Salinization and Development*

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Abstract

Climate change–intensified seawater intrusion creates a dual shock of transitory freshwater shortages and lasting soil degradation. We study its impacts on agricultural production in the Vietnamese Mekong Delta, a major rice exporter. Combining river salinity observations and detailed canal network data to map localized hydrological shocks, we find that salinity reduces rice yields but generates disproportionately larger declines in output and revenue. These losses are driven by a contraction in land under cultivation and limited substitution toward salt-resistant crops, pointing to constrained short-run adaptation. Using household and firm data, we further document reductions in own-farm employment alongside minimal transition to non-agricultural sectors, suggesting frictions in labor adjustment. Beyond income effects predicted by Engel curves, households reallocate expenditures toward healthcare and children's schooling. The increase in schooling spending is driven by higher participation and may reflect shifts in opportunity costs, though we cannot rule out forward-looking responses.

JEL Codes: O13, Q01, Q12, Q16, Q54, Q55.
Keywords: salinization, climate change, agriculture, children, human capital.

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1 Introduction

Coastal deltas worldwide, home to more than 300 million people, are endowed with dynamic ecological systems and fertile soils enriched by river sediments (Edmonds et al., 2020). These characteristics make many deltas vital agricultural centers. However, substantial portions of these low-lying areas are projected to be submerged by the end of the century in the context of climate change and rising sea levels (Clark et al., 2016; IPCC, 2022). While anticipated inundation signals the future loss of valuable land, recurring saltwater intrusion intensified by climate change is already disrupting freshwater supplies and harming the local agricultural sectors (Rahman et al., 2019). Despite its importance, empirical evidence remains incomplete on how farmers in these deltas adapt production strategies and reallocate resources to cope with extreme salinity in the short and long run.

This paper studies the impact of rising seawater (saltwater) intrusion into river systems of agricultural coastal deltas, where production depends critically on river-based irrigation. Described as an "invisible flood," the often unseen rise in water salinity generates both transitory freshwater shortages and more persistent soil degradation, as saline water alters soil conditions beyond the immediate shock period (Tully et al., 2019a,b; Chau et al., 2021; Eswar et al., 2021). Our case study focuses on the Vietnamese Mekong Delta (MKD), a major rice-exporting region, often referred to as the country's "Rice Bowl". The MKD's combination of large-scale rice cultivation—a water-intensive and salt-sensitive crop, extremely low elevation, and increasing exposure to climate-driven salinity intrusion provides an ideal context for studying the broader effects of salinity intrusion on agriculture and rural welfare (Smajgl et al., 2015; Minderhoud et al., 2019; Nguyen et al., 2020). Additionally, the availability of detailed hydrological networks, hydrostation data, and socio-economic datasets makes the region well-suited for analyzing salinity dynamics over time.

In the MKD setting, agricultural production relies on freshwater drawn from the Mekong river system and conveyed inland through an extensive canal network to irrigate fields. When saltwater intrudes into the river system, this irrigation water becomes saline, exposing cultivated land to salinity through the very channels used for production. Measuring the extent and variation of hydrological salinity, however, has long been challenging (Werner et al., 2013; Ondrasek and Rengel, 2021). To empirically assess exposure to these hydrological salinity shocks, we construct a salinity index (SI) at the commune level that captures localized variation in water salinity.[1] The index exploits the structure of the river–canal network by mapping salinity recorded at hydrostations to inland locations, weighting observations

[1]The commune constituted Vietnam's smallest administrative unit through 2025.

by inverse waterway (river and canal) distance—hereafter "canal distance." This approach reflects the fact that saline water propagates inland along hydrological pathways rather than diffusing uniformly across space. We combine river salinity data from 2011 to 2018 with detailed geospatial information on the river and canal network to construct this measure. Using *in situ* salinity data and machine learning–based spatial predictions, we show that the index captures meaningful variation in local salinity exposure. We match this measure to household data from the Vietnam Living Standards Survey and complement it with firm-level data from the Vietnam Enterprise Survey to study production and labor market responses.

We find that, within the context of rice cultivation, localized hydrological salinity shocks lower yields but generate even larger proportional declines in total output and revenue. Reflecting rice's biophysical nature as a salt-sensitive plant, a one-standard-deviation increase in the salinity index is predicted to reduce rice yields by 5% (measured in kilogram of output per square meter of land).[2] In contrast, the estimated declines in total rice output and revenue are 16% and 19%, respectively. These disproportionate declines suggest that salinity affects production beyond yield losses alone. Beyond rice cultivation, our results indicate that households reduce their reliance on rice by about 6%. However, substitution into less-affected crops to offset revenue losses from rice production appears limited at least in the short run: a one-SD increase in salinity lowers total agricultural revenue across all crops by 12%. Global and local studies suggest that households may mitigate negative productivity shocks by adjusting input use or adopting new technologies (e.g., Olmstead and Rhode, 2011; Costinot et al., 2016; Aragón et al., 2021). Our findings, however, provide evidence that such adjustments are limited in the context of small-scale farming in the MKD. This pattern is consistent with broader evidence of constrained adaptation to climate extremes (Burke et al., 2024).

Our identification strategy exploits spatial and temporal variation in localized salinity exposure, conditional on location, time, weather, and household characteristics. A key concern is that the constructed salinity index may be measured with error. To address this, we validate the index against independent *in situ* salinity measurements and machine learning–based spatial predictions, and show that our results remain stable when excluding locations with the largest discrepancies. A second concern is that salinity exposure may be endogenous to local agricultural conditions. To mitigate this, we implement a two-stage least squares strategy that instruments salinity using exogenous variation in upstream freshwater flows in the Mekong basin, interacted with river-path proximity to estuaries. The instruments

[2] For comparison of the estimated effect's magnitude, the agronomic literature finds that a 1°C temperature increase is predicted to decrease rice yields by 8-10% (Peng et al., 2004; Song et al., 2022)

strongly predict local salinity exposure, and the resulting estimates are similar in magnitude to the baseline OLS results. Across specifications, our findings remain robust, suggesting that the results are not driven by measurement error, endogeneity, or specific data construction choices.

To uncover mechanisms underlying the disproportionate reductions in yields and revenue, we first estimate the changes in farmers' land use as an input factor. Land use is a crucial adjustment margin in this setting, as hydrological saline shocks could lower the marginal productivity of land directly by harming soil quality and indirectly by limiting the supplies of freshwater required for tending land. Recent literature finds that farmers may react to weather-induced negative productivity shocks by expanding land use and thereby attenuate total output losses (Aragón et al., 2021). Our results, however, reveal sizable contraction of both land under rice cultivation and land for all agricultural production—which helps elucidate why revenue declines are exacerbated beyond yield decreases. They further suggest a lock-in effect in rice farming and limited short-term adaptive responses, e.g., land conversion toward other crops less affected by salinity. Aligning with this notion, we examine potential adjustments in farmers' crop mix and do not find the presence of productive shifts toward salt-resistant production such as aquaculture or industrial crops.

