Salting the Earth: Shrimp Farming and Agricultural Externalities in Bangladesh

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Abstract

Climate change is raising groundwater salinity across coastal regions globally, threatening smallholder livelihoods. In southern Bangladesh, a common adaptation is to convert freshwater rice paddies into saltwater shrimp ponds. However, this adaptation comes with an externality: saltwater from shrimp ponds may seep into neighboring fields, damaging rice. This paper considers whether such private adaptation generates negative externalities on neighboring rice farmers and whether those externalities accelerate further adoption. Combining a novel household survey with a newly constructed satellite panel of 73,300 plots over nine years, we document that a neighbor's conversion reduces vegetation health on adjacent rice plots and raises own conversion probability by 18.0 percentage points. Interpreted through a model of land use based on comparative advantage, where we introduce a boundary externality, these results imply an adaptation cascade wherein 51.5 percent of ponds exist only because a neighbor converted, and a tax on conversion would raise aggregate farm profits by 11 percent. Thus, adaptation that benefits individual farmers can spread through costs imposed on their neighbors: private decisions that promote climate resilience for some can erode it for others.

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1 Introduction

It is well established that human activity is altering the global climate (IPCC, 2021). A large body of evidence shows that climate change is harming livelihoods, especially in the world's poorest countries (Dell et al., 2012; Burke et al., 2015; Carleton et al., 2022). The extent to which these changes affect human populations depends, in large part, on people's ability to adapt their livelihoods to new conditions (IPCC, 2022).

One setting where adaptation may be slow is agriculture. In developing countries in particular, the cost of new technology, barriers to learning, and heterogeneous returns are just a few well-documented obstacles that may hinder take-up.[1] Since agricultural workers are especially exposed to the climate through both physical exposure and the relationship between heat and yields, slow adoption may be especially costly in this sector. We examine a countervailing force: a production externality imposed on farmers who do not adopt. If adopting a new technology harms non-users who can avoid that damage by adopting it themselves, take-up may be faster than in the absence of the externality.

We study this dynamic in the context of southwestern Bangladesh, where farmers can respond to climate-change-induced groundwater salinity by switching from rice cultivation (the old technology) to inland shrimp farming (the new technology) in saltwater ponds. Whereas rice yields fall in the presence of sufficiently high levels of water salinity, salt-loving shrimp varieties thrive. Thus, during the dry season when fresh water is unavailable, farmers may flood their plots with salty water from groundwater, canals, or slow-flowing rivers, which protects them from the damage that saltwater intrusion would otherwise have done to their rice fields. However, this saltwater may seep into the fields of those who remain in rice, lowering yields even further than climate change-induced salinity would on its own. Neighbors therefore face a choice between continuing rice cultivation under worsening conditions or converting to shrimp themselves.

We first ask whether exposure to saltwater aquaculture affects subsequent adoption. We then ask whether the induced conversions improve or reduce aggregate farm profits and what this implies for land use policy.

This distinction is central for informing land use policy. In the absence of a production externality, farmers who convert because shrimp has become the more profitable use of their own land are adapting to a private environmental constraint. However, in a setting with a production externality, a farmer may convert because of the externality-induced decreases in rice profits: not because it was more profitable *ex*

[1] For surveys of this literature, see Magruder (2018); Suri and Udry (2022); Adamopoulos et al. (2026).

ante, but rather because it is a last resort. The first process may lead to a change in the composition of agriculture without any inefficiency; the second creates the possibility that privately rational choices reinforce one another even when the resulting allocation is not best for farmers collectively. Our empirical analysis examines whether such a cascade, which depends on neighboring choices, exists. Our model allows us to quantify the cascade's extent and assess its welfare implications.

First, using a novel survey that combines a household questionnaire (N = 739) with ground-truth salinity readings (N = 1,478), we document three stylized facts that support the paper's argument that the salinity externality exists and affects patterns of adoption. *Fact 1:* We begin by showing that farmers believe shrimp farming generates a production externality. In a hypothetical plot exercise, farmers expect that, in the year following their neighbors' conversion from rice to shrimp, their own plots will experience both higher salinity and lower yields equivalent to a 48 percent decrease in output if they do not adopt shrimp farming as well. This stated loss is much larger than estimates of the average annual decline in rice yields from long-run salinity trends alone, suggesting that farmers perceive neighboring conversions as a more immediate threat (Dasgupta et al., 2015). *Fact 2:* Farmers' beliefs about salinity are supported by our ground-truth salinity survey. Measured salinity is also higher near shrimp ponds. Rice plots bordering shrimp ponds have salinity readings 20.6 percent (0.6 decisiemens per meter) higher than those of plots that do not border shrimp ponds. We take readings in May, immediately before the onset of the annual rainy period, and show that shrimp-adjacent plots have higher readings than their non-shrimp-adjacent counterparts. *Fact 3:* Finally, these saltier rice plots that border shrimp ponds produce 7% lower rice yields (171 kg/acre less) than plots that do not border shrimp farms. While this is not causal evidence of an externality, it is notable that even in equilibrium, when farmers are responding to their neighbors, they are unable to offset these losses and equalize yields across adjacent plots, even if they are able to choose salt-tolerant rice varieties. Taken together, these facts suggest that there is scope for farmers to make land-use decisions with this production externality in mind.

Second, to study whether farmers' beliefs about this salinity externality affect patterns of adoption, we construct a new plot-level panel of land use covering 73,300 plots in coastal Bangladesh from 2017 to 2025. We apply Delineate Anything, a deep-learning model for field-boundary delineation, to high-resolution PlanetScope imagery, allowing us to recover individual plot polygons and the plot borders through which spillovers may propagate. We then classify each plot as agriculture or aquaculture during *Rabi*, the dry season from November to February when fresh water is scarce, and agricultural land is unlikely to be covered in standing water. The classi-

fication uses a water index from repeated Sentinel-2 observations and a data-driven threshold. [2] To our knowledge, this is the first plot-level, seasonal record of shrimp aquaculture adoption at this scale.

Third, leveraging our new panel data, we estimate the effect of a plot's conversion to aquaculture on neighboring plots over time. To account for staggered conversion timing and heterogeneous treatment effects across cohorts, our event study approach uses the Sun and Abraham (2021) estimator. A key identification challenge is spatially correlated shocks: both plots may be responding to the same rising underlying salinity. To address this risk, we tile the study region with hexagons that average 20 plots per hexagon and control for hexagon-by-time fixed effects. Using this approach, we show that the conversion of a plot to aquaculture induces an 18.0 percentage point increase in the likelihood that a bordering plot adopts aquaculture as well. This effect persists for five years until the end of the sample. Using the same empirical strategy, we show that among plots that remain in agriculture, a satellite-derived measure of crop health falls 3 percent of the baseline mean, in the year following a neighbor's conversion, before returning to pre-conversion levels in subsequent years. If plots which suffer the largest losses are more likely to convert, the sample of those which remain in agriculture may only provide a lower bound on the effect on initially exposed agricultural plots. Together, the findings are consistent with a neighboring-adoption externality that affects both agricultural productivity and subsequent land use.

Fourth, to interpret these effects, we develop a model of land-use choice under a production externality. We build on the Roy (1951) model of selection on comparative advantage in which profits from either shrimp or rice depend on observable plot characteristics and a Fréchet-distributed productivity for every crop à la Costinot et al. (2016); Sotelo (2020) and Farrokhi and Pellegrina (2023). However, in these models, a parcel's returns do not depend on neighbors' crop choices. We add an environmental externality that acts only at the boundary between two adjoining plots to mirror salinity spillovers through groundwater. This lowers the threshold at which a plot switches to aquaculture, creating the potential for a spatial cascade. We model the cascade as a static repeated problem because (a) we find no evidence of anticipation and (b) land-use decisions are year-over-year reversible; thus, there are no option value gains to waiting to adopt. Last, because beliefs about damages are two orders of magnitude larger than what climate change alone would imply, we do not explicitly model a global salinity trend. The event study estimate of the conversion

[2] We apply the Modified Normalized Difference Water Index (MNDWI) of Xu (2006). This index better separates water from built-up land and is more reliable in detecting shallow water compared to the unmodified NDWI.

to aquaculture identifies the size of the net externality favoring shrimp farming under the assumption that profits observed in the household survey pin down the dispersion of plots' productivity draws. We estimate the model from the cross-section of rice and shrimp farms in the household survey and the conversion event study from the satellite panel. The dispersion of realized output identifies the shape of the distribution of comparative advantage, while plots' land-use choices identify how size and distance to the river shift relative suitability. Equipped with the estimated model, we can compare the take-up of shrimp among plots where we set the externality to zero. On a stylized landscape, we find that the externality generates a substantial cascade: 51.5 percent of the plots that take up aquaculture do so only because of the externality from their neighbors.

The model and event studies together only allow us to speak to whether or not there is a cascade. To assess whether the observed extent of shrimp farming represents over- or under-adaptation, we decompose the net spillover estimated from land-use choices into (i) damage to neighboring rice and (ii) benefits to neighboring ponds, using farmers' elicited beliefs about the rice yield loss a neighbor's conversion would cause, and compare the resulting allocation with that of the social planner. The result of this exercise is that the recently announced subsidy regime for shrimp in Bangladesh (8% for exports) is in the wrong direction (Bangladesh Bank, 2026)—our model implies that the level of shrimp farming adoption in southern Bangladesh is too high relative to the planner's allocation and that a tax on the conversion of agricultural land to aquaculture would increase welfare by 11 percent.

Contributions: A large literature studies the drivers of technology adoption in agriculture. Economists have examined this question since at least Griliches (1957), who studied how the diffusion of hybrid corn tracks its profitability. Subsequent work has identified many reasons adoption may be slow even when new technologies are profitable on average. Farmers must learn about a technology's returns, either through their own experience or from their neighbors (Foster and Rosenzweig, 1995; Conley and Udry, 2010); returns are heterogeneous, so low adoption may partly reflect low returns for some farmers (Suri, 2011); and farmers may fail to notice relevant dimensions of a technology or learn from misspecified models (Hanna et al., 2014). In developing countries, a further set of frictions can slow adoption: missing credit and insurance markets (Karlan et al., 2014; Mobarak and Rosenzweig, 2013; Casaburi and Willis, 2018), exposure to downside risk (Emerick et al., 2016), factor market failures (Jones et al., 2022), behavioral biases (Duflo et al., 2011), and limited access to information (Beaman et al., 2021; Aker and Jack, 2025). We study a setting in which an externality imposed on non-adopters instead accelerates adoption. We show that plots only respond to other plots with which they share a direct border; farmers

also report that they discuss farming with their direct neighbors no more often than with other households in the village, and crop health declines on neighboring plots that never convert. Together, these patterns suggest the results are not driven by learning alone. In this setting, the new technology (i.e., shrimp farming) acts as a force that speeds adoption, even though these other frictions would, on net, lead us to expect slow uptake.

Second, we contribute to the literature on adaptation to climate change in low- and middle-income countries.[3] This literature has largely focused on whether and how households adapt and on the constraints that limit adaptation. We highlight a different dimension of heterogeneity in the consequences of adaptation: adaptive behavior by some households can make others worse off. In our setting, conversion to aquaculture accelerates further adoption, while also imposing costs on those who do not convert. In this respect, our paper relates to work showing that adaptation can generate costs for others, such as groundwater depletion from competitive pumping (Ryan and Sudarshan, 2022; Blakeslee et al., 2020) and conflict arising from pastoralist migration in response to drought (McGuirk and Nunn, 2025). Relative to this work, we observe the externality directly at the level of individual plots and their neighbors, allowing us to trace how damage to one plot affects its owner's subsequent decisions and how adoption spreads across space. We show that in responding to climate shocks, people can exacerbate the very shocks for others that they themselves sought to avoid.

Third, within the climate adaptation literature, we contribute to a growing body of work on responses to salinity. Rising salinity in coastal Bangladesh has been linked to migration (Chen and Mueller, 2018), economic precarity (Chen et al., 2022), early-life health (Guimbeau et al., 2024), and lower returns to high-yielding rice varieties (Dasgupta et al., 2015), while recent work studies the adoption of salt-tolerant rice (Patel, 2025). Closest to our work, Haque (2025) shows that fragmented land markets and religious homogeneity can impede the adoption of shrimp aquaculture, but that land may be reallocated toward shrimp through the rental market. A related study documents higher salinity and lower paddy profits on plots closer to shrimp ponds (Morshed et al., 2020). We complement this work with a plot-level seasonal panel tracking land use across 73,300 plots over nine years, which allows us to study adoption dynamically rather than at a single point in time. By observing plot boundaries and the adjacency network between plots, we show that the externality from conversion can generate a cascade in which each adoption raises the likelihood of further conversions nearby.

The remainder of the paper proceeds as follows. Section 2 introduces the setting.

[3]See Kala et al. (2026) and Carleton et al. (2024) for reviews.

Section 3 discusses the data. Section 4 introduces the model. Section 5 presents the stylized facts. Section 6 presents the empirical strategy and event-study results. Section 7 discusses estimation of the model and the counterfactuals. Finally, Section 8 concludes.

2 Setting

This section provides background information on the key features of southwestern Bangladesh where this study takes place. It discusses the salinity conditions of the setting and the extent to which saltwater shrimp farming can be accurately described as climate adaptation.

2.1 Climate Change in Bangladesh

This project takes place in the Khulna and Satkhira districts of southwestern Bangladesh. Appendix Figure B1 shows the locations of unions (the smallest administrative unit of Bangladesh) in which we collect survey data; unions used in the satellite analysis are shown in pink. Both districts are bounded by mangrove forests and the saltwater Bay of Bengal to the south, and inland Bangladesh to the north. These districts sit within the Ganges-Brahmaputra-Meghna delta and are low-lying and densely populated. A large share of households work in agriculture, and rice dominates (Bangladesh Bureau of Statistics, 2022). In addition to other climate-induced shocks such as heatwaves, droughts, and flooding that affect the entire country, people living in these districts face disparate additional threats such as storm surges and saltwater intrusion (World Bank Group, 2024). Among these threats, salinity is notable in that it builds gradually and directly reduces agricultural productivity.

Two different processes may govern the evolution of soil salinity, operating on two different time scales. The first is a slow regional change driven by climate and upstream water use. Sea-level rise and storm surges push saline water further inland, while reduced freshwater flows in the dry season allow tidal salinity to travel further up coastal rivers and permeate groundwater (Dasgupta et al., 2015). According to the Bangladesh Ministry of Environment, Forest, and Climate Change, the area under critical saltwater intrusion of 5–10 parts per thousand is expected to increase by 68% by 2050 (Ministry of Environment, Forest and Climate Change, Government of the People's Republic of Bangladesh, 2018). This is a long-run, ongoing process: the Soil Resource Development Institute in the Bangladesh Ministry of Agriculture has found that from 1973 to 2009, salt-affected areas increased by 26.7% (Soil Resource Development Institute, 2010). The second process is both faster and more localized. When a plot is converted to aquaculture, saline water is brought onto the plot and

can spread to neighboring fields within a season, as we show in Section 6. This process is shaped, in part by distance from the coast and by infrastructure: the system of polders and embankments built from the 1960s was designed to keep saline water out of agricultural land, but shrimp farmers have been documented breaching embankments to bring saline water inland (Brammer, 1990). The regional trend thus gradually changes which plots are close to the margin between rice and aquaculture, while the local externality determines how conversion spreads among neighbors within much shorter periods, as we document below.

Policies that may limit salinity exist, but often require coordinated management that has been difficult to achieve in coastal Bangladesh. A key tool for addressing groundwater intrusion is the enforcement of limits on over-pumping, a mechanism which is informed by regular water balance assessments (Stein et al., 2023). Other adaptation approaches include those that facilitate the recharge of groundwater such as shifting demand to other water sources, reducing water consumption, or otherwise changing production processes, such as by switching to salt-tolerant seed varieties. Because groundwater is a common-pool resource, regulation requires central authority; however, de facto water governance suffers from weak coordination among agencies and ineffective local water management institutions (Esha et al., 2026). Even if central policy were agreed upon, smallholder water users may also resist limits, which drives up the cost of monitoring and enforcement.

2.2 Shrimp Farming as Climate Adaptation

Shrimp farming in Bangladesh involves flooding ponds with saltwater, generally drawn from the sea or saline rivers, at high tide and retaining it at low tide (Morshed et al., 2020). This takes place largely on paddy fields or salt pans on tidal flats, ringed by low earthen levees that are often built inside government flood-control polders. At the end of a growing season, salt ponds may be pumped out to allow for agriculture or to introduce new saline water for a new season of shrimp. This use need not be permanent: representative sampling suggests approximately two-thirds of shrimp plots are used intermittently for rice cultivation when fresh water is available (Mondal et al., 2013). The most commonly farmed species is the black tiger shrimp (Penaeus monodon, locally *bagda*), which is stocked at low densities, with little or no external feed and reliance on tidal water exchange, so the shrimp largely subsist on the natural plankton and organisms that develop in the pond. The critical input is the seed stock, which is purchased from a network of hatcheries across coastal areas.

