximum EVI across the growing season. Intuitively, this procedure differences out non-agricultural vegetation. We refer to this measure as EVI delta.

To test where EVI delta reasonably approximates ground truth data, We aggregate the EVI delta to the district level and plot it against district-level crop production data from the Directorate of Economics and Statistics for Agriculture, We see in Figure 22 that, though the correlation is positive, the relationship appears weak. Given these validation concerns and previous research assessing the validity of vegetation indices as proxies for crop yields (Jin et al., 2018), we do not include EVI-based analyses in our main results.

Figure 22: EVI Validation vs. Ground Truth

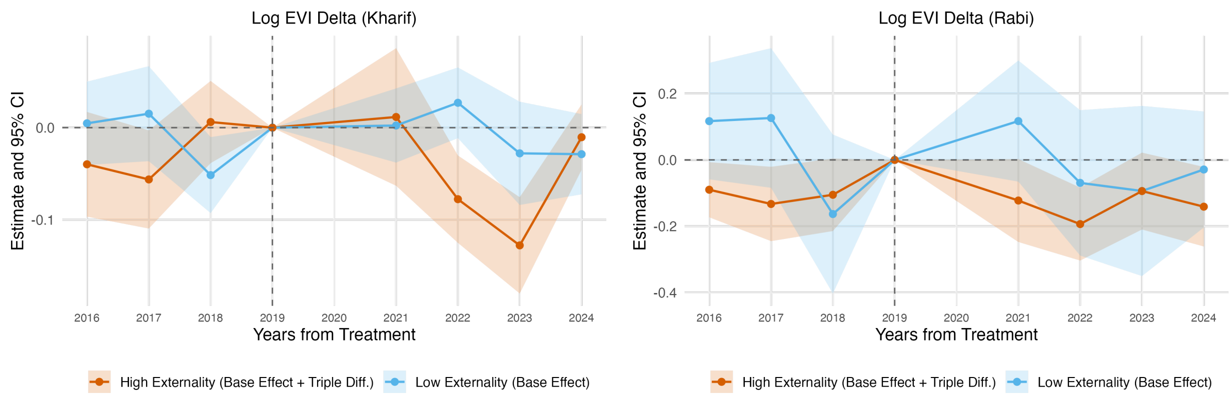


C.2 Evapotranspiration

In this section, we provide additional results on evapotranspiration (ET), measured as the sum of evaporation and transpiration, the water consumed by plants and evaporated through its leaves. We obtain ET estimates from NASA's MODIS at 500-meter resolution in 8-day composites. We aggregate the 8-day ET values to the subdistrict level.

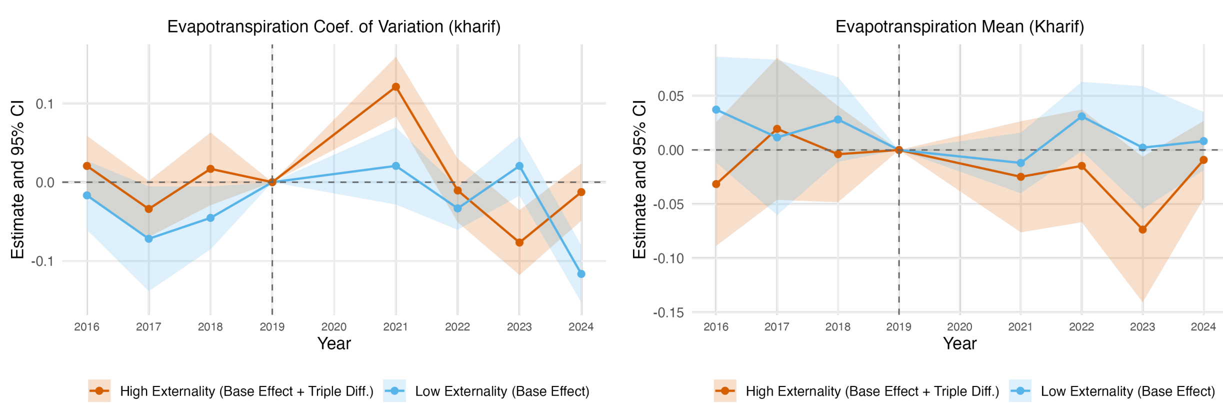
Because ET measures the total water consumption by plants, it is commonly used as a measure of plant health and agricultural water input. We measure two outcomes, the

Figure 23: EVI Delta, by Season



intra-season mean and the intra-season coefficient of variation of ET. The former informs whether plants consumed more water overall throughout the season, while the latter reveals whether that consumption was smooth. We focus on the Kharif (Monsoon) season because Kharif crops are typically rain-dependent. Thus, Kharif crops are more vulnerable to volatility in rainfall, and groundwater has a more salient purpose as a substitute for rainfall when it is insufficient. The event study graphs in Figure and 24 report coefficients using a nearly identical triple-differences to that in Section 5.2.2. The sole difference is that, to isolate the effect of irrigation input, we control for the intra-season mean and the intra-season coefficient of variation of rain. The residual variation in ET is then, arguably, the water input to crops that is not able to be explained by variation in rainfall, which is presumably from groundwater irrigation.

Figure 24: Evapotranspiration, Kharif



D Additional Tables

Table 2: Groundwater as Buffer Stock

Dep. Var: Log(Extraction)	(1) Low Rain	(2) Low Rain	(3) Low Rain × High Volatility	(4) Low Rain × High Volatility
Low Rain	0.030***	0.114***	-0.028**	0.004
	(0.011)	(0.028)	(0.013)	(0.027)
Low Rain × High Volatility			0.089***	0.207***
			(0.018)	(0.049)
Sample	Control	Full Sample	Control	Full Sample
Years	All	Pre-ABY	All	Pre-ABY
N	3,392	1,505	3,392	1,505

OLS regressions with Log(Extraction) as dependent variable. `Low Rain = 1` if annual rainfall is less than 750mm. Columns vary independent variable and sample. All specifications include subdistrict and year fixed effects. Standard errors clustered at the subdistrict level. Units are entropy balanced for consistency with main regression results.