We next assess labor reallocation as an additional adjustment margin. If households respond to salinity shocks by shifting labor away from agriculture, this could help offset income losses. Instead, we find that salinity reduces the likelihood of working on own-farm activities, without corresponding increases in wage employment or other outside options. This pattern suggests that salinity shocks generate short-run unemployment rather than facilitating sectoral reallocation. Evidence from firm-level data corroborates this finding, showing no absorption of displaced agricultural labor by local manufacturing or service sectors. Together, these results point to substantial frictions in labor reallocation, consistent with limited adjustment opportunities in the local economy (Henderson et al., 2017; Santangelo, 2019; Albert et al., 2021).

In the final part of the analysis, we assess how salinity shocks affect household well-being and consumption. We first document that household living conditions—captured by hospitalizations, debt incidence, and subjective assessments—deteriorate as salinity intensifies. While weather shocks typically affect consumption through income, these effects may also induce direct adjustments in resource allocation. To examine this, we estimate Engel curve relationships and isolate the association between salinity and budget shares across consumption categories. We find that, holding income constant, households reallocate their budgets in response to salinity shocks. Expenditures on less essential and more discretionary goods—such as festive food, durables, and housing—decline, while spending on healthcare increases. Households also increase spending on children's schooling. This pattern may reflect short-run substitution, as lower agricultural productivity reduces the opportunity cost of schooling (Kruger, 2007; Shah and Steinberg, 2017). At the same time, it may be consistent with forward-looking responses to declining agricultural viability, though our data do not allow us to distinguish between these mechanisms. Further analysis shows that the increase in schooling expenditures is driven by the extensive margin, as households become more likely to send children to school. This shift is accompanied by higher school enrollment in the short run, indicating a measurable change in human capital investment behavior.

Our study contributes to several strands of the literature. We first build on work documenting the impacts of weather fluctuations and climate change on crop yields and farm income (Deschênes and Greenstone, 2007; Welch et al., 2010; Burke and Emerick, 2016; Chen et al., 2016). We add evidence on a less-studied form of weather variation and provide direct evidence on the limited ability of smallholder farms to adapt to negative shocks (Hornbeck, 2012; Burke and Emerick, 2016; Zaveri and Lobell, 2019; Burke et al., 2024). Second, we contribute to a growing literature emphasizing input adjustments as a key adaptation margin. Focusing on land use, we show that such adjustments are crucial for accurately measuring aggregate production effects beyond yield changes (Aragón et al., 2021). While existing work highlights land expansion as a mitigating response (Aragón et al., 2021; He and Chen, 2022; Cui and Zhong, 2024), we document that salinity shocks instead induce land contraction, amplifying revenue losses beyond productivity declines. Third, our findings relate to the literature on labor reallocation following weather-induced agricultural shocks (Jayachandran, 2006; Henderson et al., 2017; Santangelo, 2019; Blakeslee et al., 2020; Albert et al., 2021; Colmer, 2021b; Liu et al., 2023). While some studies find smooth transitions of displaced agricultural labor into manufacturing (Colmer, 2021b; Blakeslee et al., 2020), our results align with evidence that such shocks may not induce sectoral reallocation and can also depress local service activity (Santangelo, 2019; Albert et al., 2021; Liu et al., 2023).

We complement the literature on agricultural shocks and children's human capital (Beegle et al., 2006; Kruger, 2007; Shah and Steinberg, 2017; Nordstrom and Cotton, 2020). Our findings on increased parental investment in children are most closely related to Jensen (2000) and Colmer (2021a), who examine realized educational outcomes. Extending this line of work, we focus directly on household monetary spending, thereby providing complementary evidence on the underlying resource allocation decisions. Finally, we contribute to the emerging literature on the effects of saltwater intrusion on livelihoods, production, and health in coastal regions (Dasgupta et al., 2014; Chen and Mueller, 2018; Patel, 2023;

Guimbeau et al., 2024).

The paper continues as follows. Section 2 provides a background on agricultural production, irrigation system, and saltwater intrusion in the MKD. Section 3 details the salinity index construction, socio-economic data, and weather controls. Section 4 outlines our empirical framework. Section 5, 6, and 7 discuss results on agricultural production, labor reallocation, household living conditions and budget reallocation, respectively. Section 8 concludes.

2 Background

This section first provides background on rice cultivation in the Vietnamese Mekong Delta, highlighting its central role in farmers' livelihoods. It then describes the region's irrigation and canal infrastructure. Finally, to motivate the empirical analysis, it discusses saltwater intrusion in the Delta and presents descriptive evidence of the effects on rice production.

2.1 Rice cultivation and farmers' livelihoods

The major branches of the Mekong River, which is about 4,900 km and the longest in Southeast Asia, split into nine tributaries in southern Vietnam before entering the sea, depositing sediment to create the alluvial basins of the Vietnamese Mekong Delta (MKD). This condition favors environmental endowments for agricultural production, such as fertile soil and dynamic ecosystems. Rice cultivation has been around for thousands of years. Today the MKD is a national agricultural center and a major rice exporter. While its total area (40,816 km^2) and population (approximately 17 million) take up about 12% and 17% of the national totals respectively, the MKD contributes to over half of the national rice output—e.g., 56% in 2019 (GSOV, 2021). The Delta produces over 90% of Vietnam's rice exports—which was valued at 2.2 billion USD in 2018, making the country the world's third-largest rice exporter (Dao et al., 2020). Populations in the MKD rely heavily on agriculture for their livelihoods. Within our study area, roughly 61% of the working-age, employed labor force is concentrated in agriculture. Specifically in this context, the share of those working a household agricultural job is 56%. Among the agricultural households in our data, 42% cultivate rice (i.e., report rice output) whereas 39% generate income from rice production (i.e., report revenue from selling produced rice). Rice-producer households largely depend on rice cultivation, which accounts for 66% of their total agricultural revenue on average.[3]

[3]We compare rice reliance in the coastal study area with that in three inland provinces not exposed to saltwater intrusion (Appendix Figure A.5). Although the inland provinces are substantially more productive in rice cultivation (Appendix Figure A.2, Panels a–c), Appendix Figure A.3 shows that, among rice-producing households, the share of revenue from rice is not so different between the two regions.