Figure 1 shows benchmark ranges for salt tolerance of the crops considered in this paper. For non-tolerant rice, we use the standard threshold of 3 dS/m (soil saturation extract), above which yield declines by about 12 percent per additional

dS/m (Maas and Hoffman, 1977). These non-salt-tolerant varieties remain the most common varieties in the dry season in the area of our study (Islam et al., 2024). For salt-tolerant rice, we use 8 dS/m, the upper end of the whole-season tolerance of BRRI dhan67 (Paul et al., 2024). Newer rice varieties such as BRRI dhan97 and BRRI dhan99 are available at higher salinity tolerances, but produce lower average yields and are still rarely adopted, making up less than 1 percent of current use (Debsharma et al., 2024).

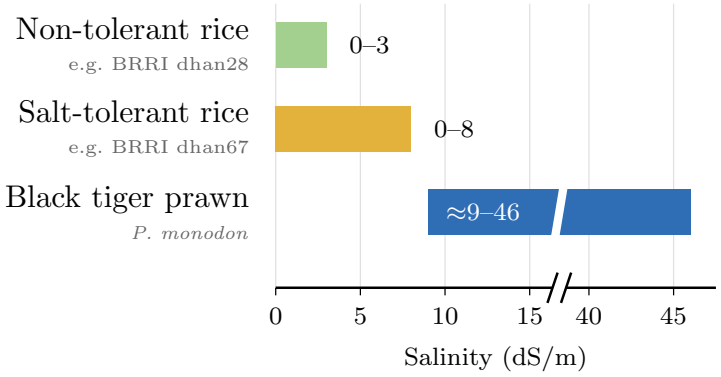


Figure 1. Salinity Ranges for Rice and Shrimp

Black tiger prawns (*Penaeus monodon*) tolerate water salinity of roughly 5–35 ppt, and farming in Bangladesh typically takes place at 5–20 ppt (Rahi et al., 2021). In controlled trials with Bangladeshi stock, growth and survival were highest at 20 ppt and lower but viable at 5 ppt (Rahi et al., 2021). Converting parts per thousand measures into decisiemens for consistency with the ground-truth salinity measures we will take below, we convert to electrical conductivity at 25 °C using the Practical Salinity Scale (UNESCO, 1981), which places this range at approximately 9–46 dS/m. On these benchmarks, shrimp aquaculture becomes feasible at a salinity just above the whole-season tolerance of the most widely grown salt-tolerant rice varieties.

Households report that converting a plot between rice and shrimp is neither slow nor, for most households, difficult to finance. Asked about converting a randomly selected plot to aquaculture, 72 percent of non-shrimp-farming households and 79 percent of shrimp-farming households report that they could take out a loan large enough to cover the cost (Appendix Table A3). Few could pay for it from savings alone: fewer than a fifth in either group report enough savings to cover the cost, so conversion is typically financed by borrowing. Respondents expect the physical work of conversion, mainly raising earthen dikes and preparing the pond, to take about three weeks. Converting a pond back to rice cultivation is perceived as similarly feasible, with comparable access to loans and an expected duration of two to four weeks.

The primary inputs for saltwater shrimp farming are post-larval fry, saltwater, and feed. Fry are sourced from approximately 50 hatcheries in the southeastern district of Cox's Bazar and then transported and distributed to retailers throughout coastal areas. Shrimp yields in Bangladesh are low by international standards: about 0.35 tonnes per hectare, compared with roughly 3.9 tonnes in India and 4.3 tonnes in Thailand (Nurullah et al., 2024). This gap reflects the extensive nature of farming in Bangladesh, its reliance on the low-yielding black tiger shrimp at a time when major producers have shifted to the higher-yielding Pacific white shrimp (*Litopenaeus vannamei*), and recurrent disease outbreaks, particularly white spot syndrome (Nurullah et al., 2024).[4] After farming, shrimp are sold at local fish markets to consumers or middlemen who transport to processing and packaging centers where up to 80% of shrimp is then exported (Islam et al., 2014). The primary export partners are the European Union, the United States, Japan, and Russia (Kabir et al., 2023).

International development efforts have also sought to expand shrimp farming in the region. The World Bank-financed Sustainable Coastal and Marine Fisheries Project, valued at US$281.6 million and running until 2023, supported the fisheries sector as a whole while targeting shrimp farmers in particular. It aimed to organize marginal shrimp farmers into production clusters and offered matching grants in the form of feed in exchange for farmers' investment in deepening their ponds, alongside training in good aquaculture practices. The Climate-Smart Agriculture and Water Management Project, valued at US$155.3 million and running from 2021 to 2026, improved flood control and drainage infrastructure, established cold storage facilities, and strengthened farmers' links with buyers, among other support to the sector (Kabir et al., 2023).

3 Data

This section describes the data used in the paper. It then discusses the approach we use to detect and differentiate between plots used for agriculture and plots used for aquaculture with remote sensing data.

3.1 Household Survey

We conducted a household agricultural survey between May and June of 2025 covering 739 households across fourteen unions from the Khulna and Satkhira districts of

[4] In *extensive* systems, shrimp are stocked at low densities and depend mainly on the natural productivity of the pond, with little or no supplemental feed, minimal aeration, and water exchanged with the tides. *Intensive* systems stock shrimp at much higher densities and rely on formulated feed, mechanical aeration, and active management of water quality.

Bangladesh. To select the sample, enumerators first identified a 'marginal' plot triple within villages where they could observe an active saltwater shrimp pond adjacent to two agricultural plots.[5] This construction (i.e., a central agricultural plot with a saltwater shrimp pond on one side and a traditional agricultural plot on the other side) allowed us to collect salinity readings that could provide salinity readings at both an agriculture–agriculture boundary and an agriculture–aquaculture boundary. After selecting the plots, enumerators identified the plot operators to interview. After obtaining consent and completing the modules with the operators, they returned to the plots to take salinity readings.

Our survey is deliberately not a representative cross-section of all farmers, either working in rice or in shrimp. Rather, it captures a cross-section of those who are at the adoption frontier: farmers who are either operating a shrimp farming plot near a rice farming plot or vice versa. Operators need not be owners of the sample plot–we consider respondents eligible for the sample if they have the right to make land use decisions.

3.2 Salinity Readings

We collected salinity readings in May and June of 2025, contemporaneous with the household survey. For each plot triple used to select the sample, enumerators took readings of soil or water salinity at the boundary between each plot, as shown in Appendix Figure B2. The soil salinity reading protocol for enumerators is reported in Appendix D.

Enumerators collected salinity readings using portable salinity meters with an electrical conductivity range of 0–10 deciSiemens (dS)/cm. The meter has a metal probe that is inserted directly into moist soil, where it passes a small electrical current between its tips and measures how easily that current flows. Because dissolved salts carry electricity, saltier soil conducts the current more readily, and the meter converts this into a salinity reading shown on its screen. Enumerators read the salinity reading off of the screen and enter the reading into a tablet alongside the household survey questions. The primary advantage of this type of meter is that it provides a nearly instantaneous reading and requires minimal training to operate. However, it is important to note that the meters measure overall electrical conductivity, which will depend on soil moisture, texture, and compactness. These sensors are less accurate than lab tests, but take very little time (about 5 seconds per reading), and have close to zero marginal cost for additional readings. To improve quality, we calibrated all meters using a standardized saline solution prior to the survey and took each reading

[5] See Appendix Figure B2 for an diagram.

twice. We averaged the two readings before using them in the analyses presented in this paper.

We chose May and June for the timing of the survey because they fall immediately before the beginning of the monsoon season and thus gave us an opportunity to observe salinity at or near its peak, following salt accumulation throughout the dry winter and spring period. The salinity data presented here are therefore best interpreted as showing a gradient between plots at or near its greatest extent (Rahman et al., 2025).

3.3 River Data

River locations come from OpenStreetMap (OpenStreetMap, 2026), from which we keep only features tagged as `waterway=river`, excluding smaller channels such as streams, canals, drains, and ditches. For each plot in our satellite analysis, we compute the shortest distance from the plot's boundary to the nearest river segment. Because OpenStreetMap relies on volunteer contributions, its coverage of waterways is partially incomplete. Large rivers are well documented, but smaller canals, including the saline canals and irrigation channels that supply many shrimp ponds, are only partially mapped, so we exclude them rather than rely on uneven coverage. Thus we capture well proximity to the nearest major waterways, but it is an imperfectly proxy a plot's access to saline water, which for many plots runs through canals not observed in our data.

3.4 Satellite Data

The analysis of remote sensing data in this paper combines two data sources to first delineate plots, and then categorize those plots as either agricultural land or aquaculture.

Boundaries of plots are first delineated using preprocessed high-resolution Planet basemaps, which are single seamless images that aggregate cloud-free pixels from repeated satellite passes over a common area. Because this imagery is essentially a mosaic of different time periods, it can be used to recognize permanent and semi-permanent features of the landscape, such as the boundaries between plots, but cannot be used to categorize the use of the plot during any season. At Bangladesh's latitude, the pixels captured by the sensors on the satellite will correspond to 4.4×4.4 meters. We process this imagery by applying the Delineate Anything model, a deep learning approach that performs instance segmentation (i.e., identifies individual plots, rather than the lines between plots). The algorithm is pre-trained on a sample of 73 million plots across the world and is discussed further in Appendix C. Because the mosaics

are already cloudless composites, they are an ideal sample on which to extract plot geometry. We retain the resulting field polygons (i.e. plot shapes) as the fixed spatial units which make up our panel dataset.[6] Panels 1 and 2 of Figure 2 show the first step of the approach. Panel 1 displays the base map mosaic from Magurkhali Union, one of the 51 unions that make up the sample. Panel 2 shows the delineated plots—distinct polygons that outline the boundaries of recognized plots. We drop those polygons that fall above the 99th percentile of plot size.

Delineated polygons make up the unit of analysis of the satellite analysis in Section 6, and also provide the network over which we propose that the physical salinity externality may take place. It is important to note here that classical algorithms which, rather than identifying individual polygons, divide regions into units that fully tile space would be insufficient here because they would mechanically give every plot which was defined a neighbor, potentially oversaturating the links through which spillovers may happen.

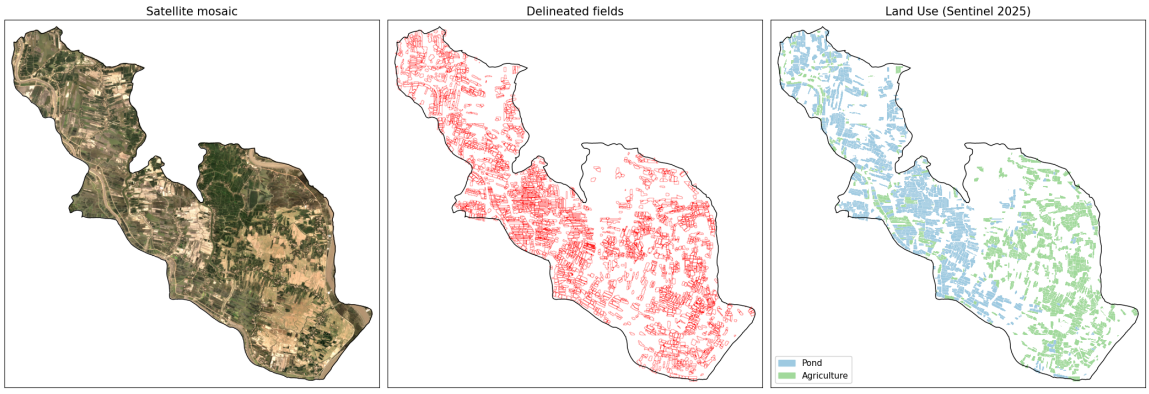


Figure 2. Illustrative Plot Classification - Magurkhali Union

To measure land use over time, we use Sentinel-2 satellite imagery, a lower-resolution but higher-frequency dataset from a European satellite program with a spatial resolution of 10 to 20 meters per pixel depending on the spectral band. For every plot from 2017 to 2025, we compute two indices from the Sentinel-2 bands. The first is the Modified Normalized Difference Water Index (MNDWI), a canonical formula combining a green and a shortwave-infrared band that produces high values over standing water and low values over vegetation and soil, which we use to

[6]Note that because we hold plot boundaries fixed over time, we are abstracting away from the division of one plot into multiple plots or the combination of multiple plots into one larger plot during the span of the satellite portion of our analysis (i.e., 2017–2025). Table 1 shows plots are held for an average of 12 years. Agricultural plots are commonly separated by earthen mounds, and saltwater ponds are enclosed by earthen dikes, so while plots may be joined or split occasionally, it is moderately costly and uncommon.

detect ponds.[7] Intuitively, this index captures that areas which are covered in surface water will absorb shortwave infrared (SWIR) light and reflect relatively more green light. The second index constructed for each plot is the Normalized Difference Vegetation Index (NDVI), likewise a canonical greenness measure that is high over healthy vegetation and low over bare or waterlogged ground, which we use as a proxy for agricultural productivity.[8]

We discard any Sentinel-2 scene with more than 50 percent cloud cover. Within the retained scenes, we mask individual pixels flagged as cloud, cloud shadow, or cirrus – thin high-altitude cloud – using the imagery's built-in scene-classification band. We then combine the surviving clear-sky pixels within each season by taking the median value at each location, which suppresses any residual haze, and we then average the clear pixels falling inside each field boundary to obtain one MNDWI and one NDVI value per field during the Rabi (i.e., dry) season of each year, aggregating readings from 1 November to 28 February each year. We chose the dry season to gain the cleanest differentiation between plots that are flooded with saltwater and those that are not flooded, but may have residual water from other uses. Plot-seasons based on fewer than three clear pixels are flagged as unreliable and dropped. Finally, a plot is classified as in aquaculture in a given season when its MNDWI exceeds a season-specific cutoff chosen as follows: we apply Otsu's method to the distribution of MNDWI values within each season and year, which selects the threshold that best separates the two modes of the distribution rather than imposing a fixed cutoff of zero.[9] Appendix Figure B3 shows dry season histograms of the MNDWI readings for all plots in the sample, grouped by year. The vertical line shows that year's cutoff as determined by the Otsu method to be the cutoff between agriculture and aquaculture.

3.4.1 Validating Plot Detection and Classification

To conduct meaningful analysis using the satellite-derived panel, we need two conditions to hold: (i) the plot recognition algorithm is able to detect enough plots at a density that permits them to border one another frequently enough that we have sufficient variation in whether or not an agricultural plot is bordered by an aquaculture plot for an event-study approach; and (ii) the land use classification algorithm

[7] The Modified Normalized Difference Water Index is defined as $\text{MNDWI} = \frac{\rho_{\text{Green}} - \rho_{\text{SWIR}}}{\rho_{\text{Green}} + \rho_{\text{SWIR}}}$, where ρ_{Green} and ρ_{SWIR} are reflectance in the green and shortwave-infrared bands.

[8] The Normalized Difference Vegetation Index is defined as $\text{NDVI} = \frac{\rho_{\text{NIR}} - \rho_{\text{Red}}}{\rho_{\text{NIR}} + \rho_{\text{Red}}}$, where ρ_{NIR} and ρ_{Red} are surface reflectance in the near-infrared and red satellite bands, respectively.

[9] Otsu's method chooses the threshold t^* between the two groups that maximizes the between-group variance: $t^* = \arg\max_t \ \omega_0(t)\,\omega_1(t)\left[\mu_0(t) - \mu_1(t)\right]^2$, where $\omega_0(t), \omega_1(t)$ are the proportions of observations below and above t and $\mu_0(t), \mu_1(t)$ are their respective means.

is not merely noise, i.e., it contains a sufficiently large signal about the actual use of that plot. Among the 51 unions that make up the satellite sample, areas designated as plots cover 36.8% of total space (see Table A1). Estimates place the share of land under cultivation at approximately 60%, implying that our delineated plots cover approximately 60% of cultivated land (Bari et al., 2024).[10]

Accurately classifying plots as agriculture or aquaculture is difficult in this setting because the water we are attempting to detect is shallow and murky, so errors may arise from either under- or over-classification of wetness. Appendix Figure B3 shows the distribution of MNDWI readings for our sample by year. The vertical lines show the water threshold chosen each year by Otsu's method, which selects the cutoff that maximizes the between-class variance of the index. Although the index is normalized, the selected threshold is above zero in every year, and many plots have intermediate values. Thus, although hereafter we refer to plots above the threshold as *ponds* or as being in *aquaculture*, the classification is more generally interpreted as placing a plot above a data-driven threshold of pond likelihood.