Table 3: Comparison of High- vs Low-Externality Subdistricts (Analysis Sample)

	High Externality		Low Externality		
Variable	Mean	SD	Mean	SD	Diff
A. Geographic and Physical Characteristics					
Elevation (mean, meters)	193.3	(105.2)	371.2	(165.5)	−177.9
Elevation (std dev)	14.88	(26.21)	48.87	(44.83)	−33.99
Terrain Ruggedness Index (mean)	4.06	(1.39)	5.65	(2.92)	−1.60
Terrain Ruggedness Index (std dev)	2.41	(1.73)	4.79	(3.16)	−2.38
Annual Total Precipitation (mm)	975.8	(334.1)	969.4	(557.7)	6.4
Intra-annual SD of Rainfall (mm)	213.4	(72.1)	192.5	(75.0)	20.9
Average Groundwater Depth (meters)	10.82	(4.37)	14.92	(6.46)	−4.10
B. Agricultural Structure and Intensity					
Share of Sown Area Irrigated	0.975	(0.321)	0.808	(3.839)	0.167
Share of Irrigated Area with Drip/Sprinkler	0.140	(0.142)	0.227	(0.159)	−0.086
Share of Cultivable Area Sown	0.647	(0.135)	0.626	(0.170)	0.021
Share of Sown Area in Kharif Season	0.913	(0.101)	0.897	(0.202)	0.016
Share of Sown Area in Rabi Season	0.814	(0.157)	0.622	(0.238)	0.191
Share of Sown Area in Other Seasons	0.206	(0.119)	0.238	(0.208)	−0.032
C. Irrigation Sources					
Share Irrigated by Canal	0.128	(0.189)	0.092	(0.148)	0.035
Share Irrigated by Groundwater	0.755	(0.215)	0.725	(0.230)	0.030
Share Irrigated by Surface Water	0.036	(0.066)	0.055	(0.087)	−0.019
Share Irrigated by Other Sources	0.081	(0.097)	0.127	(0.160)	−0.046
D. Infrastructure and Services					
Share of Households with Piped Water	0.278	(0.264)	0.261	(0.190)	0.017
Has Internal Paved Road	0.494	(0.224)	0.497	(0.182)	−0.003
Connected to All-Weather Road	0.859	(0.113)	0.812	(0.136)	0.047
Has Panchayat Building	0.657	(0.199)	0.675	(0.185)	−0.018
Broadband Available	0.481	(0.235)	0.498	(0.240)	−0.017
Bank Available	0.292	(0.158)	0.301	(0.205)	−0.009
ATM Available	0.181	(0.141)	0.223	(0.187)	−0.042
E. Agricultural and Environmental Support Services					
Fertilizer Shop Available	0.270	(0.181)	0.335	(0.210)	−0.066
Soil Testing Center Available	0.057	(0.099)	0.070	(0.085)	−0.013
Government Seed Center Available	0.162	(0.137)	0.225	(0.147)	−0.063
Livestock Extension Services Available	0.305	(0.227)	0.453	(0.230)	−0.148
Rainwater Harvesting System Available	0.526	(0.243)	0.575	(0.212)	−0.049
Watershed Development Program Available	0.180	(0.192)	0.301	(0.194)	−0.121
F. Land and Demographics					
Total Households	66,946	(42,673)	51,670	(23,690)	15,276
Households in Farm Activities	37,675	(26,795)	29,247	(13,584)	8,428
Share of Households in Farm Activities	0.552	(0.144)	0.576	(0.143)	−0.024
Share of Households in Non-Farm Activities	0.251	(0.097)	0.204	(0.100)	0.047
Land Area (sq. km)	584.4	(357.4)	1,036.3	(1,308.1)	−451.9
Net Sown Area (hectares)	35,463	(26,130)	43,869	(37,464)	−8,406
Total Cultivable Area (hectares)	53,516	(33,682)	73,286	(65,065)	−19,770

Notes: This table compares pre-treatment characteristics between subdistricts with high and low externality scores in the analysis sample (Stage of Groundwater Extraction $\geq 70\%$). Means and standard deviations (in parentheses) are shown for each group.

Table 4: Comparison of High- vs Low-Externality Subdistricts (Full Sample)

	High Externality		Low Externality		
Variable	Mean	SD	Mean	SD	Diff
A. Geographic and Physical Characteristics					
Elevation (mean, meters)	153.1	(227.3)	499.2	(559.7)	−346.1
Elevation (std dev)	31.36	(71.37)	97.08	(153.66)	−65.72
Terrain Ruggedness Index (mean)	5.17	(4.76)	9.28	(9.40)	−4.11
Terrain Ruggedness Index (std dev)	3.52	(3.68)	6.75	(5.23)	−3.23
Annual Total Precipitation (mm)	1,356.3	(561.6)	1,190.1	(607.3)	166.2
Intra-annual SD of Rainfall (mm)	213.4	(72.1)	192.5	(75.0)	20.9
Average Groundwater Depth (meters)	7.97	(3.38)	11.05	(4.22)	−3.08
B. Agricultural Structure and Intensity					
Share of Sown Area Irrigated	0.788	(0.386)	1.328	(38.742)	−0.540
Share of Irrigated Area with Drip/Sprinkler	0.162	(0.147)	0.219	(0.172)	−0.057
Share of Cultivable Area Sown	0.607	(0.156)	0.596	(0.166)	0.011
Share of Sown Area in Kharif Season	0.896	(0.133)	0.897	(0.173)	−0.001
Share of Sown Area in Rabi Season	0.667	(0.230)	0.535	(0.229)	0.132
Share of Sown Area in Other Seasons	0.240	(0.151)	0.237	(0.187)	0.003
C. Irrigation Sources					
Share Irrigated by Canal	0.229	(0.281)	0.147	(0.212)	0.083
Share Irrigated by Groundwater	0.517	(0.317)	0.533	(0.319)	−0.016
Share Irrigated by Surface Water	0.091	(0.136)	0.112	(0.152)	−0.020
Share Irrigated by Other Sources	0.163	(0.181)	0.208	(0.219)	−0.046
D. Infrastructure and Services					
Share of Households with Piped Water	0.252	(0.238)	0.354	(0.272)	−0.102
Has Internal Paved Road	0.513	(0.233)	0.520	(0.223)	−0.006
Connected to All-Weather Road	0.789	(0.178)	0.783	(0.191)	0.006
Has Panchayat Building	0.575	(0.263)	0.685	(0.242)	−0.110
Broadband Available	0.476	(0.262)	0.488	(0.270)	−0.012
Bank Available	0.276	(0.174)	0.266	(0.206)	0.010
ATM Available	0.183	(0.159)	0.191	(0.196)	−0.007
E. Agricultural and Environmental Support Services					
Fertilizer Shop Available	0.296	(0.226)	0.301	(0.245)	−0.004
Soil Testing Center Available	0.057	(0.105)	0.074	(0.132)	−0.017
Government Seed Center Available	0.147	(0.161)	0.197	(0.196)	−0.049
Livestock Extension Services Available	0.303	(0.248)	0.437	(0.272)	−0.134
Rainwater Harvesting System Available	0.421	(0.266)	0.530	(0.253)	−0.109
Watershed Development Program Available	0.171	(0.185)	0.263	(0.212)	−0.093
F. Land and Demographics					
Total Households	45,427	(36,468)	31,481	(24,151)	13,946
Households in Farm Activities	24,022	(22,895)	17,408	(12,446)	6,614
Share of Households in Farm Activities	0.526	(0.157)	0.592	(0.162)	−0.066
Share of Households in Non-Farm Activities	0.232	(0.098)	0.200	(0.101)	0.032
Land Area (sq. km)	347.5	(308.2)	557.4	(688.4)	−209.9
Net Sown Area (hectares)	18,499	(19,396)	22,106	(24,472)	−3,608
Total Cultivable Area (hectares)	30,004	(27,894)	37,378	(40,735)	−7,374

Notes: This table compares pre-treatment characteristics between subdistricts with high and low externality scores in the full sample (all levels of groundwater development). Means and standard deviations (in parentheses) are shown for each group.