Moreover, these small-scale farmers are the primary producers forming the rice supply chain (Dao et al., 2020). Supporting this, Appendix Figure A.2 (Panel d) shows that the study area has about 0.5 agricultural firms per 10,000 inhabitants, well below the rest of the Delta, and experience only modest growth over time.

2.2 Irrigation and canal infrastructure

Irrigation in the MKD rests upon both the naturally bifurcating river system and an extensive human-made canal network. Water from the river system is the main source used for irrigation, followed by groundwater and harvested rainwater to a lesser extent (Dang et al., 2007; Ozdemir et al., 2011; Nguyen et al., 2021). Over the past three centuries, the Delta has developed a dense canal network, originally constructed for trade and strategic military purposes (Biggs, 2005). Today its main roles are for irrigation and regional transportation. This network comprises approximately 7,000 km of primary canals drawing water directly from rivers, and about 4,000 km of secondary canals connecting primary canals and tertiary on-farm systems (VMARD, 2003; Hoanh et al., 2012; Tran and Weger, 2018). Appendix Figure B.2 illustrates this three-tier structure. While the canal network serves as a conduit leading water from rivers into farmlands, it also facilitates the inland dispersion of saltwater during the dry season (Dang et al., 2007; Le et al., 2007).

2.3 Saltwater intrusion and its impacts on rice production

> The year 2016 was a particularly bad year. Farmers who had never experienced saline conditions before were suddenly forced to grapple with up to 70% of their rice being affected by salt and 30% of their crops dying, yielding no grain. Last year, 2020, also brought severe drought and salinity events amidst the global COVID-19 pandemic.
>
> Australian Centre for International Agricultural Research (2021)

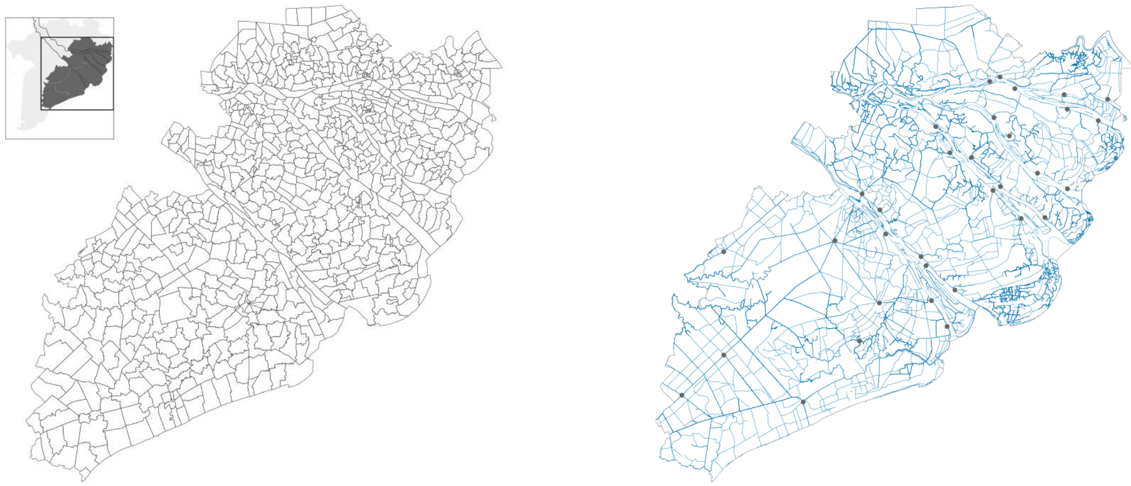
The Mekong Delta is among the lowest areas worldwide and up to one-third of its total surface is projected to be submerged if the sea level rises by 20 cm (Minderhoud et al., 2019). Situated within the monsoon climate, its flood season typically lasts from July to October, while its dry season from December to May. Seawater intrudes into the riverine system in the dry months, with February to April marking the most saline period. In recent years, salinity intrusion tends to be longer and more intense. It was especially severe in 2016 and 2020, receiving great public attention. Retrieving Google Trends data for search terms "xâm nhập mặn" (saltwater intrusion) and "hạn mặn" (salt drought), in Appendix Figure A.4

we observe the spikes in their relative search traffic in these two years. Hydrological studies identify three main drivers that exacerbate saltwater intrusion in the MKD. First, rising sea levels increase tidal amplitude, allowing saline water to travel further inland (Khang et al., 2008; Eslami et al., 2019). Second, naturally lower freshwater discharge during the dry season reduces the ability of river tributaries to repel seawater (Le et al., 2007, p. 40), which is aggravated during drought periods (CCAFS SEA 2016). More recently, upstream hydropower development in the Mekong basin has intensified this effect by further limiting flow discharge and sediment supply (Eslami et al., 2019; Schmitt et al., 2021). Third, local sand mining contributes to riverbed incision, deepening channels and enabling saltwater to intrude farther upstream (Eslami et al., 2019).

Saltwater intrusion adversely affects agriculture, particularly rice as a salt-sensitive and water-intensive crop, through two main channels. First, it reduces freshwater availability in rivers, canals, and interconnected groundwater (Le et al., 2007; Smajgl et al., 2015; Nguyen et al., 2021).[4] Second, more saline water poses persistent and potentially irreversible threats to soil quality. Saltwater intrusion is a major driver of climate change–induced soil salinization in coastal deltas (Eswar et al., 2021). Global and local evidence further shows that it disrupts other soil biogeochemical properties and impairs long-term soil health (Tully et al., 2019a,b; Chau et al., 2021). Tully et al. (2019a) describe saltwater intrusion as an "invisible flood", because the often unseen rise in water salinity brings about novel transitions in coastal wetland ecology, mobilizes soil nutrients, and reduces agricultural productivity. Transitory increases in hydrological salinity, coupled with longer-lasting soil degradation, may make saltwater intrusion distinct from other weather shocks.

To provide preliminary evidence on the effects of saltwater intrusion, we compare household-level rice outcomes in the coastal study area with those in three inland provinces (An Giang, Dong Thap, Can Tho) that were not exposed to salinity intrusion even in peak years (see Appendix Figure A.5). The dynamic differences estimated in Appendix Figure A.6 offer two insights. First, coastal rice output and revenue decline sharply over time relative to inland area. Second, although 2016 corresponds to the most severe salinity episode, the coastal-inland gaps widen through 2018, suggesting potentially persistent effects of the 2016 intrusion. In the next sections, we leverage within-coastal variation to identify the causal impacts of saltwater intrusion.

[4] Appendix A.4 provides details on rice's characteristics and estimates on regional salinity-induced freshwater shortage prevalence.