To compare the classification with ground observations, we match the GPS coordinates recorded for each surveyed household's main plot to the delineated polygons. Coordinates were recorded at salinity-reading locations, which by protocol lie on plot boundaries, so we first identify, by visual inspection of the satellite imagery, the 415 coordinates that fall within a plot. Of these, 127 fall inside a sattelite delineated polygon; 87 are rice plots and 40 are shrimp ponds according to the survey, preserving the two-to-one composition of our sampling triplets (Appendix Table A2). In the dry season immediately before the survey, the year-specific threshold classifies most matched plots as aquaculture regardless of their surveyed use, with a false-positive rate of 0.85 and a balanced error rate of 0.51. In aggregate, the classification yields a share of aquaculture in line with estimates for coastal Khulna and Satkhira, but it classifies a much higher share of plots as ponds in the matched sample. As an alternative classification, we use a single, higher threshold, MNDWI > 0.241, held fixed across all years and chosen to minimize the balanced error rate in this matched sample. Because it lies above the year-specific threshold in every year, it applies a stricter definition of a pond, reducing the false-positive rate to 0.67 at the cost of a higher false-negative rate (.325). The main empirical result of the paper (the event-study estimate of the effect of a neighbor's adoption of aquaculture on one's own adoption) is robust to this reclassification (Appendix Figure B4).

One additional concern specific to satellite-delineated plots is that the segmentation may split a single pond into two adjacent polygons. If it does, the two halves

[10]This percentage includes both the city of Khulna, which has very little agricultural land as well as mangrove forests in the Khulna Division, so it is best interpreted as a lower bound.

would fill with water in the same season and appear as a plot converting at the same moment as its neighbor, mechanically generating a spillover. To test for this, we compare plot pairs that convert in the same season with other adjacent pond pairs. If two polygons were in fact one pond, they should be ponds in the same years and, while both are ponds, have nearly identical MNDWI readings that move together from year to year; we measure this only in years when both plots are ponds, since any two plots that convert together will have correlated readings over the full panel simply because of the shared switch. Same-season pairs are slightly more likely than other adjacent ponds to look like a single pond: 11% versus 8% under the strictest similarity criteria, and 21% versus 19% under the strict criteria (Appendix Figure B5). Some simultaneous conversions may therefore reflect split ponds, but the excess is small, and we show below that our results are robust to dropping these plots.[11]

A final concern with the classification exercise is that some ponds in our setting may be used for freshwater aquaculture rather than saline shrimp farming, and our water index cannot distinguish the two. Three features of the setting limit how much this matters. First, freshwater aquaculture is considerably less common than brackish shrimp farming in our study area: in Khulna and Satkhira districts combined, shrimp (*bagda*) farms cover about 91,300 hectares, against about 28,400 hectares for freshwater prawn (*golda*) farms (Department of Fisheries, 2025). Second, where it does occur, the most common freshwater system rotates prawns in the wet season with boro rice in the dry season (Jamal et al., 2023), so these plots are typically under rice, rather than open water, during the dry-season window we use for classification. Third, to the extent that misclassified freshwater ponds do not affect their neighbors' land use, because they generate no salinity spillover, they attenuate our estimates toward zero. If they do affect their neighbors, for example by waterlogging adjacent fields, they contribute to the net externality that our event study measures and that the model's parameter δ is designed to capture.

4 A Model of Land Use with a Boundary Externality

This section proposes a model of land allocation between rice and saline aquaculture in which a plot's returns depend on whether its neighbors are in aquaculture. It separates selection on comparative advantage from the externality, and shows how the externality propagates across a landscape.

[11] See Appendix Figure B6.

4.1 Environment

There are plots which are each operated by an individual farmer. Plots, indexed by i, are contiguous, and each is either in rice ($d_i = 0$) or in saline aquaculture ($d_i = 1$). Plot i has an unobserved productivity in each use, a_i^R and a_i^S which are independently drawn from Fréchet distributions. These capture everything that makes a plot more or less profitable in rice or shrimp, respectively beyond its observed characteristics: soil, drainage, access to fresh or saline water, and the skill and capital of whoever farms it.

We consider a plot to be exposed if it borders another plot that has adopted shrimp:

$$b_i = \{\text{plot } i \text{ shares a boundary with at least one shrimp plot}\}. \tag{1}$$

4.2 Payoffs and land use

Profit for each plot is productivity times observable shifters:

$$\pi_i^S = a_i^S \cdot \underbrace{e^{w_i'\gamma^S}}_{\text{characteristics}} \cdot \underbrace{e^{-c}}_{\text{conversion cost}}, \tag{2}$$

$$\pi_i^R = a_i^R \cdot \underbrace{e^{w_i'\gamma^R}}_{\text{characteristics}} \cdot \underbrace{e^{-\delta b_i}}_{\text{net damage}}, \tag{3}$$

where w_i contains plot size and distance to the river. In order to adopt shrimp, a plot pays a conversion cost which is common to all plots. If a plot shares a boundary with at least one shrimp plot (i.e. $b_i = 1$), then profit shifts by $e^{-\delta b_i}$, the relative damage to rice profits caused by the boundary externality. Each plot is allocated to the use that pays more:

$$d_i = 1 \iff \underbrace{\log a_i^S - \log a_i^R}_{\Delta_i} > c - \delta b_i - w_i'\gamma, \qquad \gamma \equiv \gamma^S - \gamma^R. \tag{4}$$

The breakeven condition is thus the relative productivity draws a_i^S, a_i^R such that profits from the new technology, shrimp, are equal to profits in the old technology, rice. Δ_i is the plot's comparative advantage in aquaculture. An aquaculture neighbor lowers the threshold by δ without changing Δ_i.

It is important to note that δ is a net damage effect: the loss of rice profit from an aquaculture neighbor plus any gain in shrimp profit from one. Both make aquaculture relatively more attractive, and land use responds only to their sum; writing δ on rice profit is a normalization. The multiplicative form makes the effect proportional, so

a given exposure changes returns by the same fraction on every plot. The conversion cost c is common across plots. It cannot be separated from the intercept of $w_i'\gamma$ and is absorbed into it; plot-level variation in conversion costs is absorbed into Δ_i.

4.3 Productivity Draws and Land-Use Probabilities

Productivities are independent Fréchet draws with common shape θ, and unit scale since w_i enters explicitly:

$$\left(a_i^k \leq a\right) = \exp\left(-a^{-\theta}\right), \qquad k \in \{R, S\}. \tag{5}$$

Then Δ_i is logistic with scale $1/\theta$, and with Λ the logistic function,

$$P_i \equiv (d_i = 1 \mid b_i, w_i) = \Lambda\big(\theta(w_i'\gamma - c + \delta b_i)\big). \tag{6}$$

θ indexes the dispersion of comparative advantage. When θ is low, plots differ widely, and land use responds little to a change in returns. In other words, plot fundamentals are the main determinant of land use. Alternatively, when θ is high, plots are close substitutes and the same change reallocates more land.

As is standard with the Fréchet setup, realized profit $\pi_i = \max\{\pi_i^S, \pi_i^R\}$ has the same distribution whichever use is chosen,

$$(\pi_i \leq x \mid d_i = k) = \exp\Big[-\left(e^{\theta(w_i'\gamma^S - c)} + e^{\theta(w_i'\gamma^R - \delta b_i)}\right) x^{-\theta}\Big], \qquad k \in \{R, S\}, \tag{7}$$

so the dispersion of realized returns identifies θ.

Independence across plots is a substantive assumption. It rules out, for example, a single operator farming several adjoining plots, whose joint conversion the model would read as a cascade. In southern Bangladesh, land markets are fragmented, and it is common for a household operating multiple plots to be unable to rent or purchase them in a contiguous area. This is consistent with our household survey, which documents that farmers are operating plots an average of 153 meters apart as compared to 19 meters apart for true neighbors.

4.4 Interpretation

It is important to note that the model does not require the externality to be salinity. δ captures any channel through which an aquaculture neighbor changes a plot's relative returns, whether negative for rice, such as salinity, waterlogging or disease, or positive for shrimp, such as shared embankments and canals, information, or access to buyers and inputs. Changes in land use derived from the satellite data identify only the

net effect. While this net externality is sufficient to simulate, the split between these channels matters for over- or underadoption and thus the correct policy response. We return to these concerns in Section 7.

The model also does not include time. An equilibrium describes where land use settles given current returns, not the path or speed of adjustment, and plots respond to their neighbors without anticipating future conversions. We justify this modeling approach as follows: Because the focus of our study, and the event study estimates that will be used to estimate the model, are both marginal plots, the plot represented by the model is not in an area where saltwater intrusion is so severe that plots are in aquaculture the entire year. As monsoon rains arrive in June each year, salt levels are reset, and at the beginning of the next dry season, plots must again make the decision of whether to adopt shrimp or rice. As such, year-over-year the decision is reversible; thus, there is no scope for option value of waiting to adopt in the setting or the model. Further, there is no anticipatory action, as supported in this setting, as evidenced by the lack of pre-treatment trends in the event study estimates in Section 6.

Even without pre-treatment trends, we might be concerned about anticipatory action if farmers believe salinity may increase in a future period, and so adapt to avoid the negative effect of climate change directly. While we cannot rule this out explicitly, the year-over-year changes in salinity in this setting account for $\approx 0.5\%$ decreases in rice yields per year (Dasgupta et al., 2015). This is two orders of magnitude less than the yield losses farmers report expecting from rice yields in the year following their neighbor's first adoption of shrimp farming (see Section 5), so we assume decision-making is driven by plot fundamentals and the externality alone. Thus, the model is best interpreted as a medium-run framework, net of climate change: productivity in both uses is held at current levels, so the model does not capture a secular decline in rice returns from rising salinity.

5 Stylized Facts

This section presents brief demographic information about the farmers and plots represented in the household survey. Then it introduces three stylized facts about the shrimp farming industry in Bangladesh.

Key features of the households surveyed are shown in Panel A of Table 1. Recall that respondents are selected from among marginal plot operators (i.e., those who are cultivating rice near other shrimp plots or cultivating shrimp near other rice plots). Both groups are of similar age, sex, and education. They are very concerned about climate change. On the 1–3 scale for climate change concern, almost all respondents

Table 1. Farmer and Plot Demographics

Panel A: Households			
	Shrimp farming	Non shrimp farming	p-value
Age	45.7	47.0	0.151
	(0.6)	(0.7)	
Male	0.970	0.962	0.591
	(0.009)	(0.010)	
Individual income (1,000 taka)	282.5	217.3	0.000***
	(12.5)	(10.2)	
Completed secondary school	0.297	0.258	0.238
	(0.023)	(0.024)	
Muslim	0.670	0.568	0.004***
	(0.024)	(0.027)	
Number of non-homestead plots	2.46	2.02	0.000***
	(0.05)	(0.06)	
Climate change concern (1–3)	1.24	1.21	0.341
	(0.02)	(0.02)	
Panel B: Plots			
	Shrimp pond	Agriculture	p-value
Plot size (decimals)	131.5	69.6	0.000***
	(7.5)	(3.4)	
How acquired			
Bought	0.071	0.091	0.182
	(0.012)	(0.010)	
Rented	0.478	0.384	0.001***
	(0.025)	(0.018)	
Inherited	0.349	0.444	0.000***
	(0.024)	(0.019)	
Year acquired	2012.6	2012.1	0.459
	(0.6)	(0.5)	
Water source			
Rainfed	0.482	0.746	0.000***
	(0.026)	(0.017)	
River	0.367	0.082	0.000***
	(0.026)	(0.011)	
Canal	0.296	0.029	0.000***
	(0.022)	(0.006)	
Pond	0.002	0.023	0.000***
	(0.002)	(0.005)	
Groundwater	0.379	0.716	0.000***
	(0.025)	(0.020)	
Plot count	496	1138	
Household count	394	345	

Notes: Means are reported with standard errors in parentheses. Panel A: robust standard errors; a household is classified as shrimp farming if it has at least one shrimp pond. Climate change concern is coded 1 = very serious threat, 2 = somewhat serious threat, 3 = not a threat at all. Panel B: cultivable/arable plots and shrimp ponds only; standard errors clustered by household. The last column reports the p-value of the difference in means between columns 1 and 2. One decimal equals 1/100 acre. Acquisition categories are not exhaustive (user-right, gifted, government land, and other are omitted), so rows do not sum to one. Water source categories are not mutually exclusive. The household count in Panel B is the number of households with at least one plot of that type. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

in both groups considered climate change a "1 = very serious threat". Respondents engaged in shrimp farming report 30% higher individual income (282.5 thousand Bangladeshi taka annually for shrimp farming households vs 217.3 for non-shrimp farming households). This gap is also reflected in the number of plots operated by each group: shrimp farming households operate 2.46 non-homestead plots relative to non-shrimp farming households' 2.02. Shrimp farming households are 10 percentage points more likely to be Muslim. Conversion to shrimp also appears to be within reach for most households: among those that do not farm shrimp, 72 percent report that they could take out a loan large enough to convert a randomly selected plot to aquaculture, although fewer than a fifth have enough savings to cover the cost themselves, and respondents estimate that conversion would take about three weeks (Appendix Table A3). Panel B shows plot differences across plots that operate as shrimp ponds at any time of the year and those that do not. Shrimp ponds are much larger, averaging 1.32 acres relative to 0.70 acres for agricultural plots. Land allocated to either use is rarely purchased outright (7.1% for shrimp ponds vs 9.1% for agriculture). The two dominant forms of plot acquisition are renting (47.8% for shrimp and 38.4% for agriculture) as well as inheritance (35% for shrimp and 44.4% for agriculture). These plots have been operated by their current owners for, on average, 12 years at the time of the survey in 2025. We also record all of the water sources that farmers report each plot uses throughout the year. Both shrimp farming plots and rice plots operators report highly varied use of water sources. Shrimp ponds are more likely to report using water from rivers and canals, as these can supply saltwater during the dry seasons. Both types of plots report rainwater as a major source. This reflects that shrimp ponds use both freshwater and saltwater sources and freshwater sources to control the level of plot salinity. It is also consistent with mixed-use plots, which are used for saltwater shrimp farming during the dry season and then switch to agriculture during the summer monsoon season when they are rain-fed. For the analysis which follows, we focus on pre-monsoon conditions.

Fact 1: Farmers Expect Neighboring Ponds to Raise Salinity and Lower Their Yields

Figure 3 presents the distributions of two elicited outcomes among rice farmers—perceived water salinity (left panel) and subjective rice health (right panel)—under two scenarios. In scenario one, we ask farmers about the status quo salinity and rice health on their plots: what are the conditions on one of your plots currently used for agriculture? Under scenario two we ask farmers to report the same conditions on that same plot after one of the plots next to it converts to saltwater shrimp farming. The salinity scale runs from 1 (no salt in the water) to 7 (the saltiest water the

respondent has ever encountered). Rice health is an inverted scale where low scores correspond to less salt-affected and thus healthier rice. Respondents are shown images corresponding to progressively poorer plant growth, so 1 denotes the healthiest rice and 7 the least healthy, with higher values reflecting the visible damage associated with greater salinity. The images shown to farmers are drawn from Grattan et al. (2002) and are shown in Appendix Figure B7. The green bars show the scenario one (i.e., status-quo) distribution: for each plot, respondents report their current water access and their current rice condition. The red bars show the distribution under the scenario two hypothetical in which a neighboring plot has converted to saline aquaculture. In both panels, the distribution shifts markedly to the right when a neighboring plot converts—perceived salinity moves from an average of 3.0 to 4.2, and rice health shifts from an average subjective score of 2.2 toward the damaged end of the scale at 4.9. In other words, farmers expect that a neighbor's conversion will both raise the salinity of their own water and worsen the health of their rice.

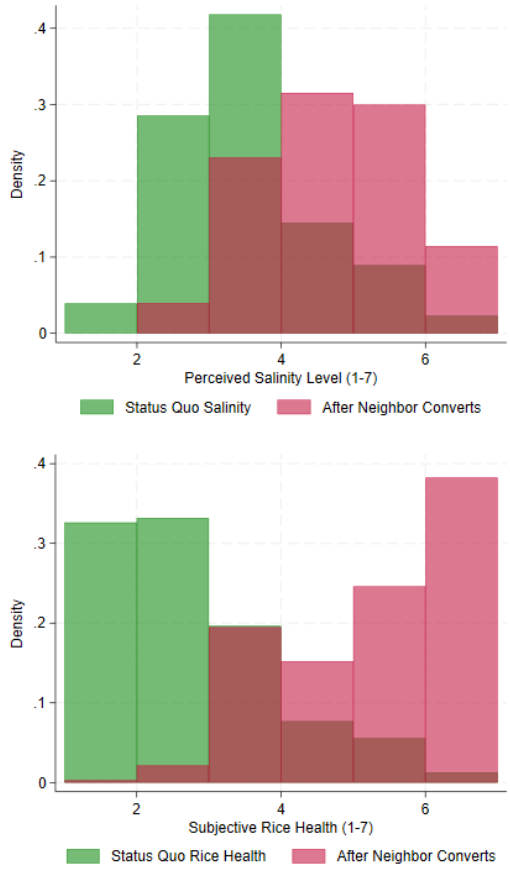


Figure 3. Salinity and Rice Outcomes After Neighbor Conversion

In addition to this qualitative exercise, we ask farmers a hypothetical question in which they are told to consider a plot that is the same size as one of their randomly chosen existing plots that is growing rice and does not border any shrimp farms. When asked whether yields from that plot will change (from a benchmark of 100 kg) in the year following a neighbor's conversion to shrimp farming, they report an expected decrease in yields of 48% (see Appendix Figure B8). This shows that the qualitative results from Figure 3 map onto a large quantitative decrease in expected yields.