E Entropy Balancing

We select the following variables from the 2020 Mission Antyodaya survey on village facilities (items 1-3), aquifer data from the WRIS (item 4), and remote sensing data (item 5). All are measured prior to treatment.

1. Existence of Village Council Office (*Panchayat Bhawan*)
2. Existence of a Watershed Development Program
3. Area Under Efficient Irrigation
4. Average Aquifer Depth
5. Evapotranspiration, Seasonal Means and Standard Deviations

Items 1-3 concern mechanical parts of ABY implementation, while items 4 and 5 concern farmers' experience of groundwater stress. In order to receive funding, each village council (*gram panchayat*) needed to construct a budget in consultation with surrounding villages. This required a physical office in which to do so, justifying item 1. Items 2 and 3 arise from how ABY is implemented – by funding existing programs. Watershed development programs describe a general class of government schemes targeting sustainable use and conservation of water, including groundwater[20], precisely the programs that ABY funds. A similar logic holds for the area under efficient irrigation methods – these technologies are predominantly adopted with the help of government programs[21], and thus ABY often funds micro-irrigation through these schemes. Finally, though program documents do not directly state what constitutes the experience of groundwater stress, we intuit that two main factors may contribute. First aquifer depth, the distance below ground level of the aquifer itself, not its thickness, may contribute the experience of groundwater being more difficult to access and thus may lead to distress over its availability. Second, evapotranspiration measure the sum of transpiration – water consumed by plants and evaporated through its leaves – and evaporation. Commonly used as an indicator of plant health, low means of evapotranspiration can indicate insufficient water input. The standard deviation of evapotranspiration may indicate lumpy water input, which may occur if, for example, farmers are not able to smooth over intra-season variability of rain using groundwater.

Using these variables we generate both entropy balancing weights (Hainmueller, 2012) and inverse propensity score weights. We report the diagnostics of these weights in Table 5. In our main specifications, we prefer entropy balancing weights due to superior balance and larger region of common support between the weights of the treated and control groups, however our results are qualitatively similar using inverse propensity score weights. Figure 25, reports the imbalance between control and treated groups in the covariates before and after entropy weighting.

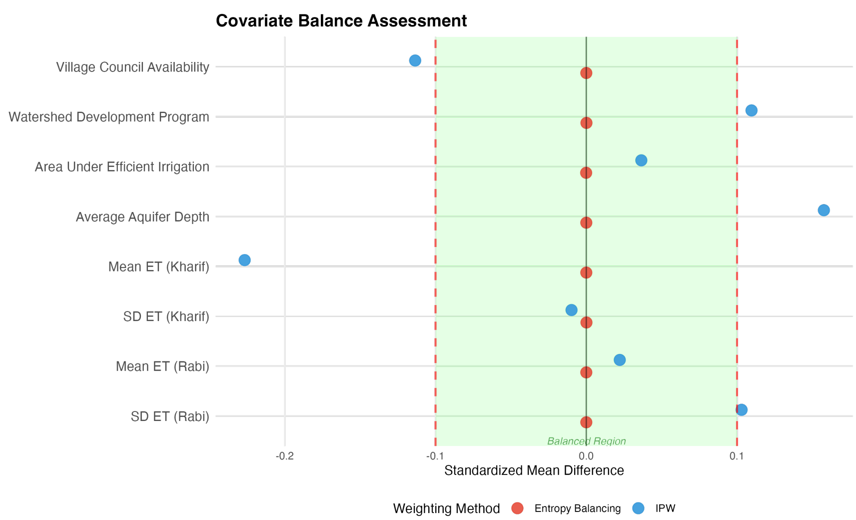
[20] In practice, these programs can also target surface water sources and canals. In our trimmed sample, less than 5% of villages use surface water for irrigation and less than 12% have canals.

[21] India's flagship micro-irrigation program is Pradhan Mantri Krishi Sinchai Yojana (PMKSY), which ABY targets. Our data do not allow us to measure the PMKSY treatment directly.

Table 5: Diagnostics: Entropy Balancing vs. Inverse Propensity Score Weights

	Entropy Balancing	**IPW**
Effective Sample Size	564.4 (68.9%)	641.9 (80.5%)
Maximum Weight	17.4	10.6
Common Support	795 (97.1%)	723 (90.6%)
Covariate Joint AUC	0.776	

Figure 25: Covariates Before and After Entropy Balancing



Model Appendix

For completeness, we restate the setup of the model and provide more formal derivations of our propositions and comparative statics below.

F Model Setup

We consider a continuum of farmers indexed by $i \in [0, 1]$. The model has two periods. We assume model parameters ensure interior solutions throughout.

Each farmer chooses a groundwater extraction rate $x_i(t) \geq 0$. Aggregate extraction is $X(t) = \int_0^1 x_i(t)di$. Each farmer begins with an initial depth to water $d_i(1) = D(1)$.

F.1 Moisture Index and Rainfall

Total moisture reaching crops is:

$$z_i(t) = \lambda x_i(t) + \rho R(t)$$

Rainfall $R(t)$ is stochastic. For period 2, we consider a binary distribution for simplicity:

$$R(2) = \begin{cases} R_H & \text{with probability } p \\ R_L & \text{with probability } 1 - p \end{cases}$$

Period 1 rain R_1 is known when $x_i(1)$ is chosen. The parameter $\lambda > 0$ is irrigation efficiency – scaling how effectively a unit of groundwater turns into agricultural yield – and $\rho \in (0, 1]$ is the utilization rate of rainfall – the share of rainfall that turns into effective soil moisture to feed crops.