(a) (b)

Figure 1: Communes, hydrological network, and hydrostations
Panel (a) displays the communes within the study area ($n = 801$) in the main map. The inset at the top left locates the study area (shaded) within the Mekong Delta and shows the main Mekong River tributaries (lines). Panel (b) maps local river system and canal network (lines), together with hydrostations (dots).

3 Data

Our study area encompasses seven provinces situated along the major branches of the Mekong and prone to saltwater intrusion (Figure 1, Panel (a) and details in Appendix Figure A.1). Five coastal provinces share the coastline to the sea east of Vietnam. Two adjacent, inland provinces (Vinh Long and Hau Giang) also experience saltwater intrusion.[5] We have the river salinity recorded by the hydrostations in these provinces, enabling our construction of a localized salinity measure.[6] In the following, we detail how exposure to salinity is measured and describe the socio-economic and weather control data employed in our empirical analysis.

3.1 Measuring local exposure to hydrological salinity

Because systematic, time-variant water salinity measurements are not available, we construct a salinity index at the commune level to capture households' exposure to hydrological saline shocks induced by seawater intrusion. Specifically, we map the transmission of salinity through hydrological pathways by calculating river salinity weighted by inverse waterway

[5] These two inland provinces are mentioned by CCAFS SEA 2016 and World Bank 2017 and part of the affected area shown by the officially reported saltwater intrusion borders in Appendix Figure A.5.

[6] We are careful to note that while our study area is referred to as "coastal region", it does not include three coastal provinces of Long An, Ca Mau, and Kien Giang due to data availability. However, these provinces are fundamentally different from our study area regarding geology.

(river and canal) distance to each commune.

We first draw on river salinity observations from hydrostations of the Vietnam Meteorological and Hydrological Department, covering 2011–2018 and recorded by 33 stations. Figure 1, Panel (b), shows station locations. River salinity (gram/liter) is typically measured bi-hourly during the dry season, when upstream freshwater and local precipitation are low, thus inducing saltwater intrusion into the riverine system. Monthly aggregated data show that river salinity typically peaks in March and decreases substantially at the onset of the flood season, as upstream flow and local precipitation pick up (Appendix Figure B.1). We also observe that salinity levels in 2015 and 2016 remain longer at the high levels, with 2016 having four months of salinity persisting at least at the high annual mean. Appendix B.1 provides more information on the river salinity data. To map the transmission of river salinity to the commune, we use granular geospatial data on the regional river system and canal network provided by Can Tho University. Figure 1 (Panel b) shows the river system and canal network employed in our analysis. As introduced in Section 2, the MKD canal network is three-tiered. The data we use include only primary and secondary canals, while excluding tertiary canals that are more closely linked to household production. For each commune shown in Figure 1 (Panel a), we compute the waterway distance to hydrostations, referred to as "canal distances", in two steps: (i) the straight-line distance from the commune centroid to the nearest point on the canal network, and (ii) the distance along the canal and river networks from that point to the hydrostations. Appendix Figure B.3 shows how these distances are computed for an example commune in the sample. Summary statistics of the canal distance are provided in Appendix Table B.2. The salinity index is constructed as follows:

$$SI_{c(s),t_m} = {Distance_{c,s}}^{-1} \times Salinity_{s,t_m}, \tag{1}$$

in which $SI_{c(s),t_m}$ is the salinity index measured for commune c in year t up to month m, with s being the hydrostation nearest to the centroid of commune c by canal distance. $Distance_{c,s}$ is the canal distance between the centroid of c and s. $Salinity_{s,t_m}$ is the river salinity content recorded at station s in year t up to month m, which is the average of reported daily salinity.[7]

Conceptually, the constructed salinity index helps us capture localized hydrological saline

[7]Formally,

$$Salinity_{s,t_m} = \frac{1}{N_{s,t_m}} \sum_{d \in t_m} Salinity_{s,d,t_m},$$

where $Salinity_{s,d,t_m}$ denotes the river salinity measured at station s on date d within the year t up to month m, and N_{s,t_m} is the number of days that station s reported salinity data for the same time period. We aggregate the data up to a particular month of a given year to match the salinity index with socio-economic data collected in a particular sub-wave month.

shocks, instead of region-wide dispersion. First, rivers are the primary source of irrigation water in the Delta, and the canal network transports river water inland. Salinity intrusion hence propagates primarily along this hydrological routing rather than diffusing isotropically across space (see e.g., Dang et al., 2007; Bhattachan et al., 2018). Mapping communes to the river-canal network thus allows us to translate observed river salinity into localized exposure to saline shocks. Second, exposure intensity declines with hydrological distance based on the first law of geography. As saline water moves inland, dilution and tidal attenuation tend to reduce its concentration. Canal distance thus provides the economically relevant measure of spatial attenuation. One caveat is that due to the lack of data, we cannot account for the presence of dykes and sluice gates, which serve as salinity intrusion-preventing measures in practice. However, because their operation is likely correlated with local agricultural production, including this factor in the SI construction may introduce an endogeneity problem for the empirical estimation.

We examine whether the salinity index (SI) constructed in Equation 1 reflects meaningful variation in local hydrological salinity in three steps.

Temporal pattern alignment In a first step, we assess whether the constructed salinity index captures the temporal patterns documented in the anecdotal evidence presented in Section 2. The yearly average SI depicted in Appendix Figure B.4 shows that saltwater intrusion was most intense in 2016, consistent with the broadly documented evidence.

In situ-based validation Second, we draw on in situ measures of water salinity from 181 samples collected across the study area in April 2016. Sample locations, measurements, and summary statistics are reported in Appendix C.1. The index constructed using river salinity in April 2016 and assigned to the commune of each sampling location correlates with in situ water salinity at 0.43 in logs (Appendix Figure C.2), suggesting that the index captures a non-trivial share of local salinity variation. Importantly, this comparison is based on in situ samples collected during a period of high salinity and thus captures primarily variation along the intensive margin. Moreover, local salinity conditions depend on additional factors, e.g., micro-level water management and soil characteristics, that are not captured by the index. The salinity index should therefore be interpreted as a proxy measure of local hydrological salinity exposure. Next, we run a falsification exercise which randomly assign SI to sampling points. This yields correlations near zero (Appendix Figure C.3), confirming that the observed relationship reflects genuine local salinity exposure rather than chance. In addition, the R^2 reported in Appendix Table C.3 suggest that models including the index and further location or weather characteristics could explain between 52% and 78% of the variation in log in situ salinity. These estimates reflect in-sample fit and indicate that the index—in combination with observable geographic and climatic factors—captures a substantial share of local hydrological salinity variation.