This is important for two reasons. First, it shows that farmers' beliefs are consistent with the physical saltwater spillover mechanism: their subjective expectations move in the direction the agronomic evidence on salt transmission would predict (Yu et al., 2024; Braaten and Flaherty, 2001). Second, they link the intermediate channel (rising salinity) to the downstream outcome of falling rice yields. The two responses are internally consistent with a salinity-induced loss of rice productivity. Because hypothetical plot exercise instructed farmers to treat the change of neighbors land use as the only change between scenarios one and two, this is strong evidence that they believe there is a causal effect neighbor shrimp adoption on their own plots conditions.

If farmers are forward looking and anticipate that that a neighbor's conversion will salinize their water and depress their rice yield, they may adjust their own cropping choices—or their own decision to convert to shrimp aquaculture—in response to what they expect their neighbors to do. This sets up a strategic, potentially self-reinforcing dynamic in which conversion decisions are interdependent across neighboring plots, which motivates the analysis of conversion behavior that follows.

Fact 2: Rice Plots Bordering Ponds Are Saltier

Figure 4 reports average soil salinity (green bars, dS/m) alongside a reading taken directly from the saline aquaculture pond (blue bar), pooled across all sample plots and measured in May–June 2025. The four bars are arranged by distance from the saltwater shrimp pond. The leftmost bar is the water reading inside the saltwater aquaculture plot itself, which averages 10.3 dS/m. This is within the target range for shrimp as discussed in Section 2. The two middle bars show the soil salinity boundary readings taken on a plot that borders both a saline aquaculture plot and an agricultural plot: the aquaculture/agriculture boundary (4.3 dS/m) and the agriculture/agriculture boundary (3.9 dS/m). The rightmost bar is taken from an agricultural plot that borders only other agricultural land (3.4 dS/m).

We see in the figure two important gradients. First, there is a steep drop in salinity between the aquaculture reading and the agricultural readings—salinity readings

fall by more than half between the pond and the nearest agricultural reading. Second, among the dry tradings from agricultural plots there is a smaller but consistent declining gradient as one moves further from the saline plot, from 4.3 to 3.9 to 3.4 dS/m.

This pattern is suggestive evidence that local salinity on a farmer's land may be

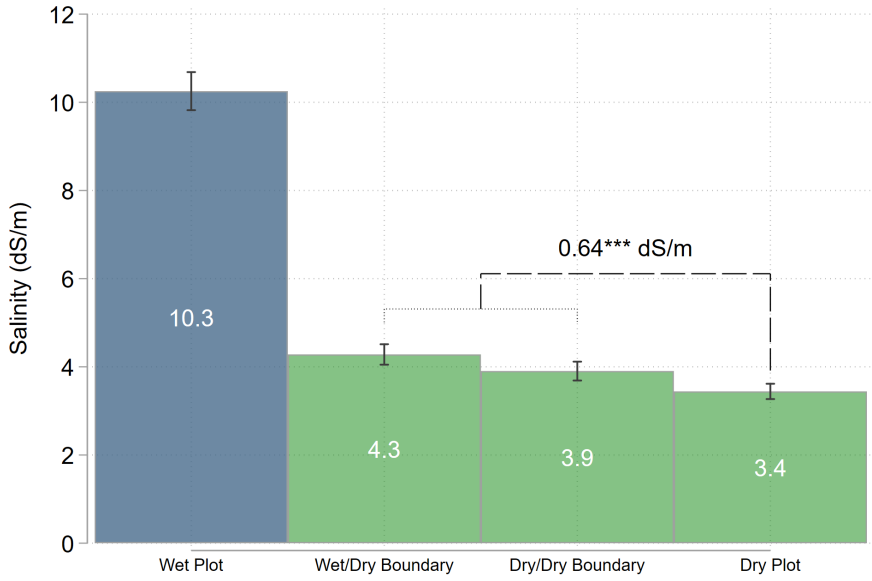


Figure 4. Salinity Readings Across Test Plots

shaped by the land-use decisions of neighboring farmers, rather than by that farmer's own choices alone.

An important caveat is that, like Fact 1, this is cross-sectional evidence. We may worry that the direction of causation is not from land use to salinity but from land use to salinity. For example, selection on a pre-existing, static salinity gradient: if some areas were already saltier, those plots may have been the ones converted to saline aquaculture, leaving the underlying spatial gradient—not the conversion—as the true driver of what we observe. However, both farmer beliefs and the agronomic literature makes lateral transmission of salt between adjacent plots physically plausible. Controlled monitoring and numerical modeling of onshore aquaculture farms document both vertical and lateral saltwater intrusion, showing that salt infiltration at ponds gradually invades neighboring farmland unless physically blocked by a guard wall, though evidence from Bangladesh is mixed (Ayers et al., 2017; Yu et al., 2024). Salt-balance studies of inland shrimp ponds similarly find that lateral seepage through pond walls and direct discharge of saline water into irrigation canals are the most significant salt-transfer pathways, raising salinity in adjacent canals and rice paddies

above yield-damaging thresholds (Braaten and Flaherty, 2001). In this sense, salt can move across plot boundaries much as fertilizer or other soil inputs can spill over between neighboring fields. To distinguish this dynamic, spillover-based account from the static-gradient explanation, we supplement the cross-sectional comparison with the event studies below.

Fact 3: Rice Plots Bordering Ponds Have Lower Yields

If proximity to a saline aquaculture pond raises the salinity of neighboring agricultural land, as Figure 4 suggests, then we should expect elevated salinity to depress the productivity of the affected plots. Figure 5 tests this directly, comparing annual rice yields—measured in kilograms per decimal (one decimal being 1/100 of an acre)—across agricultural plots according to whether they border a shrimp pond. Plots that do not border a pond yield approximately 23.5 kg/decimal, compared with 21.8 kg/decimal for plots sharing a boundary with a pond: a difference of −1.71 kg/decimal, or roughly seven percent, significant at the ten percent level. The salinity gradient documented in Figure 4 thus appears to carry through to agricultural outcomes—plots exposed to a neighboring pond are not only saltier but measurably less productive.

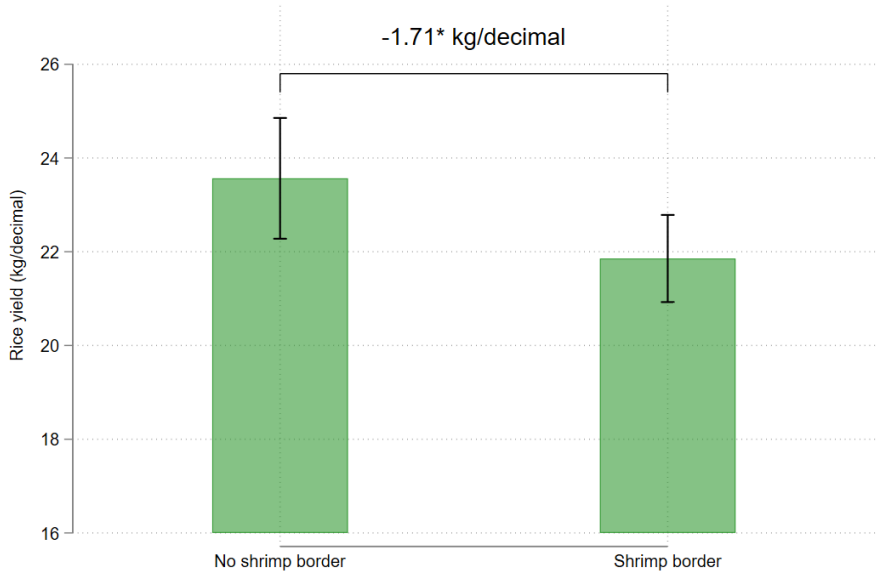


Figure 5. Rice Yields Across the Plot Distribution

As with the salinity readings, this comparison is cross-sectional and does not identify a causal effect. Border and non-border plots may differ systematically for reasons unrelated to the pond—in unobserved soil quality, location, or the characteristics of

the farmers who operate them—and the same selection concern raised for the salinity gradient applies here: if plots that were already lower-yielding were the ones near which aquaculture was established, the yield gap would reflect pre-existing differences rather than the pond's influence. The figure should therefore be read as descriptive corroboration that the salinity spillover has real economic consequences, motivating the panel research design developed below, which uses the timing of neighbors' conversions to isolate the causal effect on land use and productivity.

6 Empirical Strategy & Event Study

We estimate whether a plot's conversion to shrimp aquaculture (hereafter a *pond*) induces its neighbors to convert. The central challenge is that adoption is spatially clustered for reasons unrelated to peer influence—soil salinity, water access, and proximity to processing infrastructure vary smoothly across space and jointly determine the profitability of aquaculture for neighboring plots. A naive comparison of conversion rates between plots with and without pond neighbors would conflate genuine contagion with these shared locational fundamentals. Our strategy exploits the *timing* of neighbors' conversions within a difference-in-differences design, comparing a plot's own adoption trajectory before and after a neighbor converts with that of plots in the same small neighborhood whose neighbors have not converted.

The unit of observation is a delineated plot i observed in Rabi (dry) season t, for $t = 2017, \ldots, 2025$. Let $Y_{it} = 1$ if plot i is classified as a pond in period t and 0 otherwise. Each plot's treatment date E_i is the first period in which any plot sharing a boundary with i is classified as a pond. We estimate the event-study model:

$$Y_{it} = \alpha_i + \lambda_{h(i)t} + \sum_{k \neq -1} \beta_k \, D_{it}^k + X_i' \eta_t + \varepsilon_{it}, \tag{8}$$

where D_{it}^k indicates that plot i is k periods from the first period in which a neighbor is a pond, α_i are plot fixed effects, and $\lambda_{h(i)t}$ are hexagon-by-period fixed effects for the hexagon $h(i)$ containing plot i. The hexagons form a regular grid over the study area, sized so that each contains on average 20 plots of the estimation sample, which gives hexagons 1.03 km across; hexagons containing a single plot are dropped. X_i contains log distance to the nearest river and log plot area, each interacted with period so that their effects can vary over time. The period $k = -1$ is omitted as the reference, so each β_k measures the change in the probability that i is a pond at event time k relative to the period immediately preceding a neighbor's conversion. Extreme leads and lags are binned at ± 5 years, so that the endpoint coefficients are not identified off a single treatment cohort.

The plot fixed effects α_i absorb all time-invariant determinants of aquaculture suitability—soil type, elevation, baseline salinity, distance to water channels, and unobserved operator characteristics—so that identification comes entirely from within-plot changes over time. The hexagon-by-period fixed effects $\lambda_{h(i)t}$ absorb any shock common to a neighborhood of about 1 km in a given year, such as an advancing salinity front, local waterlogging, or shifts in local shrimp prices, as well as region-wide movements in prices and aggregate weather. Identification therefore comes only from differences in the timing of neighbors' conversions among plots in the same hexagon and year. The period interactions $X_i'\eta_t$ allow plots nearer rivers and larger plots to follow different trends. Because Y_{it} is binary, (8) is a linear probability model and the β_k are interpreted in percentage-point units.

A well-defined event study requires that treatment onset be observable within the panel. We therefore restrict the estimation sample in two ways. First, we exclude plots with no delineated neighbors, as neighbor exposure is undefined for them. Second, we drop plots that already border a pond in the first period of the panel. These plots are always-exposed: their treatment date is left-censored, and no clean pre-period exists against which to measure the effect of a neighbor's conversion. The retained sample consists of plots that begin the panel with no pond neighbor, for which the first appearance of a pond neighbor is an observed transition rather than a pre-existing state. The estimand is accordingly local to the expansion frontier—plots at the margin of the aquaculture landscape—and does not describe the already-saturated core.

Because treatment timing is staggered and treatment effects may be heterogeneous across adoption cohorts, the two-way fixed-effects estimator of the β_k can be contaminated by comparisons in which already-treated plots serve as effective controls for later-treated plots; with dynamic effects, these comparisons enter the estimate with potentially negative weights (Goodman-Bacon, 2021; de Chaisemartin and D'Haultfœuille, 2020). We therefore report the interaction-weighted estimator of Sun and Abraham (2021), which estimates a separate coefficient for each adoption cohort and event time and aggregates them using each cohort's share of observations at that event time, so that all weights are non-negative. Never-treated plots—those whose neighbors never convert during the panel—form the control group. Because both land use and its unobserved determinants are spatially correlated, we compute standard errors following Conley (1999), allowing for correlation across plots within 2 km of each other in the same period, with weights declining linearly in distance, and for arbitrary correlation within a plot across periods.

6.1 Identifying Assumption

The identifying assumption is parallel trends: absent a neighbor's conversion, treated plots would have followed the same own-adoption path as control plots. This is not directly testable, but its plausibility is assessed through the pre-treatment coefficients $\{\beta_k\}_{k<-1}$, which should be jointly indistinguishable from zero if treated and control plots were on common trajectories before treatment. The salient threat is a plot-specific, time-varying shock that drives both a neighbor's conversion and the plot's own—most plausibly a localized intrusion of saline water that renders a cluster of contiguous plots newly suitable for aquaculture in the same period. Such a shock would generate the appearance of contagion absent any causal peer effect. Time-invariant salinity differences are absorbed by α_i and region-wide salinity trends by $_{h(i)t}$; only *local, time-varying* salinity movements pose a threat.

6.2 Extensive Margin Effects

Figure 6 presents the event-study estimates for the probability that a plot is classified as a pond. Following a neighbor's conversion, a plot's own probability of being a pond rises sharply and immediately, by 18.0 percentage points in the period following conversion. The effect persists across all subsequent periods, ranging between 0.14 and 0.22 over the following five years, and shows no evidence of decay. Own-conversion thus appears to be a durable rather than transitory response: once a neighbor converts, the elevated likelihood of the plot itself becoming a pond is sustained rather than fading over time. The pre-treatment coefficients are small but show a slight downward trend: relative to the year before a neighbor's conversion, treated plots were about 2.5 percentage points more likely to be classified as ponds four and five years earlier, declining to zero by two years before treatment. We cannot reject that the pre-treatment coefficients are jointly zero at the 5 percent level ($\chi^2(4) = 9.06$, $p = 0.06$). This trend runs opposite to the post-treatment effect, so extrapolating it would, if anything, increase our estimate. The pre-trend does not reflect plots that were already ponds before their neighbor converted: excluding the 6.4 percent of treated plots that were ponds at baseline leaves the pre-treatment coefficients essentially unchanged ($p = 0.07$) and slightly raises the estimated effect, to 19.3 percentage points (SE 1.1).

The effect emerges at event time zero—in the same period as the neighbor's conversion—rather than building gradually over subsequent years. This timing is informative about the mechanism. A gradual, increasing response would be consistent with social learning, in which a farmer observes a neighbor's outcomes over several seasons before updating and eventually converting. The immediate response

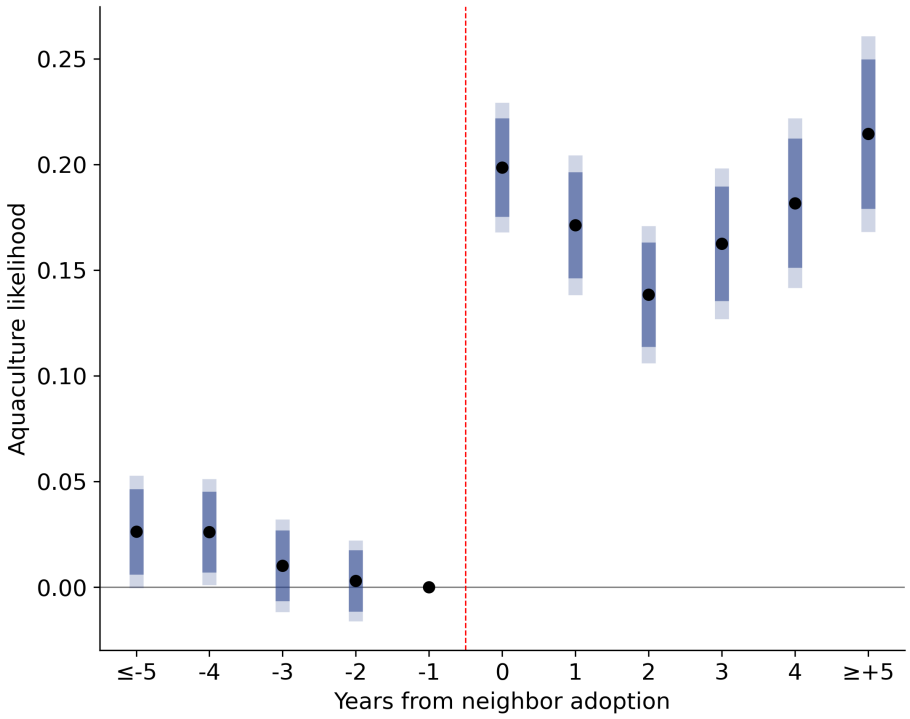


Figure 6. Aquaculture Event Study

Notes: The figure plots Sun and Abraham (2021) event-study estimates of own aquaculture status against years since a plot's first adjacent neighbor became a pond, for plots with no adjacent pond at baseline. The specification includes plot and hexagon × year fixed effects and river-distance × year and plot-size × year controls, and shaded bands show 95% (dark) and 99% (light) confidence intervals using Conley standard errors with a 2 km cutoff.

we observe instead suggests that the second farmer acts concurrently with, or very shortly after, the neighbor's conversion. Such timing is consistent with an anticipatory mechanism: if farmers believe that an adjacent pond will depress their own yields—for instance, through saline intrusion—the optimal response is to convert immediately rather than to wait and learn, since remaining in agriculture beside a pond becomes less viable as soon as the neighbor converts.