F.2 Production, Costs, and Preferences

Yield is concave in soil moisture:

$$y_i(t) = \log(z_i(t))$$

The cost of extraction is linear in depth:

$$\psi(x_i(t), d_i(t)) = x_i(t) \cdot d_i(t)$$

Consumption is output net of extraction cost:

$$c_i(t) = \log(\lambda x_i(t) + \rho R(t)) - x_i(t) \cdot d_i(t)$$

Utility is CRRA with coefficient $\gamma > 0$:

$$u(c) = \frac{c^{1-\gamma} - 1}{1 - \gamma}$$

F.3 Extraction Cost Externality

The change in depth to water for farmer i is:

$$d_i(t) - d_i(t-1) = (1-\theta)x_i(t) + \theta X(t) - (1-\rho)R(t)$$

The parameter $\theta \in [0,1]$ governs the extent of the externality. In a symmetric equilibrium $(x_i(t) = X(t), d_i(t) = D(t) \forall i)$, the aggregate law of motion is:

$$D(t) - D(t-1) = X(t) - (1-\rho)R(t)$$

F.4 Parameter Restrictions

We maintain the following assumptions throughout to ensure interior solutions and well-defined optimization problems:

- **A1 (Interior Solutions):** Parameters ensure positive extraction and consumption, requiring that the marginal product of water exceeds its marginal cost at low extraction levels.
- **A2 (Well-defined Utility):** Consumption remains positive: $c_i(t) = \log(z_i(t)) - x_i(t)d_i(t) > 0$ for optimal choices. This ensures CRRA utility $u(c)$ is well-defined over the domain of optimal consumption levels.
- **A3 (Concave Optimization):** The production function $\log(\lambda x + \rho R)$ is strictly concave in x. This curvature dominates the linear cost function, ensuring strictly concave objective functions and unique interior solutions to all optimization problems.
- **A4 (Positive Extraction in Period 2):** For all rain realizations, $\frac{1}{D(2)} > \frac{\rho R}{\lambda}$, ensuring $X(2; R) > 0$. This assumption rules out corner solutions in period 2; relaxing it would require analyzing boundary conditions for the optimization problem, which would not qualitatively change our main results.

G Social Planner's Problem

The planner chooses extraction $\{X(1), X(2; R)\}$ to maximize total discounted expected utility:

$$\max_{X(1), X(2;\cdot)} W = u(C(1)) + \beta \mathbb{E}_R[u(C(2; R))]$$

subject to the resource constraints, the law of motion of the depth to water, and aggregate consumption:

$$\begin{aligned}
C(1) &= \log(\lambda X(1) + \rho R_1) - X(1)D(1) \\
C(2; R) &= \log(\lambda X(2; R) + \rho R) - X(2; R)D(2) \\
D(2) &= D(1) + X(1) - (1-\rho)R_1
\end{aligned}$$

G.1 Planner's First-Order Conditions

G.1.1 Period 2 FOC

For any rain realization R, the planner chooses $X(2;R)$ taking $D(2)$ as given. The FOC is:

$$\begin{aligned}
\frac{\partial W}{\partial X(2;R)} &= 0 \\
\beta u'(C(2;R)) \cdot \frac{\partial C(2;R)}{\partial X(2;R)} &= 0 \\
\frac{\partial C(2;R)}{\partial X(2;R)} &= \frac{\lambda}{\lambda X(2;R) + \rho R} - D(2) = 0
\end{aligned}$$

This yields the optimal period-2 extraction rule:

$$\boxed{\frac{\lambda}{z_{SP}(2;R)} - D(2) = 0} \quad \Rightarrow \quad X^*_{SP}(2;R) = \frac{1}{D(2)} - \frac{\rho R}{\lambda} \tag{SP.FOC2}$$

G.1.2 Period 1 Euler Equation

The planner chooses $X(1)$, internalizing its effect on $D(2)$:

$$\begin{aligned}
\frac{\partial W}{\partial X(1)} &= 0 \\
u'(C(1))\frac{\partial C(1)}{\partial X(1)} + \beta \mathbb{E}_R\left[u'(C(2;R))\frac{\partial C(2;R)}{\partial D(2)}\frac{\partial D(2)}{\partial X(1)}\right] &= 0
\end{aligned}$$

Computing each term:

$$\begin{aligned}
\frac{\partial C(1)}{\partial X(1)} &= \frac{\lambda}{z(1)} - D(1) \\
\frac{\partial C(2;R)}{\partial D(2)} &= -X(2;R) \\
\frac{\partial D(2)}{\partial X(1)} &= 1
\end{aligned}$$

Substituting and using (SP.FOC2) yields the Euler equation:

$$\boxed{\frac{\lambda}{z_{SP}(1)} - D(1) = \beta \mathbb{E}_R\left[\frac{u'(C_{SP}(2;R))}{u'(C_{SP}(1))} \cdot X_{SP}(2;R)\right]} \tag{SP.Euler}$$

H Decentralized Equilibrium (DE)

Each farmer i chooses $\{x_i(1), x_i(2; R)\}$ to maximize own utility, taking aggregate extraction $X(t)$ and the depth evolution as given:

$$\max_{x_i(1), x_i(2;\cdot)} u(c_i(1)) + \beta \mathbb{E}_R[u(c_i(2; R))]$$

subject to:

$$\begin{aligned} d_i(2) &= d_i(1) + (1-\theta)x_i(1) + \theta X(1) - (1-\rho)R_1 \\ c_i(1) &= \log(\lambda x_i(1) + \rho R_1) - x_i(1) d_i(1) \\ c_i(2; R) &= \log(\lambda x_i(2; R) + \rho R) - x_i(2; R) d_i(2) \end{aligned}$$

We focus on a symmetric equilibrium: $x_i(t) = X(t), d_i(t) = D(t)$.

H.1 Decentralized First-Order Conditions

H.1.1 Period 2 FOC

The farmer's problem in period 2 is static. The FOC is identical to the planner's:

$$\boxed{\frac{\lambda}{z_{DE}(2; R)} - D(2) = 0} \quad \Rightarrow \quad X^*_{DE}(2; R) = \frac{1}{D(2)} - \frac{\rho R}{\lambda} \tag{DE.FOC2}$$

H.1.2 Period 1 Euler Equation

The key difference emerges in period 1. The farmer's FOC is:

$$\begin{aligned} \frac{\partial}{\partial x_i(1)}[u(c_i(1)) + \beta E[u(c_i(2))]] &= 0 \\ u'(c_i(1)) \frac{\partial c_i(1)}{\partial x_i(1)} + \beta \mathbb{E}_R \left[u'(c_i(2; R)) \frac{\partial c_i(2; R)}{\partial d_i(2)} \frac{\partial d_i(2)}{\partial x_i(1)} \right] &= 0 \end{aligned}$$

Computing the terms, noting the different effect on $d_i(2)$:

$$\begin{aligned} \frac{\partial c_i(1)}{\partial x_i(1)} &= \frac{\lambda}{z_i(1)} - d_i(1) \\ \frac{\partial c_i(2; R)}{\partial d_i(2)} &= -x_i(2; R) \\ \frac{\partial d_i(2)}{\partial x_i(1)} &= (1-\theta) \end{aligned}$$

Imposing symmetry and using (DE.FOC2) yields the decentralized Euler equation:

$$\boxed{\frac{\lambda}{z_{DE}(1)} - D(1) = \beta(1-\theta)\mathbb{E}_R\left[\frac{u'(C_{DE}(2;R))}{u'(C_{DE}(1))} \cdot X_{DE}(2;R)\right]} \tag{DE.Euler}$$

The only difference from (SP.Euler) is the multiplicative factor $(1-\theta)$ on the right-hand side.