Machine learning-based validation The in situ samples come with two important caveats. First, they were collected in April 2016—a period with intense saltwater intrusion (see Sections 2). As a result, the data exhibit high salinity and contain no zero-salinity observations, thereby capturing only the intensive margin.[8] Second, the 181 in situ sampling locations cover limited spatial extent. Because these data are static and restricted to the intensive margin, temporal extrapolation would introduce substantial errors. Nonetheless, spatial extrapolation within the collected period is more robust and would allow us to examine the alignment of SI across a broader geographic range. In this next validation step, we thus apply machine learning on the in situ data to generate spatially predicted estimates of local hydrological salinity. To do so, we assemble a set of 26 geomorphological and hydrological predictors from observed, remote-sensing, and reanalysis sources.[9] Using nested cross-validation, we select Random Forest, which performs best with a correlation of 0.79 with observed in situ salinity. We then apply this model to extrapolate in situ measurements across the entire study area. Appendix C.2 provides further details on model calibration, selection, and prediction procedure. Our baseline salinity index correlates with region-wide extrapolated in situ salinity at 0.64 in logs (Appendix Figure C.4). This is higher than the correlation with observed in situ samples reported in the preliminary validation (0.43). The result provides additional support that the baseline salinity index captures meaningful spatial variation in water salinity.

Building on evidence that the salinity index captures variation in measured and predicted salinity, we note that both may also reflect other climatic, geographic, or production factors. The index is therefore not intended to fully replicate measured salinity, but to isolate a component that plausibly varies exogenously with respect to economic outcomes. In Section 5.2, we directly evaluate this identification assumption and present evidence supporting the index as a relevant measure of exogenous local hydrological salinity.

3.2 Socio-economic outcomes

For household-level information, we use repeated cross-section data from the Vietnam Household Living Standards Survey (VHLSS), conducted by the Vietnam General Statistics Office

[8] Appendix Table C.1 shows that mean in situ water salinity is 7.38 g/L, classified as severely saline water (Scianna et al., 2007).

[9] Predictors used to train the models exclude SI components (river salinity and canal distance), ensuring that the subsequent comparison between predicted salinity and SI is not mechanically driven.

with technical support from the World Bank. The survey has been implemented nationwide every two years since 2002, collecting household-level data on demographics, agricultural production, and expenditures from randomly drawn, representative samples of households and communes within each province. Each survey wave is conducted in four sub-waves: March, June, September, and December. We use data from the 2012, 2014, 2016, and 2018 waves. Our main estimation sample includes 1,020 rice-producing households across 202 communes, defined as households reporting any rice output. For analysis of land use transfers, we further use information on 2,422 agricultural producer households located in 304 communes. They are defined as those reporting output from rice, non-rice staple crops, fruits, industrial crops, aquaculture, livestock, or forestry. The VHLSS also allows construction of individual-level variables to look into employment, health, and education outcomes. Detailed variable definitions are provided in Appendix B.2, with summary statistics in Appendix Table B.3. The outcome variables in our analysis reflect household or individual activities over the year preceding the survey. For example, the rice output question asks, "What is the household's total quantity of rice produced in the past 12 months?" To align with this, we match the salinity index and weather controls to the survey month by averaging values over the previous year and the portion of the current year up to the survey month. The matching timeline is illustrated in Appendix Figure B.5. We further draw firm-level data from the Vietnam Enterprise Survey (VES) to study labor shifts to non-agricultural sectors. VES is the annual survey conducted by the Vietnam General Statistics Office to collect detailed business information from all formally registered firms operating in Vietnam. We use data from survey waves 2012 to 2018 and construct a firm panel based on unique firm tax IDs. This yields a sample of 18,358 firms located in 767 communes. Our outcome variable measures within-year labor changes in the agriculture, manufacturing, and service sectors. Appendix Table B.5 reports summary statistics of the firm data.

3.3 Weather controls

Saltwater intrusion may co-move with other weather variation. As discussed in Section 2, local saline intrusion is partly driven by freshwater availability and thus correlated with drought intensity. Because weather shocks can affect agricultural productivity both directly and indirectly through salinity, we control for local temperature and precipitation to isolate the effects of hydrological saline shocks.[10] In addition, we account for evaporation, another climatic factor that can exacerbate soil salinization in low-lying coastal areas (Yu et al., 2021). We obtain high-resolution weather data at the 1 km pixel level from the CHELSA

[10]For example, Auffhammer and Schlenker (2014) discuss the inclusion of additional weather controls when estimating the effect of a single weather variable.

version 2.1 downscaling algorithm developed by Karger et al. (2017, 2025). We use monthly measures of mean temperature and precipitation. To capture evaporation, we use Penman-Monteith-derived potential evapotranspiration, which reflects surface evaporation and transpiration rates.[11] A commonly used measure of water availability is climate moisture index (CMI), which is the difference between precipitation and potential evapotranspiration. By controlling for these two variables, our specification implicitly accounts for CMI. All weather data are aggregated to the commune level and matched to the survey month as previously discussed (see also Appendix Figure B.5). Appendix Table B.7 provides summary statistics of the weather variables.

4 Empirical framework

To study the impact of hydrological saline shocks induced by saltwater intrusion, we estimate the following regression model using the OLS estimator:

$$outcome_{i,c,t(m)} = \beta SI_{c,\tilde{t}} + f(w_{c,\tilde{t}}) + \varphi' \mathbf{X}_{i,c,t} + \lambda_c + \pi_t + \gamma_m + \varepsilon_{i,c,t}, \qquad (2)$$

in which $outcome_{i,c,t(m)}$ is the outcome reported by household i residing in commune c in the survey year t and (sub-wave) month m. $SI_{c,\tilde{t}}$ denotes the salinity index measured for commune c. As described in Section 3, because outcomes from the VHLSS capture data in the 12 months preceding the survey time, we take the average of the salinity index across the previous year and the contemporaneous year up to the survey month, indicated by $\tilde{t}$. Salinity index is standardized in all regressions. We control for $f(w)$, a linear function of weather variables w including temperature, precipitation, and potential evapotranspiration. Analogous to the salinity index, the weather controls are matched to the survey month m and averaged across the previous and contemporaneous year.[12] $\mathbf{X}$ is a vector of household demographic variables including household size, household head's age and education. In all regressions, we add commune fixed effects λ_c, thus controlling for time-invariant local characteristics that influence households' production such as geography, history, or culture. They also capture persistent differences in local irrigation conditions, including reliance on surface water. Survey year fixed effects π_t absorb the annual time trends that affect outcomes across communes uniformly, while sub-wave month fixed effects γ_m account for any seasonality inherent in the weather variables and outcomes. Throughout, standard errors are

[11] Due to the difficulties in capturing actual evaporation, potential evapotranspiration is the FAO-recommended measure in lieu (Allen et al., 1998).