6.3 Effects on Neighboring Rice Greenness

Figure 7 presents the event-study estimates with Normalized Difference Vegetation Index (NDVI) NDVI—a satellite proxy for vegetative greenness, and hence crop productivity—as the outcome. This specification is estimated only on the sample of plots that had no pond neighbor at baseline and that never themselves convert to a pond at any point in the panel, so that NDVI always reflects standing agriculture rather than the greenness of open water. Following a neighbor's conversion, green-

ness falls sharply and immediately: the effect is −0.019 at the time of conversion, indicating a contemporaneous decline in crop productivity. The effect then attenuates steadily over the following years, converging back toward zero by year five. The pre-treatment coefficients are flat and indistinguishable from zero, consistent with parallel trends. As with the extensive-margin result, the decline appears at event time zero rather than emerging gradually, indicating that the productivity cost of an adjacent pond—plausibly through saline intrusion—is felt immediately rather than accumulating slowly. The subsequent recovery toward baseline suggests that farmers who remain in rice may, over time, adopt mitigating practices that partially restore greenness to its pre-conversion level.

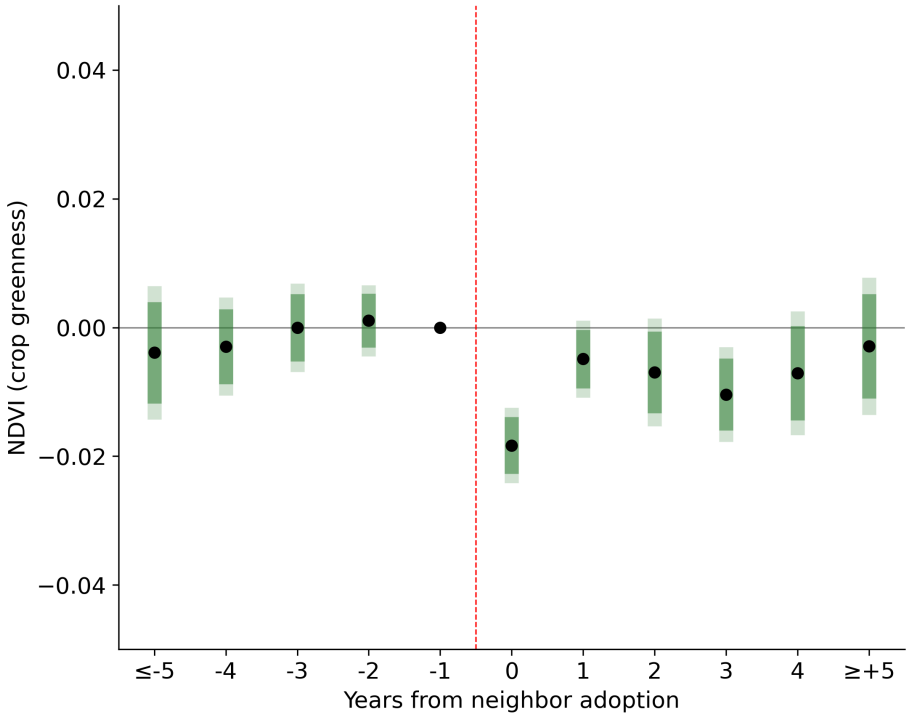


Figure 7. Vegetation Index Event Study

Notes: The figure plots Sun and Abraham (2021) event-study estimates of Rabi-season NDVI against years since a plot's first adjacent neighbor became a pond, for plots that are never classified as aquaculture and have no adjacent pond at baseline. The specification includes plot and hexagon × year fixed effects and river-distance × year and plot-size × year controls, and shaded bands show 95% (dark) and 99% (light) confidence intervals using Conley standard errors with a 2 km cutoff.

Two features of the sample warrant caution in interpreting these magnitudes. Because the estimation is restricted to plots that never convert, the sample is not representative of all plots initially exposed to a converting neighbor: precisely those plots that experience the largest productivity losses may be the ones most likely to

abandon rice and convert to shrimp themselves, thereby exiting the sample. Conditioning on non-conversion therefore selects on an outcome that is itself affected by treatment, and it does so in a direction that biases the estimated harm toward zero—the worst-affected plots are absent. The coefficients reported here should thus be read as a conservative lower bound on the true productivity cost of a neighboring pond, capturing the effect among the subset of farmers who chose to remain in agriculture despite it.

6.4 Robustness

6.4.1 Distance Rings

To examine how the effect of a neighboring conversion decays with distance, we re-estimate the event study separately for four distance rings: plots that share a boundary with the new pond, plots within 50 meters that do not share a boundary, plots between 50 and 200 meters away, and plots between 200 and 500 meters away. Distances are measured edge to edge. In each specification, treatment is the first year a pond appears in that ring, and plot-years are censored once a closer ring is exposed, so that each estimate isolates the effect of ponds at that distance. Appendix Figure B9 reports the results. The effect is concentrated entirely among plots that share a boundary with the new pond, for which the probability of conversion rises by 18.0 percentage points on average over the post-period (SE 1.1). Beyond the shared boundary, we find no meaningful spillover. The average post-period effects are -0.2 percentage points for non-adjacent plots within 50 meters (SE 0.5), -0.2 percentage points between 50 and 200 meters (SE 0.2), and -0.6 percentage points between 200 and 500 meters (SE 0.2). All three estimates are small, and their confidence intervals rule out effects larger than about one percentage point in either direction. The absence of an effect on nearby but non-adjacent plots is consistent with a spillover that operates only between immediate neighbors, as would be expected if saline water spreads primarily through seepage across shared boundaries.

6.4.2 Instrumental Variables

A remaining concern is that a plot and its neighbors convert together because of a common shock rather than because of the neighbor's conversion. Following Bramoullé et al. (2009), we instrument a plot's exposure to an adjacent pond with the share of its second-degree neighbors (neighbors of its neighbors that do not border it directly) that were ponds in the previous year. A second-degree neighbor's pond raises the chance that a plot's direct neighbor converts, but should not affect the plot itself except through that neighbor. The distance-ring results support this exclusion restriction:

ponds on nearby but non-adjacent plots have no detectable effect on a plot's own conversion. The instrument is strong (first-stage $F = 66$), and the 2SLS estimate of the effect of exposure is 54.0 percentage points (SE 11.3), larger than the event-study estimate of 18.0 percentage points (Appendix Figure B10). The two estimates are not directly comparable, since the 2SLS specification uses a static exposure indicator and identifies the effect for plots whose exposure is shifted by conversions two plots away. But the IV estimate gives no indication that common shocks inflate the event-study result.

6.5 Alternative Mechanisms

Our interpretation is that a neighbor's pond contaminates adjacent land with saline water, lowering the expected returns to rice and inducing conversion. We consider two alternative explanations for the conversion response.

6.5.1 Shared Ownership

If adjacent plots belong to the same operator, an apparent neighbor effect could instead reflect a single decision applied across several of the operator's own fields. This is unlikely in our setting. Among surveyed shrimp farmers who cultivate more than one plot, the average distance between their own plots is 153 meters, compared with 19 meters between a plot and its neighbors. This is consistent with the fragmented land markets documented in southwestern Bangladesh (Haque, 2025), in which a single household's holdings are typically scattered rather than contiguous. Moreover, shared ownership would predict conversions concentrated in the same period as the neighbor's conversion, whereas the effects in our event study persist and remain large in the years after the neighboring pond appears.

6.5.2 Information Spillovers Between Plot Owners

Farmers may also learn about the profitability of shrimp from neighbors who have converted and follow them. Such learning likely plays some role: 18.2% of converters report that someone in their village recommended shrimp farming, compared with 1.5% who cite advice from an NGO or the government (Appendix Table A4). However, three features of our results suggest that learning does not drive the effects we estimate. First, the effect appears immediately, in the year of the neighbor's conversion, before a neighbor's returns could be observed. Learning from a neighbor's experience would instead produce a response that builds over subsequent seasons. Second, farmers' discussion networks extend well beyond their immediate neighbors: only about half of the people they most often discuss farming with farm plots that

border their own. Comparing contacts named by the same respondent, farmers are no more likely to discuss shrimp farming with bordering contacts than with others, although they talk with them slightly more often (Appendix Table A5). Learning, whether through conversation or from observing a neighbor's decision, would therefore be expected to extend beyond shared boundaries, to ponds that farmers can see and discuss just as easily. Instead, the effect we estimate is concentrated among plots that share a boundary with the new pond and is absent for non-adjacent ponds less than 50 meters away (Appendix Figure B9), as a physical spillover would predict. Third, adopters do not appear to hold more optimistic beliefs about returns, as they would if conversion spread through information about profitability: at the time of the survey, shrimp-farming households expect rice and shrimp prices similar to those of non-shrimp households (Appendix Figure B11).

6.6 Heterogeneity

The effect of a neighbor's conversion varies with a plot's characteristics in ways that bear on both the model and the mechanism. We re-estimate the main specification separately for plots above and below the median distance to the nearest river and above and below the median plot area in the estimation sample. To test whether the effects differ between groups, we compute standard errors for the difference that allow for spatial correlation between plots in different groups, since plots in each pair of groups sit side by side.

Distance to rivers. The response to a neighbor's conversion is larger among plots close to a river. Splitting the sample at the median distance to the nearest river (1,140 meters), a neighbor's conversion raises the probability that a plot is a pond by 19.3 percentage points (SE 1.5) among plots near a river and by 14.7 percentage points (SE 1.4) among plots farther away (Appendix Figure B12). The difference of 4.7 percentage points is statistically significant at the 5 percent level (SE 2.0, $p = 0.019$). This pattern is consistent with the model. Proximity to a river lowers the cost of bringing saline water onto a plot, placing nearby plots closer to the margin between rice and aquaculture, where a given shift in relative returns reallocates more land. It is also consistent with the salinity channel: soil and groundwater near tidal rivers may be saltier at baseline, so rice on these plots is closer to the threshold beyond which yields decline (Maas and Hoffman, 1977), and additional seepage from a neighboring pond is correspondingly more damaging. One caveat is that plots far from rivers show positive pre-period coefficients. Thus, part of their response may reflect a return to aquaculture on land previously used for shrimp rather than first-time adoption.

Plot size. Smaller plots respond somewhat more strongly than larger ones. Splitting at the median plot area (3,273 m^2), the post-period effect is 19.6 percentage points (SE 1.5) for smaller plots and 17.1 percentage points (SE 1.2) for larger plots (Appendix Figure B13). The difference of 2.5 percentage points is marginally significant (SE 1.5, $p = 0.097$). Its direction is informative because the model predicts the opposite: in the survey land-use logit, larger plots are more suited to aquaculture, which places them closer to the margin where a given shift in relative returns moves more land. A boundary externality offers a natural explanation for the reversal. Because a plot's perimeter grows less than proportionally with its area, seepage across a shared border affects a larger fraction of a small plot than of a large one. The same geometry explains why larger plots are about twice as likely to be exposed during the panel (3,875 against 1,950 treated plots): a longer boundary has more neighbors that might convert. The model's δ is common to all plots and abstracts from this geometry, which would instead predict that the effect rises with the share of a plot's perimeter that borders the converting neighbor.

7 Estimation and Counterfactuals

7.1 Estimation

The model in Section 4 is characterized by four sets of parameters, which we estimate by combining the household survey with the satellite panel. Table 2 summarizes the source of identification for each.

The dispersion parameter θ governs how heterogeneous plots are in their comparative advantage between rice and shrimp. Because productivity draws are Fréchet, θ is identified from the dispersion of log output value across surveyed plots. The slopes of the relative suitability index, γ, capture how plot size and distance to the river shift the relative returns to shrimp, and are estimated from a land-use logit on the survey sample. The survey cannot identify the level of γ, because marginal sampling selected plots on both sides of the rice–shrimp boundary and so excluded unexposed ponds. We therefore anchor the intercept to the satellite population. We choose it so that, in the simulated equilibrium, the share of plots without a pond neighbor that are in aquaculture matches the 2.9 percent observed in the satellite panel.[12] Because fundamentals-driven ponds tend to induce their neighbors to convert, this observed share understates the rate implied by fundamentals alone, which the calibration puts at 5.4 percent. The intercept absorbs the conversion cost c. Finally, we recover

[12]The 2.9 percent target is the share of plot-years classified as aquaculture among plots that have at least one delineated neighbor but no neighbor classified as aquaculture in that year, pooled over 2017–2025 across the 51 study unions.

δ, the net effect of a pond neighbor on the relative return to shrimp, by matching the model's implied change in conversion probability to the event-study estimate in Section 6 ($\Delta P = 0.180$). We estimate $\theta = 1.95$ and $\delta = 0.91$.

An important feature of δ, as discussed above, is that it is a net effect. A pond neighbor may lower the return to rice through salinity damage, raise the return to shrimp through shared access to saline water and infrastructure, or both. Land-use choices depend only on the difference, so choice data alone cannot decompose δ into these components. As we show below, the decomposition does not matter for the positive predictions of the model, but it determines the sign of the optimal policy.

Table 2. Model Parameters and Sources of Identification

Parameter	**Estimated from**	**What it captures**
θ	Survey: spread of log output	Dispersion of comparative advantage
γ (slopes)	Survey: land-use logit	How plot size and distance to the river shift relative suitability
γ (level)	Satellite: share of plots without a pond neighbor in aquaculture (2.9%), matched in the simulated equilibrium	Baseline adoption; absorbs the conversion cost c
δ	Satellite panel: event-study ΔP	Net effect of a pond neighbor

7.2 Exercise 1: How Much Aquaculture Is Driven by the Cascade?

We first use the estimated model to quantify how much aquaculture is driven by the externality rather than by fundamentals. We simulate a stylized landscape of plots on a grid, draw productivities from the estimated distribution, and solve for the equilibrium allocation by iterating plots' best responses to their neighbors' land use, starting from the allocation implied by fundamentals alone. Because the externality only lowers the threshold for conversion, every plot that converts on fundamentals converts in any equilibrium, so this procedure selects the equilibrium with the least aquaculture. This is also the allocation reached when land use starts in rice and plots respond to their neighbors' choices season by season.

Figure 8 simulates land use on a stylized 60×60 grid of plots, each with four neighbors and with plot size and distance to the river drawn from the observed distributions. Each plot draws its productivity in rice and shrimp from the estimated

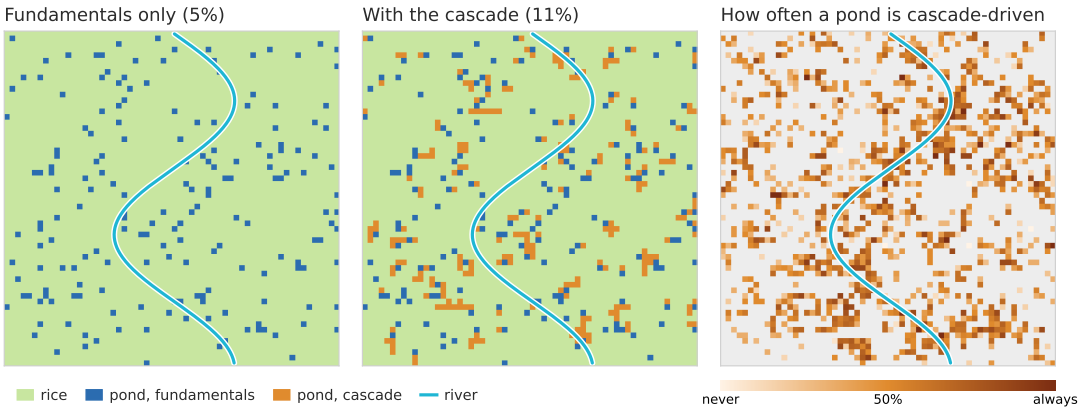


Figure 8. Shrimp Cascade on a Stylized Economy

Fréchet distribution, with dispersion θ and covariate effects γ estimated from the survey, and the level set so that, in the simulated equilibrium, the share of plots without a pond neighbor that are ponds matches the 2.9 percent observed in the satellite panel. The left panel shows the allocation if every plot chose on fundamentals alone, ignoring its neighbors: 5.4% of plots become ponds. The middle panel adds the spillover: a converted neighbor shifts a plot's relative return to shrimp by δ, calibrated so the model reproduces the event-study effect of a neighbor's conversion, and choices are iterated to a fixed point. Aquaculture rises to 11.4%, and the orange plots are ponds that exist only because a neighbor converted first; they grow outward from the fundamentals-driven ponds in blue. The simulated landscape is not intended to reproduce the overall level of aquaculture in our study area, where roughly half of delineated plots are classified as ponds. Each component of the calibration is drawn from the margin of the aquaculture landscape: the dispersion of comparative advantage and the effects of plot characteristics are estimated from survey plots sampled at the boundary between rice and shrimp, the externality is estimated from plots with no pond neighbor at baseline, and the intercept matches the share of aquaculture among plots without a pond neighbor. The simulation therefore describes land at the expansion frontier rather than the saturated core, and the cascade share should be read as describing how adoption spreads at that margin. The right panel repeats the exercise over 40 productivity draws and shows, for each plot, how often it is cascade-driven when it is a pond (grey plots are ponds in fewer than 15% of draws). The exercise separates aquaculture that farmers would choose on their own land's merits from aquaculture that spreads through the externality, and shows that the cascade roughly doubles conversion, with 51.5% of all ponds owing their existence to a neighbor.