I Propositions

I.1 Proposition 1: The Externality Wedge

For any $\theta > 0$, decentralized first-period extraction is greater than the social planner's first period extraction: $X^*_{DE}(1) > X^*_{SP}(1)$.

Proof. Define the function $F(X(1)) \equiv \frac{\lambda}{\lambda X(1)+\rho R_1} - D(1)$, which is the net marginal benefit of period-1 extraction. Its derivative is:

$$\frac{dF}{dX(1)} = -\frac{\lambda^2}{(\lambda X(1) + \rho R_1)^2} < 0$$

so F is strictly decreasing in $X(1)$.

The Euler equations define the optimal extraction levels:

$$\begin{aligned} \text{SP:} \quad F(X^*_{SP}(1)) &= \beta\mathbb{E}_R\left[\frac{u'(C_{SP}(2))}{u'(C_{SP}(1))}X_{SP}(2)\right] \equiv \Gamma_{SP} \\ \text{DE:} \quad F(X^*_{DE}(1)) &= \beta(1-\theta)\mathbb{E}_R\left[\frac{u'(C_{DE}(2))}{u'(C_{DE}(1))}X_{DE}(2)\right] \equiv \Gamma_{DE} \end{aligned}$$

We now show that $\Gamma_{SP}, \Gamma_{DE} > 0$. By Assumption A1, interior solutions exist, meaning extraction is strictly positive in all periods. By (SP.FOC2) and (DE.FOC2), $X(2;R) > 0$ by Assumption A4. The marginal utility ratio $\frac{u'(C(2))}{u'(C(1))}$ is strictly positive since $u'(c) = c^{-\gamma} > 0$ for all $c > 0$ (guaranteed by Assumption A2). Therefore, $\Gamma_{SP}, \Gamma_{DE} > 0$.

For $\theta > 0$, we have $(1-\theta) < 1$, which implies:

$$\Gamma_{DE} = (1-\theta) \cdot \beta\mathbb{E}_R\left[\frac{u'(C_{DE}(2))}{u'(C_{DE}(1))}X_{DE}(2)\right] < \beta\mathbb{E}_R\left[\frac{u'(C_{SP}(2))}{u'(C_{SP}(1))}X_{SP}(2)\right] = \Gamma_{SP}$$

Therefore, in equilibrium:

$$F(X^*_{DE}(1)) = \Gamma_{DE} < \Gamma_{SP} = F(X^*_{SP}(1))$$

Since F is strictly decreasing, this implies:

$$X^*_{DE}(1) > X^*_{SP}(1)$$

which completes the proof. ■ □

I.2 Proposition 2: Ambiguous Effect of Technology

The sign of the change in the social planner's optimal first-period extraction in response to an increase in irrigation efficiency is ambiguous: $\frac{dX^*_{SP}(1)}{d\lambda} \gtrless 0$.

Proof. We analyze the planner's system of equations. The optimal choice $X^*_{SP}(1)$ is defined implicitly by the Euler equation (SP.Euler). Define the function G such that the equilibrium condition is $G(X(1), \lambda) = 0$:

$$G(X(1), \lambda) \equiv \underbrace{\left(\frac{\lambda}{z(1)} - D(1)\right)}_{F(X(1),\lambda)} - \beta \mathbb{E}_R \left[\frac{u'(C(2;R))}{u'(C(1))} \cdot X(2;R)\right] = 0$$

By the Implicit Function Theorem:

$$\frac{dX(1)}{d\lambda} = -\frac{\frac{\partial G}{\partial \lambda}}{\frac{\partial G}{\partial X(1)}}$$

The denominator, $\frac{\partial G}{\partial X(1)}$, is the second-order condition of the maximization problem. By Assumption A3, the objective is strictly concave, so $\frac{\partial G}{\partial X(1)} < 0$ at an interior maximum. Thus, the sign of $\frac{dX(1)}{d\lambda}$ is the sign of the numerator, $\frac{\partial G}{\partial \lambda}$.

We compute $\frac{\partial G}{\partial \lambda}$:

$$\frac{\partial G}{\partial \lambda} = \frac{\partial F}{\partial \lambda} - \beta \mathbb{E}_R \left[\frac{\partial}{\partial \lambda}\left(\frac{u'(C(2))}{u'(C(1))} \cdot X(2)\right)\right]$$

The first term is the direct marginal benefit effect. Using the quotient rule:

$$\frac{\partial F}{\partial \lambda} = \frac{\partial}{\partial \lambda}\left(\frac{\lambda}{\lambda X(1) + \rho R_1}\right) = \frac{(\lambda X(1) + \rho R_1) - \lambda X(1)}{(\lambda X(1) + \rho R_1)^2} = \frac{\rho R_1}{(\lambda X(1) + \rho R_1)^2} = \frac{\rho R_1}{(z(1))^2} > 0$$

This effect encourages *more* extraction (a positive force on $\frac{dX(1)}{d\lambda}$).

The second term is complex and captures how the future marginal value changes with technology. From (SP.FOC2), we have:

$$\frac{\partial X(2;R)}{\partial \lambda} = \frac{\rho R}{\lambda^2} > 0$$

Higher λ increases optimal period-2 extraction. This increases future consumption $C(2;R)$, which affects marginal utilities through the CRRA specification. The term involves:

$$\frac{\partial}{\partial \lambda}\left(\frac{u'(C(2))}{u'(C(1))} \cdot X(2)\right) = \frac{\partial}{\partial \lambda}\left(\left(\frac{C(2)}{C(1)}\right)^{-\gamma} \cdot X(2)\right)$$

This term includes:

- **Income Effect:** Higher λ increases consumption in both periods through higher production from each unit of water, affecting marginal utilities.

- **Future Extraction Effect:** Higher λ directly increases $X(2;R)$, which increases period-2 consumption but also period-2 costs (through higher $X(2) \cdot D(2)$).