[12] As part of the robustness checks, we change $f(w)$ into a quadratic function to allow non-linear effects of the weather controls. The point estimates remain consistent.

clustered at the treatment level of communes. In addition, we apply the method of Conley (1999) to compute spatial-correlation robust standard errors, using a 20-km cut-off.[13] The results show that commune-clustered and Conley-robust standard errors are comparable in magnitude, with the former often producing more conservative estimates.

β captures the ceteris paribus effect of localized hydrological salinity shocks, measured as a one-standard-deviation increase in the salinity index. Identification in Equation 2 assumes that, conditional on the included controls, SI reflects localized hydrological salinity shocks and is orthogonal to unobserved determinants of the outcomes in the error term. Two main threats could violate this assumption. First, the index may mismeasure true exposure to hydrological saline shocks. Second, SI may be endogenous to agricultural production, particularly if nearby river salinity or the canal layout responds to related local activities. In Section 3.1, we take various validation approaches and document that the salinity index captures genuine variations in local hydrological salinity. In Section 5.2, we directly address threats to identification. First, we examine measurement error by probing the sensitivity of our estimates to observations recorded in locations with largest discrepancies between the constructed index and machine learning-predicted salinity. Second, to alleviate endogeneity concern, we implement a two-stage least squares strategy that instruments SI with exogenous variation in freshwater discharge from the upstream Mekong basin interacted with river-path proximity to estuaries. Finally, we present in the same section a range of robustness checks and falsification exercises providing evidence that the estimates are not dictated by certain choice of data construction or model specification.

5 Agricultural production

This section presents our estimates of saltwater intrusion's effects on rice yields, revenue, and total agricultural revenue. We further address potential threats to identification and report various tests evaluating the robustness of the results. To explain the disproportionate decreases in yields and revenues, we turn to examine household land use changes as a potential adjustment margin, which is substantiated by crop switch patterns. Finally, we present suggestive evidence on persistent effects of saltwater intrusion over the medium run.

[13] 20 km is the cut-off length optimized by the algorithm for our data. Increasing the cut-off length does not change the estimates' precision: For all outcomes reported in our robustness checks in Appendix Table D.5 (column 11), standard errors get smaller when the cut-off is specified at 30 km.

5.1 Yields and revenues

We begin by analyzing the extent to which salinity affects rice productivity for the rice-producing households in our sample. The results are presented in Table 1. Our productivity measure is yields, defined as the quantity of produced rice per unit of cultivated land (kilogram/square meter). In column 1, a one-standard-deviation increase in salinity is estimated to decrease rice yields by about 5% and the estimate is statistically significant at the 1% level. This indicates the strong negative effect of saltwater shocks on rice productivity in the MKD, aligning with the broader documented impact on rice as a freshwater-intensive, salt-sensitive crop (see e.g., Tanji and Kielen, 2002; Bouman, 2009; Dasgupta et al., 2014).[14] Furthermore, our estimates suggest that even if farmers adapt by switching to salt-resistant rice cultivars, this strategy is unlikely sufficient to fully offset the inherent negative impact of salinity on the plant growth.[15] We next investigate changes in household total rice production. Column 2 reveals a sizable decrease in total rice output (kilogram) with a one-SD increase in salinity predicted to reduce rice output by roughly 16%. Compared to the decrease in yields, this threefold drop in total output suggests that farmland expansion as a productive input adjustment does not occur (see e.g., Aragón et al., 2021). We then examine how these results translate to changes in household revenue gained from selling or exchanging produced rice, a proxy for income in our context.[16] In column 3, the estimation is restricted to households reporting positive rice revenues.[17] Aligning with the observed output reduction, rice revenue is estimated to decrease by 19%. In the survey, households also report the quantity of rice sold together with revenue received. We estimate a decline of about 20%, implying that the decline in rice revenue is primarily driven by reduced quantity sold rather than price changes. Besides, the slightly larger decline in quantity sold relative to total output (column 2) perhaps signals consumption smoothing as a response to idiosyncratic income shocks, whereby households insulate consumption by saving grain stocks (Morduch, 1995; Kazianga and Udry, 2006). Taken together, we document that the adverse effect of hydrological saline shocks on rice revenue is more than three times larger than that on yields. These dispropor-

[14] To put our estimate into perspective, the agronomic literature studying the impact of weather shocks posits that a 1°C temperature increase is predicted to decrease rice yields by 8-10% (see e.g., Peng et al., 2004; Song et al., 2022)

[15] Bareille and Chakir (2024), for example, show that the reduced-form estimated impacts of weather shocks on crop yields usually already capture both the agronomic effects on the plant's biophysical growth and adaptive responses of farmers.

[16] Data on agricultural profit is not directly reported in the VHLSS. Crucially, because households in the sample consist of small-holding, family-scale producers, costs of household labor as a primary input factor are not observed. Thus, revenue could proxy for income in our analysis—this is similar to the discussion of Rosenzweig and Wolpin (2000) and resembles the approach of Hornbeck (2012).

[17] Appendix Table E.1 reports estimates using this restricted sample, which are similar to Table 1 across all outcomes.

Table 1: Rice and agricultural production

	Log rice yields	Log rice output	Log rice revenue	Rice revenue share	Log agricultural revenue
	(1)	(2)	(3)	(4)	(5)
Salinity index (SD)	–0.053	–0.181	–0.215	–0.041	–0.129
	(0.011)***	(0.036)***	(0.038)***	(0.010)***	(0.042)***
	[0.007]***	[0.031]***	[0.031]***	[0.007]***	[0.027]***
Commune FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓
Mean dependent variable	0.547	12,890	68,904	0.663	103,936
Observations	1,020	1,020	948	1,020	1,011

Notes: 'Log rice yields' is the logarithmized amount of rice output per unit of land under rice cultivation (in kg/m^2). 'Log rice output' is the logarithmized total amount of produced rice (in kg). 'Log rice revenue' is the logarithmized revenue gained from selling or exchanging produced rice (in thousand VND). 'Rice revenue share' is the share of revenue received from rice production in total agricultural revenue. 'Log agricultural revenue' is the logarithmized total revenue from all crops including rice, non-rice staple crops, fruits, industrial crops, aquaculture, livestock, and forestry (in thousand VND). 'Salinity index' is standardized in all regressions. Commune and time (year and survey-month) fixed effects are included in all estimations. Weather control vector includes the average temperature, precipitation, and potential evapotranspiration measured for the commune. Household control vector includes household size, household head's age and years of education. Commune-level clustered robust standard errors are reported in the parentheses and Conley-robust standard errors (at 20km cutoff) are in the brackets. *p<0.1; **p<0.05; ***p<0.01.

tionate reductions suggests that short-run productive responses such as input adjustments are limited within the specific context of small-scale rice farming in the MKD.