7.3 Exercise 2: Optimal Policy

We next ask how a planner maximizing aggregate farm profit would intervene. The answer depends on a decomposition that land-use choices cannot reveal. The net effect of a pond neighbor combines two components,

$$\delta = \delta_R + \delta_S, \tag{9}$$

where δ_R is the damage that a neighboring pond imposes on rice and δ_S is the benefit it confers on a neighboring pond. Both components push an exposed plot toward aquaculture, so they are observationally equivalent in choice data, but they have opposite welfare implications. Damage to rice is a negative externality that calls for a tax on conversion, while a benefit to neighboring ponds is a positive externality that calls for a subsidy. The optimal policy is a tax when rice damage accounts for a large enough share of δ. In our calibration, this threshold corresponds to a rice yield loss of about 7% from a pond neighbor. At the other extreme, attributing all of δ to rice damage would imply a 60% yield loss.

We discipline the decomposition with two independent sources of evidence, which fall on opposite sides of the threshold. Taken at face value, our satellite estimate implies a rice loss of about 3 percent, below the threshold of about 7 percent at which a tax becomes optimal. Relying on the satellite data alone would therefore attribute most of δ to benefits for neighboring ponds and call for a subsidy. We view this estimate as a lower bound on the true damage, for two reasons: NDVI measures greenness rather than grain yield, and the estimate is obtained only from plots that do not convert, which are likely those least affected. Whether the true damage exceeds the threshold, however, is not something the satellite data or land-use choices alone can reveal. Farmers' own assessments resolve this. Farmers expect a neighbor's conversion to reduce their rice yields by 48 percent, which places the economy well inside the tax region. Taking these beliefs as expert knowledge of local conditions, the optimal tax reduces the aquaculture share from 11.4 percent to 0.1 percent and raises aggregate farm profit by about 11 percent, recovering 96 percent of the gain available to an unconstrained planner.

We view the satellite estimate as a lower bound on the true damage for two reasons. First, NDVI measures greenness rather than yield, and salinity may reduce grain yield more than vegetative growth. Second, the estimate is obtained from plots that do not convert, which are likely those least affected. The divergence between the two sources nonetheless shows that the welfare case for intervention, and even its sign, rests on the magnitude of damage to rice, which choice data alone cannot reveal.

8 Conclusion

This paper has shown that the very act of adaptation to climate change may exacerbate the damages from climate change for those who fail to adopt adaptation technology as well. In southwestern Bangladesh, we find that farmers who convert their rice plots into inland saltwater shrimp farms in turn cause a negative production externality on nearby rice farmers who fail to adopt shrimp farming themselves. We document that rice farms neighboring shrimp farms have both (i) higher levels of salinity and (ii) lower rice yields per area than plots that are further away. Furthermore, in a hypothetical plot exercise, farmers report that they believe that rice yields will fall by a large margin – 48 percent – when one of their neighbors first adopts saltwater shrimp farming relative to a scenario where they are surrounded by other rice farms. This cross-sectional evidence supports a testable theory that farmers will thus make cropping decisions (i.e., rice vs shrimp) taking into account the cropping decisions of their neighbors.

We study this using a novel satellite-derived panel dataset of plots, which we use to show that a single plot's adoption of shrimp farming raises the likelihood of shrimp farming in neighboring plots by 18.0 percentage points, an effect which is immediate, persistent, and concentrated among plots that share a direct border with the original converters. This is accompanied by a decrease in rice greenness in the plots that fail to adopt. We estimate a model of land use incorporating this boundary externality to show that there is a climate adaptation cascade. We simulate plot use decisions using the model and show that 51.5 percent of shrimp ponds that exist in the resulting equilibrium would remain in rice were the externality shut down. Whether this cascade is a problem depends on whether the effect of shrimp farming on neighbors adoption probability is due to the negative externality on rice that we document in the cross section, or some positive externality to shrimp farming such as information spillovers between farms or shared inputs like pumps or canals. If the damage is as large as farmers believe, then too much land converts to shrimp,

These findings carry policy implications. Our results show that the conversion of new land to shrimp is not welfare improving because it does not raise profits for the new adopters enough to offset the damages to those who fail to adopt. Thus, the current export subsidy for shrimp in Bangladesh of 8 percent is in the wrong direction. A tax on conversion of new land in our model would raise aggregate farm profits by 11 percent. These findings extend to other settings where adaptation to climate change will be decentralized, that is, carried out by households or firms that may create their own local negative externalities in response to the global negative externality of climate change. In these settings, evaluating adaptation by the gains

to adopters alone will overstate its benefits, and the spread of a technology will be a poor guide to its social value.

This paper points towards new avenues for research. To fully capture the winners and losers of climate adaptation via shrimp farming in this setting, it would be worthwhile to study who bears the cost of the farming beyond operators. Shrimp farming is less labor-intensive than rice farming, which leaves scope for landless workers with weak outside options to face employment reduction even when profits increase. Another valuable avenue of research would be to examine why bargaining to internalize the externality does not take place. These reasons may include fragmented land, high tenancy rates, or weak water governance, which are beyond the scope of this paper, but could inform a richer set of policy responses beyond the decision to subsidize or tax.

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A Appendix 1 - Additional Tables

Appendix Table A1. Delineation Coverage by Union

Union	Upazila	Area (km^2)	Area covered (km^2)	Share covered (%)	Plots
Anulia	Assasuni	28.82	10.54	36.6	1,202
Assasuni	Assasuni	34.86	13.64	39.1	1,528
Baradal	Assasuni	36.15	21.16	58.5	2,786
Budhhata	Assasuni	33.69	9.47	28.1	1,461
Durgapur	Assasuni	24.24	11.47	47.3	1,712
Kadakati	Assasuni	28.24	17.99	63.7	2,869
Khajra	Assasuni	37.29	18.80	50.4	1,934
Kulla	Assasuni	32.61	8.41	25.8	1,121
Sreeula	Assasuni	43.66	28.54	65.4	3,892
Atlia	Dumuria	42.01	13.52	32.2	1,506
Dumuria	Dumuria	18.68	1.34	7.2	238
Kharnia	Dumuria	21.21	2.21	10.4	509
Maguraghona	Dumuria	21.18	4.51	21.3	834
Magurkhali	Dumuria	41.66	22.75	54.6	3,359
Raghunathpur	Dumuria	34.88	12.45	35.7	1,852
Rudaghara	Dumuria	28.66	9.50	33.1	1,736
Sahas	Dumuria	25.07	7.90	31.5	1,406
Sobhana	Dumuria	45.45	7.48	16.5	918
Champaphul	Kaliganj	29.87	15.69	52.5	1,912
Krishnanagar	Kaliganj	26.22	10.10	38.5	1,800
Bidyanandakati	Keshabpur	32.76	5.69	17.4	1,051
Gaurighona	Keshabpur	25.82	4.83	18.7	1,070
Majidpur	Keshabpur	24.39	3.03	12.4	746
Mangalkot	Keshabpur	23.91	3.00	12.6	455
Sagardari	Keshabpur	28.79	3.71	12.9	1,068
Amadi	Koyra	41.87	19.95	47.6	2,744
Bagali	Koyra	48.32	23.05	47.7	2,157
Maheshwaripur	Koyra	52.03	14.35	27.6	771
Chandkhali	Paikgachha	45.67	23.52	51.5	3,657
Deluti	Paikgachha	46.09	24.72	53.6	1,433
Gadaipur	Paikgachha	20.39	8.95	43.9	860
Garuikhali	Paikgachha	42.86	28.10	65.6	1,352
Haridhali	Paikgachha	19.74	3.28	16.6	508
Kapilmuni	Paikgachha	38.01	16.92	44.5	2,233
Laskar	Paikgachha	42.16	24.92	59.1	2,516
Lata	Paikgachha	48.24	24.67	51.1	2,004
Paikgachha Paurashava	Paikgachha	4.81	0.73	15.2	56
Raruli	Paikgachha	25.36	7.74	30.5	922
Sholadana	Paikgachha	49.32	27.75	56.3	1,867
Dhulihar	Satkhira Sadar	37.95	16.68	43.9	2,078
Kashimari	Shyamnagar	34.40	16.38	47.6	1,378
Islamkati	Tala	22.18	3.38	15.2	819
Jalalpur	Tala	24.18	3.39	14.0	640
Khalilnagar	Tala	32.55	9.24	28.4	1,799
Khalishkhali	Tala	37.98	13.45	35.4	1,773
Khesra	Tala	48.02	10.83	22.6	1,066
Kumira	Tala	19.42	2.94	15.1	858
Magura	Tala	26.10	3.36	12.9	926
Sarulia	Tala	27.17	5.18	19.1	1,420
Tala	Tala	24.77	4.05	16.4	794
Tentulia	Tala	26.09	4.90	18.8	786
Total		1,655.82	610.15	36.8	76,382

Notes: The table reports the area of each union falling inside a delineated plot, and the share of the union covered. Union boundaries are from the Bangladesh Bureau of Statistics administrative boundaries. Plots are delineated from basemap imagery using Delineate Anything model described in Appendix C. Covered area is computed by clipping plots to union boundaries and merging overlapping polygons, so no land is counted twice. Plots are assigned to unions by the location of their centroid. The largest 1% of plots are included in this table, but excluded prior to analysis.

Appendix Table A2. Satellite Classification against Survey-Reported Land Use

Panel A: Matched sample	
Surveyed households	739
With main-plot GPS coordinates	415
Main plot inside a delineated polygon	127
Survey: rice	87
Survey: shrimp pond	40

Panel B: Classification errors, Rabi 2024	Year-specific threshold (Otsu)	Fixed threshold (MNDWI > .241)
False-positive rate	0.851	0.667
False-negative rate	0.175	0.325
Balanced error rate	0.513	0.496

Note: Panel A reports the number of surveyed households, those with GPS coordinates for their main plot, and those whose coordinates fall inside a delineated polygon, by survey-reported land use. Panel B reports classification errors in Rabi 2024 (November 2024 to February 2025), the dry season immediately before the survey. The false-positive rate is the share of survey-reported rice plots classified as aquaculture; the false-negative rate is the share of survey-reported shrimp ponds classified as agriculture; the balanced error rate is their average. The fixed threshold was chosen to minimize the balanced error rate. Plot coordinates were recorded at the location of each salinity reading, which by protocol lies at a plot boundary, often at the edge of a shrimp pond.

Appendix Table A3. Credit, Savings and Time Needed to Convert

Panel A: Converting to shrimp			
	Shrimp farming	Non shrimp farming	p-value
Could take out a loan	0.786	0.716	0.032**
	(0.022)	(0.024)	
Enough savings to cover cost	0.185	0.171	0.626
	(0.021)	(0.020)	
Time to convert (weeks)	3.2	2.6	0.001***
	(0.1)	(0.1)	
Panel B: Converting to agriculture			
Could take out a loan	0.789	0.791	0.955
	(0.021)	(0.029)	
Enough savings to cover cost	0.216	0.291	0.054*
	(0.021)	(0.033)	
Time to convert (weeks)	3.6	2.4	0.000***
	(0.2)	(0.2)	
Household count	394	345	

Notes: Means are reported with robust standard errors in parentheses. Respondents were asked about converting a randomly selected plot to aquaculture (Panel A) and to agriculture (Panel B). Loan and savings rows are shares answering yes. Time is the respondent's estimate of the number of weeks conversion would take; don't-know and refused answers are excluded. A household is classified as shrimp farming if at least one of its plots is a shrimp pond, and as non-shrimp farming otherwise. Households that skipped a panel's questions are excluded from that panel, so the number of respondents varies across panels. The last column reports the p-value of the difference in means between columns 1 and 2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A4. Reasons for Shrimp Farming

	Respondents	Share (%)	Sole reason (%)
Profits are better in shrimp farming	263	79.9	39.8
Rice yields went down	123	37.4	10.0
Someone in the village recommended it	60	18.2	4.3
NGO or government advised it	5	1.5	0.0
Other	40	12.2	3.3
Shrimp-farming households	394		
Answered why they converted	329		
Gave more than one reason	140	42.6	

Notes: The table shows respondents answers to the question of why they first adopted shrimp farming. Multiple answers are permitted.

Appendix Table A5. Farming Discussion Contacts

	Contact's plots		Difference	
	Border	Do not border	All contacts	Within respondent
Share of contacts with whom respondent discusses:				
Shrimp farming	0.584	0.632	-0.048**	0.002
			(0.022)	(0.014)
Salinity	0.280	0.245	0.035*	0.019
			(0.019)	(0.016)
Irrigation	0.418	0.383	0.035	0.025*
			(0.022)	(0.015)
Seed types	0.810	0.763	0.047***	0.013
			(0.018)	(0.015)
Fertilizer	0.701	0.685	0.016	0.027
			(0.021)	(0.017)
How often they talk:				
Talk at least weekly	0.933	0.899	0.034***	0.038***
			(0.012)	(0.013)
Frequency (1–5)	4.45	4.31	0.141***	0.151***
			(0.027)	(0.029)
Contacts	3027 (51.7% border the respondent's plots)			
Respondents	696			

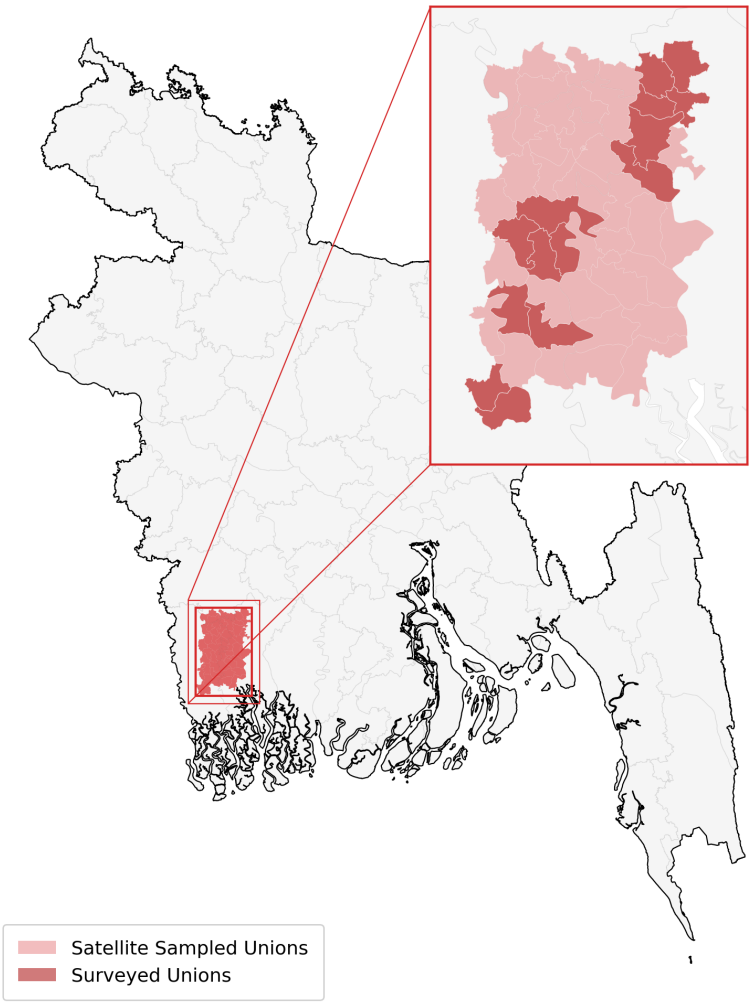
Note: Respondents name up to five people in their village with whom they most often discuss farming, and report for each the topics they discuss, how often they talk, and whether that person's plots border their own. The unit of observation is a named contact. Columns 1 and 2 report the share of contacts with whom each topic is discussed, and frequency measures, separately for contacts whose plots do and do not border the respondent's. Column 3 reports the difference (bordering minus non-bordering) with standard errors clustered by household in parentheses; column 4 reports the same difference with household fixed effects, comparing contacts named by the same respondent. Talking at least weekly corresponds to frequency categories 4 and 5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A6. Delineate Anything Parameters

Parameter	Value	Default	Description
Detection			
Minimum confidence	0.005	0.005	Model confidence required to keep a detection
Minimum detection size	256 px	512 px	Smallest detected object retained, in pixels
Super-resolution	Auto	Auto	Optional upscaling before inference
Tiling and merging			
Tile step	0.5	0.5	Overlap between adjacent tiles (50%)
Merge IoU threshold	0.8	0.8	Overlap above which detections are merged
Tile composition IoU	0.8	0.8	Overlap above which detections across tiles are merged
Filtering			
Minimum field area	200 m^2	2,500 m^2	Smallest field retained
Minimum hole area	200 m^2	2,500 m^2	Smallest interior hole retained
Input and output			
Band order	[3, 2, 1]	[3, 2, 1]	Order in which image bands are passed to the model
Polygon simplification	Off	On	Simplification of output polygon vertices

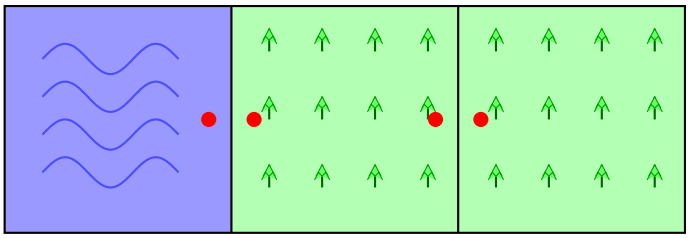
Notes: Parameters used to run Delineate Anything (Lavreniuk et al., 2025) on Planet basemap quads. "Default" refers to the value in the model's sample configuration file. We lower the minimum detection size and minimum field area relative to the defaults because fields in southwestern Bangladesh are small; 200 m^2 corresponds to 0.02 hectares (about five decimals). IoU denotes intersection-over-union. Polygon simplification is disabled for computational stability. Computational settings (batch size of 16 and half-precision inference) do not affect the output and are omitted.