- **Intertemporal Substitution Effect:** Changes in the marginal utility ratio $\frac{u'(C(2))}{u'(C(1))}$ depend on how λ affects consumption levels asymmetrically across periods.

The sign of this second term depends on parameter values, particularly:

- Risk aversion γ: Higher γ amplifies the effect of consumption changes on marginal utility ratios.

- Discount factor β: Higher β increases the weight on future values.

- Initial depth $D(1)$: Higher initial depth makes period-1 extraction more costly relative to the marginal product gain from higher λ.

- Rainfall distribution: Greater rainfall reduces the relative importance of irrigation efficiency improvements.

Since the second term can be positive or negative depending on these parameters, and it is subtracted in the expression for $\frac{\partial G}{\partial \lambda}$, the net effect $\frac{\partial G}{\partial \lambda}$ is ambiguous. Therefore:

$$\frac{dX^*_{SP}(1)}{d\lambda} \gtrless 0$$

Empirical Note: Our results from low-externality areas suggest the precautionary savings effect dominates in our setting, resulting in $\frac{dX^*_{SP}(1)}{d\lambda} < 0$. ■ □

I.2.1 Sufficient Conditions for Conservation Response

While Proposition 2 establishes that the effect of technology on socially-optimal extraction is ambiguous, we can characterize conditions under which technology improvements lead to conservation (i.e., $\frac{dX^*_{SP}(1)}{d\lambda} < 0$). The following lemma provides sufficient conditions:

Lemma 1 (Sufficient Conditions for $\frac{dX^*_{SP}(1)}{d\lambda} < 0$)**.** *The social planner reduces period-1 extraction in response to improved irrigation efficiency if any of the following sufficient conditions hold:*

1. ***High Risk Aversion:*** *γ is sufficiently large*

2. ***High Initial Depth:*** *$D(1)$ is sufficiently large relative to λ*

3. ***High Rainfall Variance:*** *$Var(R(2))$ is sufficiently large*

4. ***Strong Patience:*** *β is sufficiently close to 1*

Proof. Recall from Proposition 2 that:

$$\frac{\partial G}{\partial \lambda} = \underbrace{\frac{\rho R_1}{(z(1))^2}}_{>0} - \beta \mathbb{E}_R \left[\frac{\partial}{\partial \lambda} \left(\left(\frac{C(2)}{C(1)} \right)^{-\gamma} X(2) \right) \right]$$

and $\frac{dX^*_{SP}(1)}{d\lambda} < 0$ if and only if $\frac{\partial G}{\partial \lambda} < 0$, which requires the second term to dominate the first.

We analyze the second term. Define:

$$\Phi(\lambda) \equiv \mathbb{E}_R \left[\left(\frac{C(2;R)}{C(1)} \right)^{-\gamma} X(2;R) \right]$$

Then:

$$\frac{\partial \Phi}{\partial \lambda} = \mathbb{E}_R \left[\frac{\partial}{\partial \lambda} \left(\left(\frac{C(2;R)}{C(1)} \right)^{-\gamma} X(2;R) \right) \right]$$

Using the product rule:

$$\begin{aligned} \frac{\partial}{\partial \lambda} \left[\left(\frac{C(2)}{C(1)} \right)^{-\gamma} X(2) \right] &= -\gamma \left(\frac{C(2)}{C(1)} \right)^{-\gamma-1} \frac{\partial}{\partial \lambda} \left(\frac{C(2)}{C(1)} \right) X(2) \\ &\quad + \left(\frac{C(2)}{C(1)} \right)^{-\gamma} \frac{\partial X(2)}{\partial \lambda} \end{aligned}$$

From (SP.FOC2), $X(2;R) = \frac{1}{D(2)} - \frac{\rho R}{\lambda}$, so:

$$\frac{\partial X(2;R)}{\partial \lambda} = \frac{\rho R}{\lambda^2} > 0$$

For consumption, we have:

$$\begin{aligned} C(2;R) &= \log(\lambda X(2;R) + \rho R) - X(2;R)D(2) \\ &= \log\left(\frac{\lambda}{D(2)} \right) - 1 + \frac{\rho R D(2)}{\lambda} \end{aligned}$$

Therefore:

$$\frac{\partial C(2;R)}{\partial \lambda} = \frac{1}{\lambda} - \frac{\rho R D(2)}{\lambda^2}$$

And:

$$\frac{\partial C(1)}{\partial \lambda} = \frac{X(1)}{z(1)}$$

The sign of $\frac{\partial \Phi}{\partial \lambda}$ depends on the balance between:

- The direct effect: $\left(\frac{C(2)}{C(1)} \right)^{-\gamma} \frac{\partial X(2)}{\partial \lambda} > 0$ (more future extraction)
- The marginal utility ratio effect: $-\gamma \left(\frac{C(2)}{C(1)} \right)^{-\gamma-1} \frac{\partial}{\partial \lambda} \left(\frac{C(2)}{C(1)} \right) X(2)$ (depends on how λ

affects the consumption ratio)

Condition 1 (High γ): As $\gamma \to \infty$, the marginal utility ratio effect becomes arbitrarily large relative to the direct effect. High risk aversion amplifies the importance of consumption smoothing across states, making the planner more responsive to changes in future consumption variability induced by λ. For sufficiently large γ, the second term in $\frac{\partial G}{\partial \lambda}$ dominates, yielding $\frac{\partial G}{\partial \lambda} < 0$.

Condition 2 (High $D(1)$): When initial depth is large, the marginal cost of period-1 extraction $D(1)$ is high. This reduces the direct marginal benefit $\frac{\rho R_1}{(z(1))^2}$ (as $z(1)$ is smaller for a given λ when extraction is limited). Simultaneously, a high $D(1)$ increases the value of conservation for reducing future depth $D(2)$. For sufficiently large $D(1)$, the future value effect dominates.

Condition 3 (High Var$(R(2))$): Greater rainfall variance increases the precautionary value of groundwater as a buffer stock. When λ increases, it affects the distribution of $C(2; R)$ across states. With high variance, the planner places greater weight on insuring against bad states (low R). This amplifies the second term in $\frac{\partial G}{\partial \lambda}$, incentivizing conservation. For large enough variance, $\frac{\partial G}{\partial \lambda} < 0$.

Condition 4 (High β): As $\beta \to 1$, the planner weights future utility equally with present utility. This increases the magnitude of the entire second term $\beta \frac{\partial \Phi}{\partial \lambda}$ relative to the first term $\frac{\rho R_1}{(z(1))^2}$. For β sufficiently close to 1, the future considerations dominate, yielding $\frac{\partial G}{\partial \lambda} < 0$. ■ □

Interpretation: These conditions characterize settings where the planner's response to technology is dominated by the precautionary savings and intertemporal considerations rather than immediate production gains. In contexts with high climate risk, deep aquifers, risk-averse populations, or patient decision-makers, technological improvements may lead to *less* extraction as the enhanced productivity increases the option value of conservation.