While households largely depend on rice, more than 85% also produce non-rice crops. To uncover potential adjustments beyond rice cultivation, we next examine how saltwater shocks affect household's total agricultural revenue, consisting of rice, non-rice staple crops, fruits, industrial crops, aquaculture, livestock, and forestry. Column 4 (Table 1) first reveals that the share of agricultural revenue received from rice drops by 4 percentage points with one-SD higher salinity. Compared to the mean share at 65%, the estimate implies a reduction of 6% in households' reliance on rice. This is attributable to the level decrease in rice revenue reported in column 3, and possibly households' active choices to substitute rice with other crops less affected by salinity. If such replacement is effective, saltwater shocks would have no or only marginal effects on agricultural revenue in sum. Yet in column 5, total agricultural revenue is estimated to decline by 12% when salinity increases by one SD.[18] This estimated reduction rate in total agricultural revenue (12%) is more than half of that measured for rice revenue (19%) and doubles the decline rate in rice yields (5%).

Combined, the results in Table 1 document the negative effects of hydrological saline shocks on rice production. They further suggest that short-run adjustments to shield production

[18] The sample is restricted to households reporting positive agricultural revenues.

at both rice-specific and overall agricultural production levels are imperfect among the rice-producer households. One margin of adaptation is the adoption of salt-tolerant rice varieties, which is increasingly common in the MKD. Kosmowski et al. (2025), for example, document that roughly half of the MKD rice-farming households surveyed in the VHLSS 2022 wave planted resistant varieties. The sizable negative effects we detect, however, suggest either that adoption accelerated only after our sample period, or that it does not fully insulate rice production from intense salinity episodes. A central feature of these estimates is that total rice output, revenue, together with total agricultural revenues decrease more sharply than rice yields. To understand why this is the case, we turn to examine households' adjustments in land use and crop choices beyond rice in Section 5.3. In the next section, we first address potential threats to identification and present a range of tests assessing the robustness of the main findings.

5.2 Threats to identification

The identification in Equation 2 rests on the assumption that, conditional on included control variables, the salinity index captures local hydrological saline shocks and is uncorrelated with unobserved determinants of the outcomes in the error term. Two primary threats could invalidate this assumption. The first concern is that the salinity index may not accurately reflect local exposure to hydrological salinity shocks. The second is that the index may be endogenous to local agricultural outcomes, especially if its components—river salinity and canal distances—are correlated with household production via unobserved or reverse causal links. To address these concerns, we apply a variety of complementary approaches and document that our measure captures localized hydrological saline shocks. We further conduct a battery of robustness tests showing that the results are not driven by specific assumptions or data construction choices.

Robustness to measurement discrepancies

In Section 3.1, we document that the salinity index captures meaningful variation in both *in situ* water salinity and its predicted values across the full study area. While reassuring, these results do not eliminate measurement error as a threat to identification. We therefore assess the implications of error for our baseline estimates in Equation 2 more directly. Our identification relies on the accuracy of the constructed index in capturing local salinity variation. If discrepancies between SI and true salinity levels reflect error that is systematically related to agricultural outcomes, the estimated effects of hydrological salinity in Table 1 could be biased. To probe the role of measurement error, we leverage the machine learning predictions and examine whether our results are sensitive to excluding locations where the constructed index deviates most strongly from predicted in situ salinity. Specifically, we successively exclude communes in the top 5%, 10%, and 25% of the distribution of absolute differences between SI and predicted salinity in April 2016. As shown in Appendix Table D.1, the estimated coefficients remain qualitatively and quantitatively similar to the baseline results in Table 1. These findings suggest that our results are not driven by observations with large discrepancies between the constructed index and predicted salinity, alleviating concerns that extreme measurement error drives the baseline estimates. At the same time, this exercise does not rule out the possibility that remaining measurement error is systematically correlated with agricultural outcomes. We address this concern more directly in the subsequent identification strategy.

Incorporating information from farther stations

A potential issue is that the salinity index hinges solely on measurements from the nearest monitoring station. In an interconnected hydrological network, saline conditions in nearby river segments could simultaneously influence local exposure, implying that the baseline SI might omit relevant information. To address this, we construct alternative indices averaging salinity across multiple hydrostations weighted by inverse canal distance, sequentially adding up to the sixth-nearest station for each commune (Appendix D.2). Appendix Table D.2 shows that the estimates remain broadly similar to the baseline. However, both the magnitude and precision of the estimates decline as more distant stations are incorporated, particularly the fifth and sixth stations, whose canal distances on average more than double that of the nearest station. This pattern suggests that saline shocks are spatially localized and that including more distant stations dilutes the local signal captured by the baseline index.

Two-stage least squares estimations

Although the preceding evidence supports the salinity index as a measure of localized hydrological saline shocks, it may still be endogenous to the outcomes. For example, agricultural production could affect nearby river salinity through surface water extraction, or correlate with local activities—e.g., sand mining, that also influence salinity. To assuage this concern, we implement a two-stage least squares strategy (2SLS) separately using two instrumental variables. This approach also mitigates validity concern arising from potential measurement error in the constructed index. In detail, the IVs exploit variation in upstream freshwater discharge in the Mekong basin outside Vietnam interacted with local river-path proximity to estuaries (tidal mouths of rivers).[19,20] While the former captures river freshwater flow as a hydrological "push" factor, the latter reflects tidal saltwater gradients. As discussed in Section 2, both are key exogenous drivers of seawater intrusion into the local river system.

In the first specification, we instrument river salinity with upstream freshwater discharge interacted with the river-path distance from each station to its nearest estuary. Appendix Table D.3 reports the 2SLS and first shows that the IV strongly predicts the baseline salinity index. The second-stage coefficients are precisely estimated and comparable in magnitude with the OLS estimates reported in Table 1. This consistency alleviates concern that the baseline estimates are biased by potential endogeneity or measurement error in river salinity. Notwithstanding this result, canal distance between commune and station remains part of the first IV. If local canal layout responds to agricultural production, this could introduce endogeneity. Although the canal distance used here captures only primary and secondary canals and excludes on-farm irrigation system more closely tied to household activities, to further address this concern we construct a second IV. In this approach, SI is instrumented with upstream freshwater discharge interacted with the river-path distance directly from the commune to its nearest estuary. This method does not require assigning communes to specific stations, which could further reduce any potential measurement error. Presented in Appendix Table D.4, the first stage yields large F-statistics, indicating the IV's strong predictive power for the baseline index. Second-stage estimates closely match the OLS coefficients. To formally test for endogeneity, we implement Durbin-Wu-Hausman test for all 2SLS specifications. In only one out of ten cases is the test's p-value below 0.05, while in all remaining cases it is about an order of magnitude larger. The null hypothesis that the OLS estimator is consistent therefore cannot be rejected in most specifications. These results suggest that potential endogeneity or measurement error in river salinity or canal distance is unlikely to bias our baseline estimates. Appendix D.3 provides details on IV construction and 2SLS results.