B Appendix 2 - Additional Figures



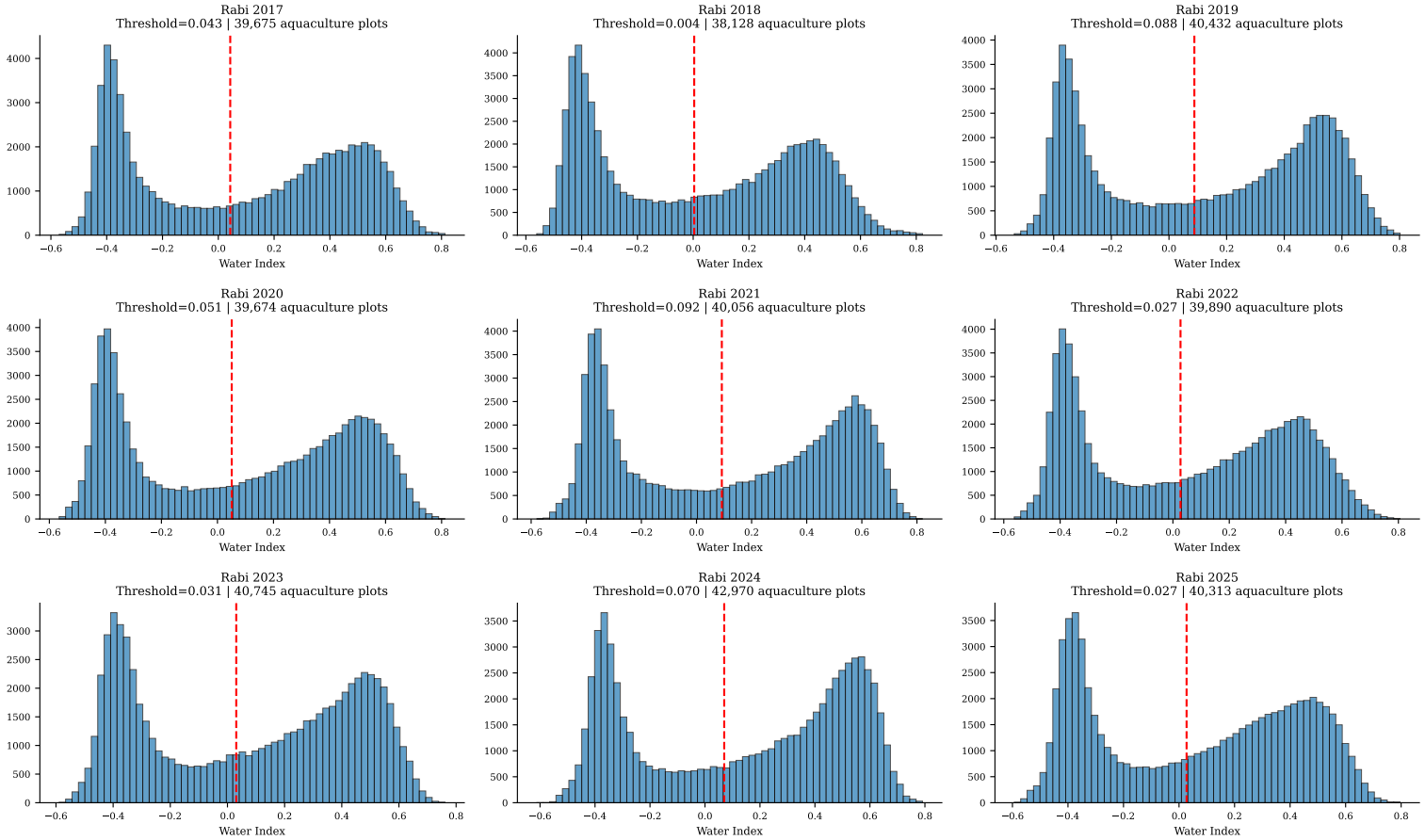
Appendix Figure B1. Sample Location

Notes: The Unions sampled in the household survey of rice and shrimp farmers across the Satkhira and Khulna Districts are shown in dark red. The satellite analysis covers unions with centroids that are southwest of the northeastern most survey-sampled union and northeast of the southwestern most survey-sampled union.



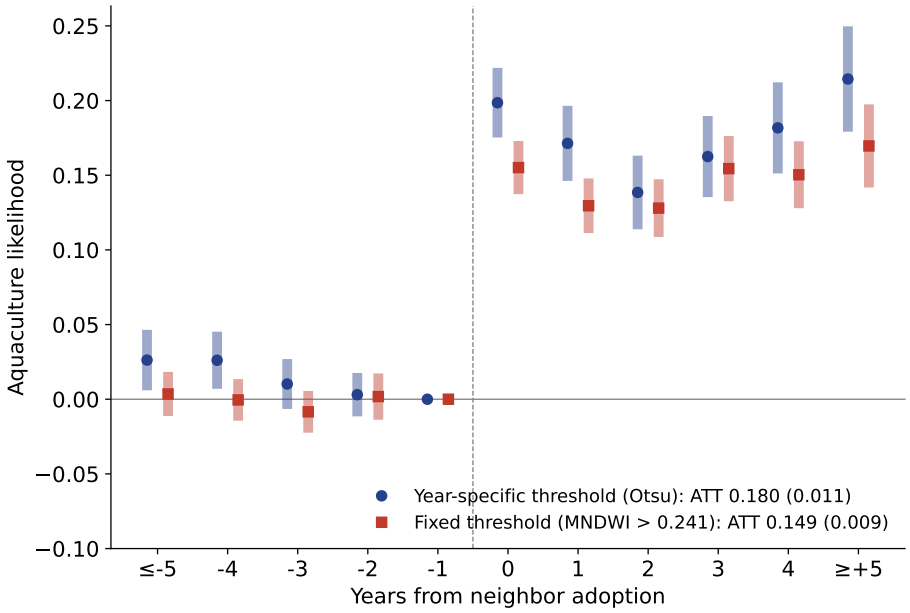
Appendix Figure B2. Salinity Test Location Diagram

Note: The diagram above shows an example of three plots, the leftmost of which is flooded with salt water for shrimp cultivation and the remaining two are used for agriculture. The red dots illustrate the approximate locations of the salinity readings.



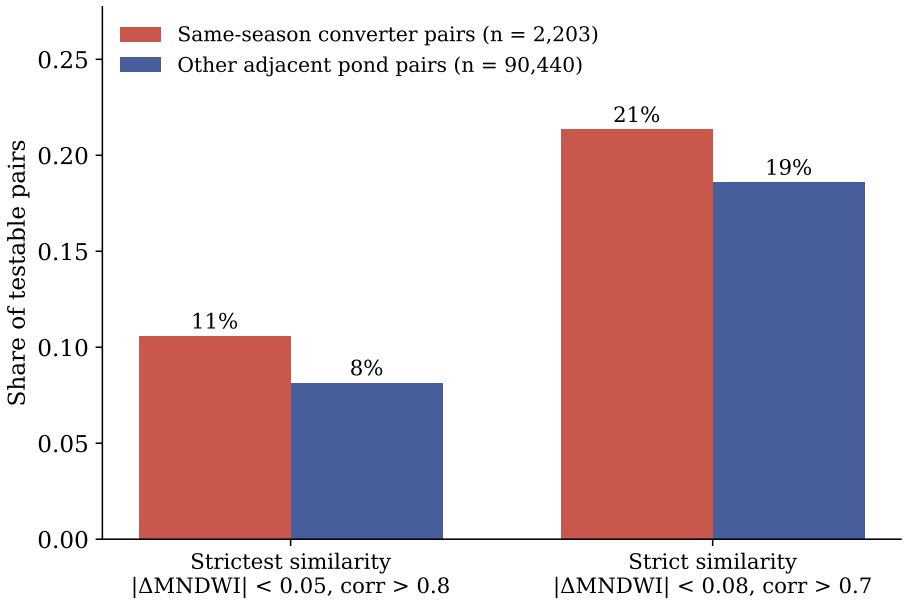
Appendix Figure B3. Modified Normalized Difference Water Indices Distribution

Notes: Distribution of the plot-level Modified Normalized Difference Water Index (MNDWI; Xu 2006) from Sentinel-2 imagery in the Rabi season (November–February), for plots with at least three valid pixels. The dashed line is that year's classification threshold, chosen by Otsu's method to maximize the between-class variance of the index; plots above it are classified as aquaculture, and the panel title reports how many.



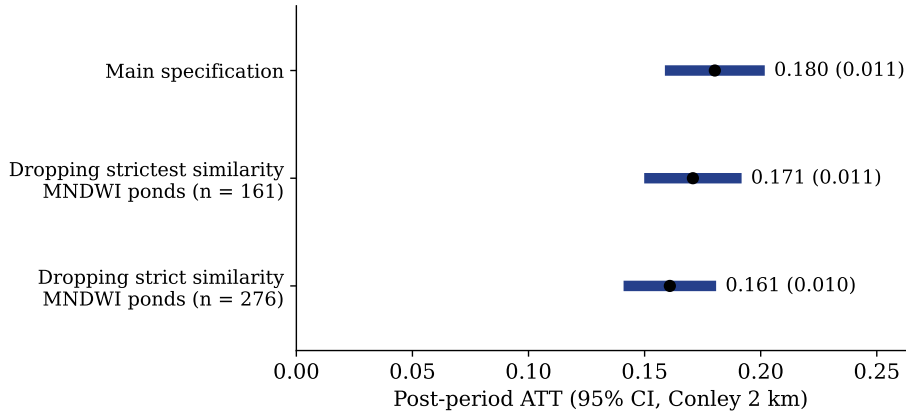
Appendix Figure B4. Robustness: Event Study with Manual Pond Threshold

Note: The figure compares Sun and Abraham (2021) event-study estimates of own aquaculture status under the main classification, which uses a year-specific Otsu threshold, with the same specification after reclassifying every plot-year using a fixed threshold of MNDWI > 0.241, chosen to minimize the balanced error rate against survey-reported land use. Both specifications include plot and hexagon $\times$ year fixed effects and river-distance $\times$ year and plot-size $\times$ year controls; bars show 95% confidence intervals using Conley standard errors with a 2 km cutoff, and the legend reports each post-period ATT.



Appendix Figure B5. Share of Adjacent Pond Pairs with Near-Identical Water-Index Readings

Note: Same-season converter pairs are a treated plot that switches from rice to aquaculture in the same Rabi season as its first pond neighbor, paired with that neighbor; the benchmark is a random sample of other adjacent pairs in which both plots are ponds at some point in the panel. Bars show the share of each group whose two plots are ponds in the same years (overlap of at least 90%) and, in the years when both are ponds, have a mean absolute MNDWI difference and a correlation of MNDWI readings within the stated thresholds; only pairs that are ponds together for at least four years are included.



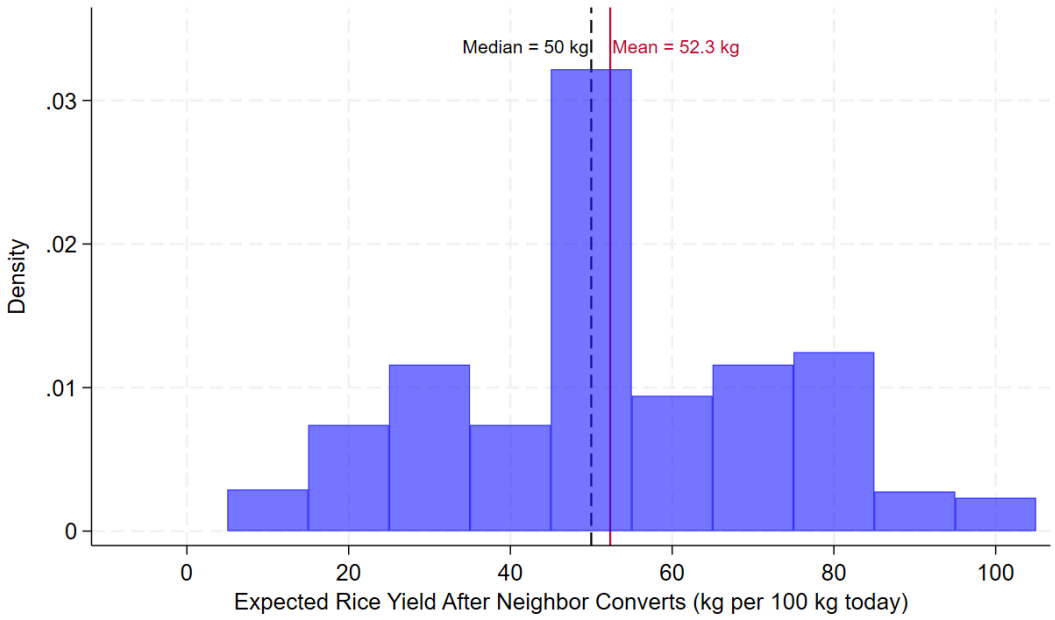
Appendix Figure B6. Robustness: Excluding Potentially Split Ponds

Note: The figure reports the post-period ATT from the main Sun and Abraham (2021) event study of own aquaculture status, and the same estimate after excluding treated plots whose same-season pair meets the strictest and strict similarity criteria shown in Appendix Figure B5. All specifications include plot and hexagon × year fixed effects and river-distance × year and plot-size × year controls; bars show 95% confidence intervals using Conley standard errors with a 2 km cutoff.