I.3 Proposition 3: Technology Amplifies the Wedge

There exists a threshold $\theta^* \in (0, 1)$ such that for all $\theta > \theta^*$, the wedge between decentralized and efficient extraction increases with irrigation efficiency: $\frac{d\Delta}{d\lambda} > 0$.

Proof. Recall $\Delta(\lambda, \theta) \equiv X^*_{DE}(1; \theta) - X^*_{SP}(1)$. Define:

$$\Psi(\theta, \gamma, \beta, \text{Var}(R)) \equiv \frac{dX^*_{DE}(1)}{d\lambda} - \frac{dX^*_{SP}(1)}{d\lambda} = \frac{d\Delta}{d\lambda}$$

The threshold θ^* is implicitly defined by:

$$\Psi(\theta^*, \gamma, \beta, \text{Var}(R)) = 0$$

We analyze how $\Psi(\theta)$ varies with θ by examining $\frac{dX^*_{DE}(1)}{d\lambda}$ and $\frac{dX^*_{SP}(1)}{d\lambda}$.

We next consider behavior at the boundaries. Notice that at $\theta = 0$, there is no externality, so the decentralized and social planner problems coincide: $X^*_{DE}(1; \theta = 0) = X^*_{SP}(1)$.

Therefore:

$$\left.\frac{dX^*_{DE}(1)}{d\lambda}\right|_{\theta=0} = \frac{dX^*_{SP}(1)}{d\lambda} \quad \Rightarrow \quad \Psi(0) = 0$$

As $\theta \to 1$, the factor $(1-\theta) \to 0$ mutes the intertemporal term in the decentralized farmer's Euler equation. The farmer's first-order condition approaches:

$$F(X(1), \lambda) = \frac{\lambda}{\lambda X(1) + \rho R_1} - D(1) \approx 0$$

Taking the derivative with respect to λ using the Implicit Function Theorem yields:

$$\lim_{\theta \to 1} \frac{dX^*_{DE}(1)}{d\lambda} = -\frac{\frac{\partial F}{\partial \lambda}}{\frac{\partial F}{\partial X(1)}} = \frac{\rho R_1}{\lambda^2} > 0$$

Meanwhile, the planner's response $\frac{dX^*_{SP}(1)}{d\lambda}$ is finite and ambiguous in sign (Proposition 2). Under the sufficient conditions of Lemma 1 (high risk aversion, high initial depth, high rainfall variance, or strong patience), we have $\frac{dX^*_{SP}(1)}{d\lambda} < 0$. Therefore:

$$\lim_{\theta \to 1} \Psi(\theta) = \frac{\rho R_1}{\lambda^2} - \frac{dX^*_{SP}(1)}{d\lambda} > 0$$

We now show that $\frac{dX^*_{DE}(1)}{d\lambda}$ is strictly increasing in θ, which implies $\Psi(\theta)$ is strictly increasing in θ.

The decentralized equilibrium is defined by $H(X(1), \lambda, \theta) = 0$:

$$H(X(1), \lambda, \theta) \equiv F(X(1), \lambda) - \beta(1-\theta)\mathbb{E}_R\left[\frac{u'(C(2))}{u'(C(1))} \cdot X(2)\right] = 0$$

By the Implicit Function Theorem:

$$\frac{dX^*_{DE}(1)}{d\lambda} = -\frac{\frac{\partial H}{\partial \lambda}}{\frac{\partial H}{\partial X(1)}}$$

The denominator $\frac{\partial H}{\partial X(1)}$ is negative (second-order condition from Assumption A3), so the sign of $\frac{dX^*_{DE}(1)}{d\lambda}$ equals the sign of $\frac{\partial H}{\partial \lambda}$.

We compute the derivative of $\frac{\partial H}{\partial \lambda}$ with respect to θ:

$$\frac{\partial}{\partial \theta}\left(\frac{\partial H}{\partial \lambda}\right) = \beta \mathbb{E}_R\left[\frac{\partial}{\partial \lambda}\left(\frac{u'(C(2))}{u'(C(1))} \cdot X(2)\right)\right] > 0$$

This derivative is positive because higher irrigation efficiency increases the marginal value of future water. Therefore, $\frac{\partial H}{\partial \lambda}$ is strictly increasing in θ, which implies $\frac{dX^*_{DE}(1)}{d\lambda}$ is strictly increasing in θ. Since $\frac{dX^*_{SP}(1)}{d\lambda}$ is independent of θ, we conclude that $\Psi(\theta)$ is strictly increasing in θ.

We now show the existence of uniqueness of the threshold θ^*. We have established that:

- $\Psi(0) = 0$
- $\lim_{\theta \to 1} \Psi(\theta) > 0$ (under the sufficient conditions)
- $\Psi(\theta)$ is strictly increasing in θ

By the Intermediate Value Theorem and strict monotonicity, there exists a unique $\theta^* \in (0, 1)$ such that $\Psi(\theta^*) = 0$.

Furthermore, since $\Psi(\theta)$ is strictly increasing:

$$\frac{d\Delta}{d\lambda} = \Psi(\theta) > 0 \quad \text{for all } \theta > \theta^*$$

This completes the proof. ■ □

Note that, if the sufficient conditions of Lemma 1 do not hold and $\frac{dX^*_{SP}(1)}{d\lambda} \geq 0$, then the existence of an interior threshold depends on the relative magnitudes of the planner and decentralized responses. However, in the empirically relevant case where precautionary motives dominate (as suggested by our low-externality area results), the conditions of Lemma 1 ensure $\theta^* \in (0, 1)$ exists.

J Comparative Statics

J.1 Comparative Static 1: Wedge and Drought Probability

The wedge Δ is increasing in the probability of a low-rainfall shock $(1 - p)$: $\frac{\partial \Delta}{\partial(1-p)} > 0$.

Proof. Consider an increase in the probability of low rain, $(1-p)$. Define $V(R) \equiv \frac{u'(C(2;R))}{u'(C(1))} X(2; R)$ as the marginal value of period-1 conservation under rain realization R.

Step 1: Show that $V(R_L) > V(R_H)$.

From (SP.FOC2) and (DE.FOC2), $X(2; R) = \frac{1}{D(2)} - \frac{\rho R}{\lambda}$. Since $R_L < R_H$, we have:

$$X(2; R_L) > X(2; R_H)$$

More extraction occurs in low-rainfall states.