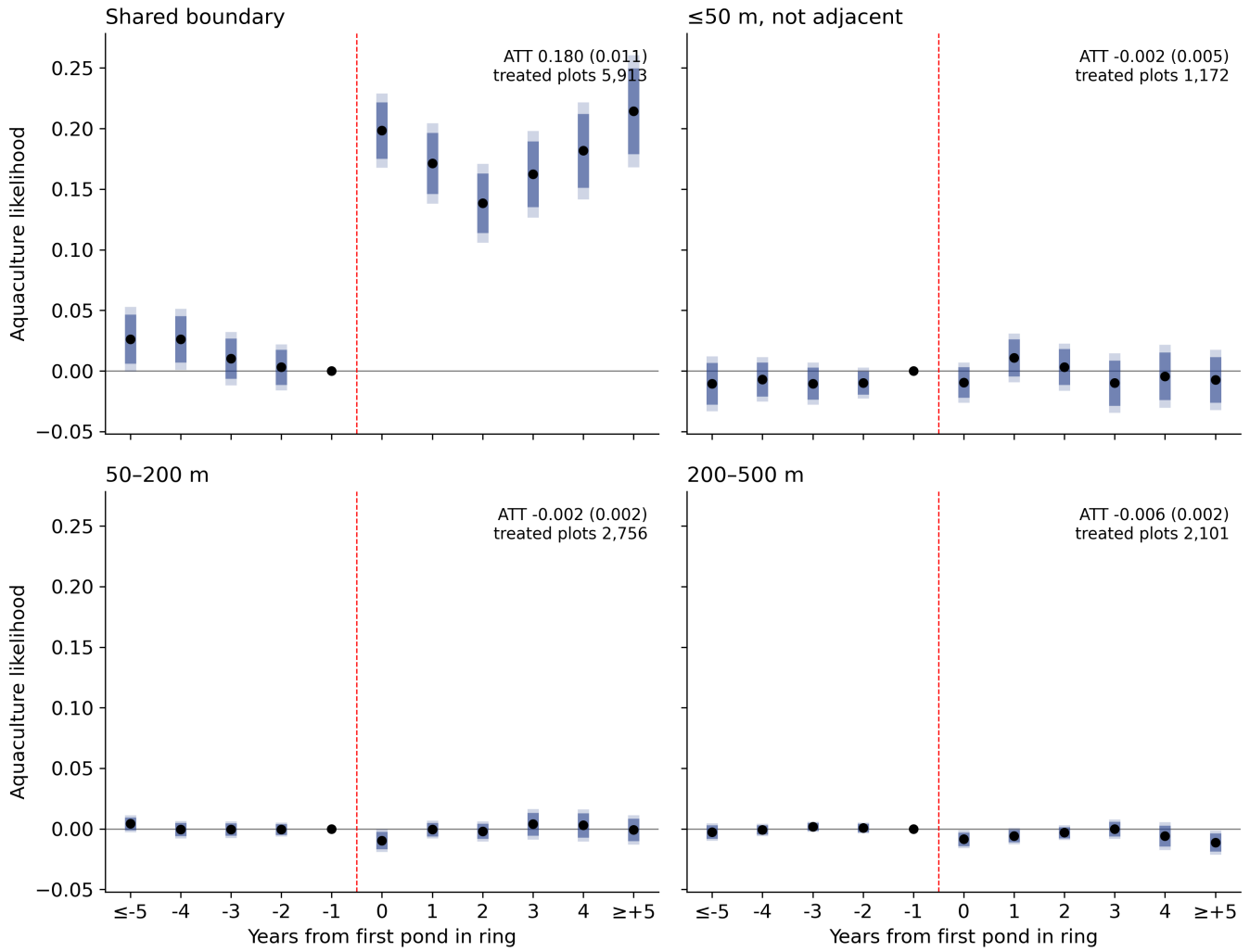
Appendix Figure B7. Rice Health Scale

Notes: The photograph is reproduced from Grattan et al. (2002) and shows rice plants grown at salinity levels increasing from 0.3 dS/m (left) to 12.0 dS/m (right), with plant growth visibly stunted at higher salinity. Enumerators showed this image to respondents when eliciting subjective rice health in Figure 3, so that a respondent's rating could be anchored to a common visual reference.



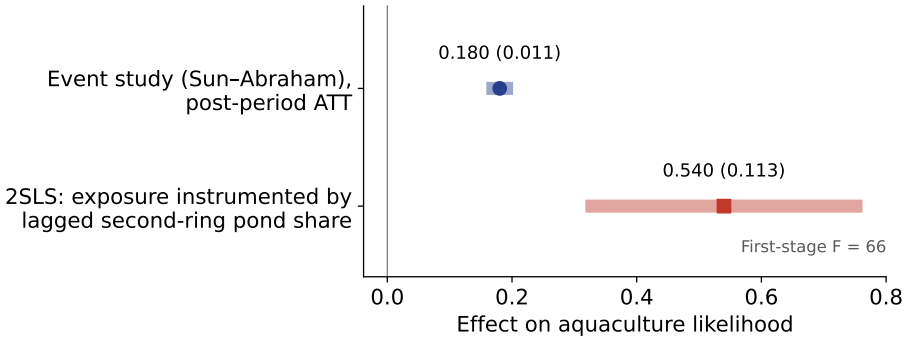
Appendix Figure B8. Quantitative Beliefs about Rice Yields if a Neighbor Converts to Shrimp

Note: Respondents were asked how the yield on their rice plot would change if a neighboring plot were converted to a shrimp pond, relative to a base of 100 kg today. Respondents expecting a decrease report the yield they would obtain out of 100 kg; respondents expecting an increase report the additional kilograms over 100 kg; respondents expecting no change are coded at 100 kg. Don't-know and invalid answers are excluded. Bins are 10 kg wide and centered on multiples of 10. The solid line marks the mean and the dashed line the median.



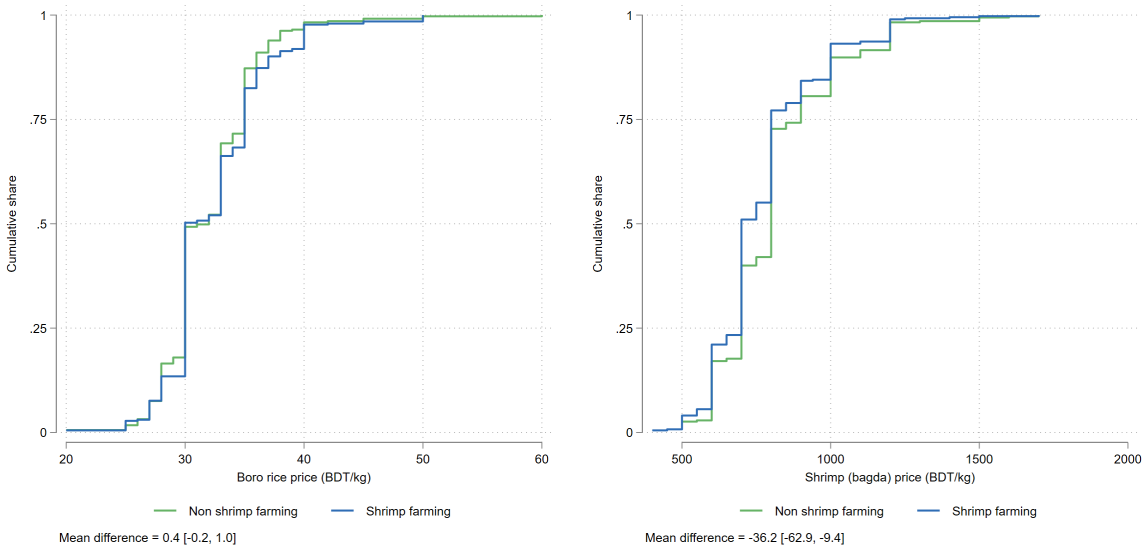
Appendix Figure B9. Treatment Effects by Plot Rings

Notes: Each panel is a separate Sun and Abraham (2021) event study of own aquaculture status. Treatment is the first year a pond appears in that distance ring, measured edge to edge and excluding adjacent plots for the outer rings, and plot-years are censored once a closer ring is exposed. All specifications include plot and hexagon × year fixed effects and river-distance × year and plot-size × year controls. Shaded bands show 95% (dark) and 99% (light) confidence intervals using Conley standard errors with a 2 km cutoff.



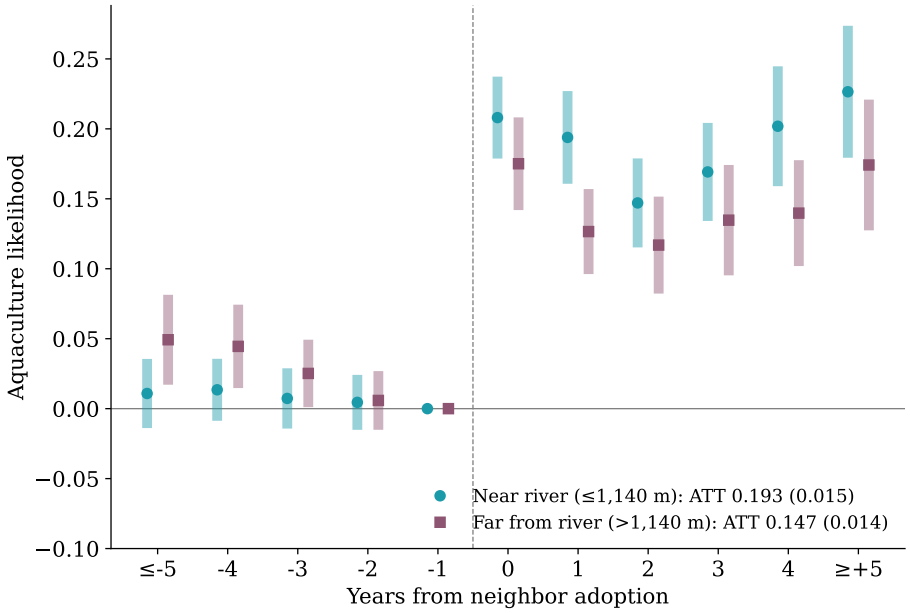
Appendix Figure B10. Robustness: Instrumental Variables Approach

Note: The top row reports the post-period ATT from the main Sun and Abraham (2021) event study of own aquaculture status. The bottom row reports a 2SLS estimate in which an indicator for having had an adjacent pond neighbor is instrumented by the share of a plot's second-degree neighbors (neighbors of its neighbors that do not border it directly) that were ponds in the previous year. Both specifications include plot and hexagon × year fixed effects and river-distance × year and plot-size × year controls; bars show 95% confidence intervals using Conley standard errors with a 2 km cutoff, and the first-stage F-statistic is reported for the IV.



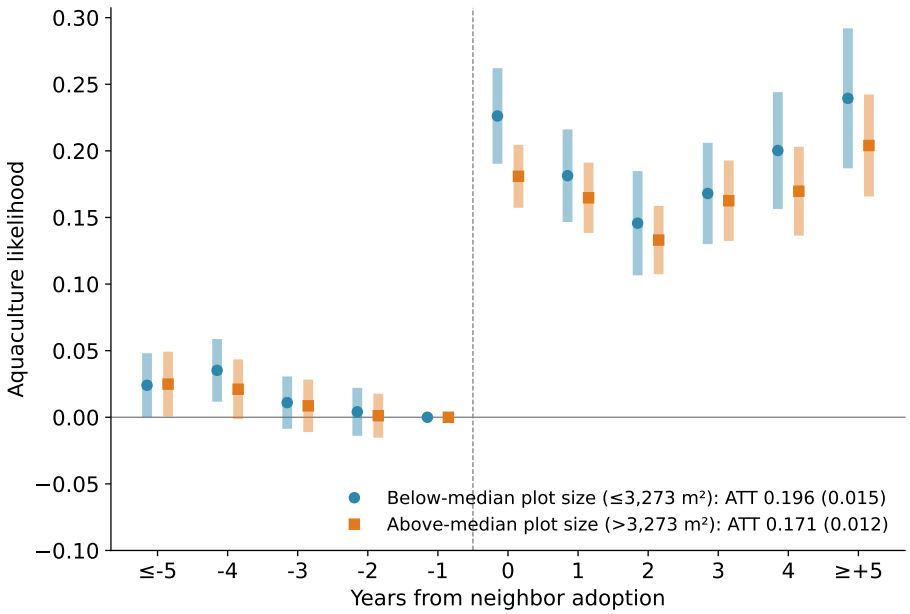
Appendix Figure B11. Respondent Beliefs About Prices

Notes: Empirical cumulative distribution functions of respondents' expected output prices, by household shrimp status. A household is classified as shrimp farming if at least one of its plots is a shrimp pond, and as non-shrimp farming otherwise. Rice is Boro-season rice; shrimp is bagda (tiger prawn). Only positive price beliefs are included. Beliefs are heaped at round numbers, which produces the steps in each curve. Each panel reports the difference in mean beliefs (shrimp minus non-shrimp farming) with a 95% confidence interval based on standard errors clustered by household.



Appendix Figure B12. Heterogeneity by distance to river

Note: The figure overlays Sun and Abraham (2021) event-study estimates of own aquaculture status for plots below and above the median distance to the nearest river, each estimated separately with the main specification. Distance is measured from the plot boundary to the nearest OpenStreetMap river segment. Both include plot and hexagon × year fixed effects and river-distance × year and plot-size × year controls; bars show 95% confidence intervals using Conley standard errors with a 2 km cutoff, and the legend reports each group's post-period ATT.



Appendix Figure B13. Heterogeneity by plot size

Note: The figure overlays Sun and Abraham (2021) event-study estimates of own aquaculture status for plots below and above the median plot area in the estimation sample (3,273 m^2), each estimated separately with the main specification. Both include plot and hexagon × year fixed effects and river-distance × year and plot-size × year controls; bars show 95% confidence intervals using Conley standard errors with a 2 km cutoff, and the legend reports each group's post-period ATT.

C Appendix 3 - Delineate Anything Field Detection

This appendix describes the field detection algorithm which converts satellite imagery into individual plot polygons that serve as the units of analysis in the main text. We use *Delineate Anything*, an off-the-shelf, pre-trained machine-learning model for field-boundary delineation (Lavreniuk et al., 2025).

The engine is a neural network built on the YOLOv11 segmentation architecture, a widely used family of models designed to simultaneously locate multiple objects in an image (Lavreniuk et al., 2025). Rather than classifying loose pixels, the model first determines objects in space (i.e., fields) and return those objects' own filled outline. Because each field is detected as a whole entity, a small imperfection along one edge should not cause it to merge with its neighbor, which we need for accurate plot-level measurement. The algorithm was trained on the Field Boundary Instance Segmentation dataset (FBIS-73M), which contains 1.5 million satellite image patches and about 73 million delineated field outlines. These training images span a wide range of spatial resolutions (from 0.25 to 10 meters per pixel), multiple satellite sensors, and several countries and seasons. Important for our approach, it is "resolution-agnostic," that is, it recognizes the general visual signature of a field—a roughly convex patch of uniform texture bounded by abrupt changes in color or tone—rather than memorizing the look of one specific sensor. This is what allows us to apply it to our imagery without retraining.

We apply the pre-trained model directly to our images without any further training or hand-labeling of Bangladeshi fields. The model requires only the three visible color bands (red, green, and blue) as input, which Planet basemap imagery provides. This is an advantage for transparency and replicability: our plot boundaries are the output of a fixed, publicly documented model applied to public imagery, with no discretionary labeling choices on our part.

Because satellite imagery tiles overlap, the same field is sometimes detected more than once in adjacent tiles. A merging step reconciles these duplicates: when two detected outlines overlap by more than a set fraction of their area, they are treated as the same field and combined into one. After merging, the model's pixel masks are converted into clean vector polygons with explicit vertices, which we then filter. Two size filters remove implausible detections: outlines smaller than $200\,\mathrm{m}^2$ and spurious holes smaller than $200\,\mathrm{m}^2$ inside a field are discarded. Both thresholds are well below the model's defaults of $2{,}500\,\mathrm{m}^2$, because fields in southwestern Bangladesh are small. Appendix Table A6 lists parameter valued.

Three caveats are worth noting for interpretation. First, the model can occasionally merge two truly distinct fields or split one field in two; because our analysis is at the plot level, such errors introduce measurement noise into plot boundaries. Second, fields at the outer edge of a quad can be clipped where two quads meet, which our cross-quad merging step mitigates but does not perfectly eliminate. Third, the boundaries are fixed from a single basemap and treated as static over the panel; genuine changes in field boundaries over time (for example, the subdivision or consolidation of plots) are not captured, which may lead to measurement error.

D Appendix 4 - Salinity Sensor Protocol

Section D.1 applies to the main plot, which was selected as a marginal shrimp or marginal rice plot and used to construct the sample as shown in Figure B2. Section D.2 applies to one randomly selected additional plot from each household's plot roster for additional salinity testing. Enumerators were provided with handheld electrical conductivity salinity meters with a range 0∼10.00ms/cm, resolution 0.01ms/cm and accuracy ±2% of the full scale. Each meter was calibrated prior to the survey using the standard calibration solution.

D.1 Main Plots

After completing the interview with the respondent, please return to the main plot and follow the steps below for aquaculture/agriculture boundaries. For agriculture/agriculture boundaries, begin at step 3 and repeat steps 3 and 4 twice instead of beginning with step 1. Rinse the sensor with bottled water and dry with a clean cloth after each reading.

1. Measure the salinity of the water at the boundary of the aquaculture plot. Submerge the entire probe of the salinity sensor. Photograph the sensor display and record the reading on the tablet.
2. Take a second reading at the same boundary, photograph the display, and record the reading on the tablet.
3. Return to the border between the aquaculture and agricultural plots and walk five paces into the agricultural plot. Insert the sensor into the soil, photograph the display, and record the reading on the tablet. Wipe the sensor clean.
4. Move five paces to the left, parallel to the border, and repeat step 4, for a total of three soil readings.
5. Record an estimate of the width of the central agricultural plot.
6. Record whether it was raining at any time during the interview.

D.2 Other Plots from the Plot Roster

For each additional agricultural plot listed in the plot roster, the enumerator follows the steps below. Rinse the sensor with bottled water and dry with a clean cloth after each reading.

1. Walk five paces into the agricultural plot. Insert the sensor into the soil, photograph the display, and record the reading on the tablet.
2. Move five paces to the left and repeat step 1 for a total of two readings.