For consumption, we have:

$$\begin{aligned} C(2; R) &= \log(\lambda X(2; R) + \rho R) - X(2; R) D(2) \\ &= \log\left(\lambda \left[\frac{1}{D(2)} - \frac{\rho R}{\lambda}\right] + \rho R\right) - \left[\frac{1}{D(2)} - \frac{\rho R}{\lambda}\right] D(2) \\ &= \log\left(\frac{\lambda}{D(2)}\right) - 1 + \frac{\rho R D(2)}{\lambda} \end{aligned}$$

Taking the derivative with respect to R:

$$\frac{\partial C(2; R)}{\partial R} = \frac{\rho D(2)}{\lambda} > 0$$

Therefore, $C(2; R_L) < C(2; R_H)$, implying $u'(C(2; R_L)) > u'(C(2; R_H))$.

The marginal value of conservation is:

$$V(R) = \frac{u'(C(2;R))}{u'(C(1))} X(2;R) = \frac{C(2;R)^{-\gamma}}{C(1)^{-\gamma}} X(2;R) = \left(\frac{C(2;R)}{C(1)}\right)^{-\gamma} X(2;R)$$

Since $C(2; R_L) < C(2; R_H)$ and $X(2; R_L) > X(2; R_H)$, and $\gamma > 0$, we have:

$$V(R_L) = \left(\frac{C(2;R_L)}{C(1)}\right)^{-\gamma} X(2;R_L) > \left(\frac{C(2;R_H)}{C(1)}\right)^{-\gamma} X(2;R_H) = V(R_H)$$

Water is more valuable (in terms of marginal conservation benefit) in drought states.

Step 2: Analyze the effect on extraction.

The planner's Euler equation is:

$$F(X_{SP}(1)) = \beta \left[p \cdot V(R_H) + (1-p) \cdot V(R_L)\right]$$

An increase in $(1-p)$ increases the right-hand side (RHS) since $V(R_L) > V(R_H)$. Since F is decreasing in $X(1)$, the planner responds by *decreasing* $X^*_{SP}(1)$.

The decentralized farmer's Euler equation is:

$$F(X_{DE}(1)) = \beta(1-\theta) \left[p \cdot V(R_H) + (1-p) \cdot V(R_L)\right]$$

The same increase in $(1-p)$ increases the RHS, but it is scaled by $(1-\theta) < 1$. Therefore, the absolute increase in the RHS is *smaller* for the farmer than for the planner.

Let $\Delta V \equiv V(R_L) - V(R_H) > 0$. Then:

$$\frac{\partial}{\partial(1-p)} \text{RHS}_{SP} = \beta \Delta V$$
$$\frac{\partial}{\partial(1-p)} \text{RHS}_{DE} = \beta(1-\theta)\Delta V < \beta \Delta V$$

Since F is strictly decreasing with $\frac{dF}{dX(1)} = -\frac{\lambda^2}{z(1)^2} < 0$, we can apply the implicit function theorem:

$$\frac{dX(1)}{d(1-p)} = -\frac{\partial \text{RHS}/\partial(1-p)}{\partial F/\partial X(1)} = \frac{\partial \text{RHS}/\partial(1-p)}{\lambda^2/z(1)^2}$$

Therefore:

$$\left|\frac{dX^*_{SP}(1)}{d(1-p)}\right| = \frac{\beta \Delta V}{\lambda^2/z(1)^2}$$
$$\left|\frac{dX^*_{DE}(1)}{d(1-p)}\right| = \frac{\beta(1-\theta)\Delta V}{\lambda^2/z(1)^2}$$

Since both derivatives are negative and $\left|\frac{dX^*_{DE}(1)}{d(1-p)}\right| < \left|\frac{dX^*_{SP}(1)}{d(1-p)}\right|$, we have:

$$\frac{d\Delta}{d(1-p)} = \frac{dX^*_{DE}}{d(1-p)} - \frac{dX^*_{SP}}{d(1-p)} > 0$$

The wedge increases with drought probability. ■ □

J.2 Comparative Static 2: Wedge and Rainfall Variance

The wedge Δ is increasing with the variance of period-2 rainfall (under a mean-preserving spread): $\frac{\partial \Delta}{\partial \mathrm{Var}(R)} > 0$.

Proof. A mean-preserving spread (MPS) increases variance while holding average rainfall constant: $pR_H + (1-p)R_L = \bar{R}$ remains fixed. An MPS can be implemented by increasing R_H and decreasing R_L (moving the realizations further from the mean) while adjusting p to maintain the mean.

Step 1: Effect of MPS on precautionary motive.

For a risk-averse agent with CRRA utility ($\gamma > 0$), consumption exhibits prudence: the third derivative $u'''(c) > 0$. This creates a precautionary savings motive. When facing increased variance in future consumption (due to rainfall variance), the agent conserves more in period 1.

Under an MPS that increases $\mathrm{Var}(R)$, the distribution of $C(2; R)$ becomes more dispersed. By the precautionary savings motive, the planner responds by extracting *less* in period 1 to build a larger buffer stock $D(2)$ to insure against worse drought realizations.

Thus, an MPS causes:

$$\frac{dX^*_{SP}(1)}{d\mathrm{Var}(R)} < 0$$

Step 2: Differential response due to externality.

The decentralized farmer is also risk-averse but faces a muted incentive due to the factor $(1-\theta)$ multiplying the entire expected future value term in the Euler equation. The precautionary motive is present but attenuated by $(1-\theta)$.

Specifically, the second-order effect of increased variance on expected marginal utility is scaled by $(1-\theta)$ in the decentralized problem. Therefore, the farmer's precautionary response—the decrease in $X^*_{DE}(1)$—is *weaker* than the planner's.

To see this formally, consider the expected marginal value terms:

$$\begin{aligned} \text{SP:} \quad & \beta \mathbb{E}_R[V(R)] \\ \text{DE:} \quad & \beta(1-\theta)\mathbb{E}_R[V(R)] \end{aligned}$$

Under an MPS, $\mathbb{E}_R[V(R)]$ increases (by Jensen's inequality applied to the convex marginal value function). However, the decentralized agent's response is proportional to $(1-\theta) \cdot \mathbb{E}_R[V(R)]$, which increases by less.

Therefore:

$$\left|\frac{dX^*_{DE}(1)}{d\mathrm{Var}(R)}\right| < \left|\frac{dX^*_{SP}(1)}{d\mathrm{Var}(R)}\right|$$

Step 3: Effect on wedge.

Since both derivatives are negative and the magnitude of the planner's response exceeds the farmer's:

$$\frac{d\Delta}{d\text{Var}(R)} = \frac{dX_{DE}^*}{d\text{Var}(R)} - \frac{dX_{SP}^*}{d\text{Var}(R)} > 0$$

The wedge widens with increased rainfall variance. ■ □