Robustness tests

Complementing the validity checks, we implement a battery of tests and document the robustness of the results in Table 1 to various choices of data construction and model specifi-

[19]We use discharge recorded at Kratie, Cambodia, the first station upstream of the Vietnamese Mekong Delta with publicly available data. Kratie is located roughly 500 km upstream of the study area along the river. River-path distance is measured along the river system, reflecting natural flow paths to estuaries.

[20]Specifically, the IVs are defined as the product of inverse freshwater discharge and inverse river-path distance from the station (IV1) or commune (IV2) to the estuary. Lower freshwater supply and closer proximity to tidal mouths increase saline intrusion, implying a positive correlation between the IVs and the salinity index, as confirmed by the first-stage results in Tables D.3 and D.4.

cation. All results are reported in Appendix Table D.5. The initial tests modify the sample's coverage. Observations from non-coastal provinces (Hau Giang and Vinh Long) and from Bac Lieu, which is farthest from the main river, may be prone to outliers due to persistent geological differences. Sequentially excluding observations in these provinces, however, does not change the results. We also test for influential observations using a bootstrapping-like procedure, randomly excluding 5% of the sample in 1,000 iterations for each outcome. The resulting estimates remain qualitatively and quantitatively stable.[21] Additionally, we vary the construction of the salinity index by (i) using canal distances and river salinity data from only high-elevation hydro-stations[22] and (ii) using river salinity data from all stations combined with straight-line distances to communes. Results remain broadly consistent, though using fewer stations increases magnitude and reduces precision. Furthermore, adding more household controls (number of children and ethnicity) or allowing non-linear weather effects produces point estimates very similar to the baseline. To probe potential self-selection of households into communes of certain salinity levels, we perform a balance check. Appendix Figure D.3 shows that there are almost no statistically significant differences in household demographics across locations and periods of varying SI levels. Finally, we conduct three falsification exercises, randomly (i) assigning the nearest station and canal distance to each commune (spatial permutation), (ii) assigning monthly salinity over time for each station (temporal permutation), and (iii) assigning the constructed SI to households (spatial-temporal permutation). For each, we run 1,000 iterations and compare the resulting point estimates for the effect on rice yields.the permuted estimates are centered around zero, while the actual estimates are in the tails of or outside these distributions. This pattern indicates that the results are unlikely to be driven by data construction choices and, by exploiting both spatial and temporal variation in salinity, are unlikely to arise by chance.

5.3 Adjustments in land use and crop mix

A key result of Table 1 is that rice output and revenue decline more than yields. To study the underlying mechanisms, we examine how households adjust land use as a production input. Adjustments in land use are particularly relevant, as local hydrological saline shocks can reduce the marginal productivity of land both indirectly by limiting the supply of freshwater needed for cultivation and directly by impairing soil quality (Section 2). We further look into patterns of crop switch to explain total agricultural revenue losses beyond rice.

[21] The mean and standard deviation of the 1,000 estimates are reported as the main point estimate and standard error, respectively.

[22] High-elevation stations are defined as those above the mean commune elevation, which reduces the number of stations available for index construction by nearly half.

Table 2: Agricultural land use

	Log total land for rice	No. of rice planting seasons	Log total land for rice	Log total land for agriculture	Rice land (y/n)	Log total land for agriculture
	(1)	(2)	(3)	(4)	(5)	(6)
Salinity index (SD)	–0.127	–0.104	–0.082	–0.082	–0.007	–0.014
	(0.037)***	(0.045)**	(0.049)*	(0.032)**	(0.004)*	(0.011)
	[0.028]***	[0.049]**	[0.040]**	[0.024]***	[0.003]**	[0.009]
No. of rice planting seasons			0.440			
			(0.086)***			
			[0.086]***			
Sample	Rice producers	Rice producers	Rice producers	Rice producers	Agricultural producers	Non-rice producers
Commune FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓	✓
Mean dependent variable	22,357	2.475	22,357	11,258	0.421	5,456
Observations	1,020	1,020	1,020	1,020	2,422	1,278

Notes: 'Log total land for rice' is the logarithmized total land area that household reports to use for rice cultivation, i.e., sum of areas used for all sub-crops, in the past 12 months (in m^2). 'No. of rice planting seasons' is the number of planting seasons in which the household cultivated rice in the past 12 months. 'Log total land for agriculture' is the logarithmized total absolute land area that household reports to use for all agricultural production activities (in m^2). 'Rice land (y/n)' is an indicator variable that equals one if household reports to have land used for rice, and zero otherwise. 'Salinity index' is standardized in all regressions. 'Rice producers' sample includes all households that report rice output. 'Agricultural producers' sample includes all agricultural producers defined as households that report output from any crop. 'Non-rice producers' sample includes agricultural producer households who do not produce rice. Commune and time (year and survey-month) fixed effects are included in all estimations. Weather control vector includes the average temperature, precipitation, and potential evapotranspiration measured for the commune. Household control vector includes household size, household head's age and years of education. Commune-level clustered robust standard errors are reported in the parentheses and Conley-robust standard errors (at 20km cutoff) are in the brackets. *p<0.1; **p<0.05; ***p<0.01.

Land use

To understand why rice output and revenue decline more sharply than yields, we examine land-use responses to salinity. Recent literature emphasizes land use as a key adjustment margin when interpreting total output changes beyond productivity (Aragón et al., 2021; Cui and Zhong, 2024). In our context, reductions in cultivated area could provide one plausible explanation for the larger declines in output and revenue. A central mechanism behind land contraction may be seasonal adjustment. Rice cultivation in the Mekong Delta typically takes place across up to three seasons per year. Farmers may respond to increased salinity by reducing or foregoing cultivation during the dry season, when salinity levels are highest. While our data do not allow a decomposition by season, all outcomes are measured over the past 12 months and therefore capture both within-season (intensive-margin) responses and across-season adjustments, including decisions to skip cultivation in high-salinity periods.

Table 2, columns 1-3, presents evidence on land use changes under rice cultivation. In column 1, the outcome measures total land used for rice cultivation, defined as the sum of land allocated to all seasons the household planted rice in the past year.[23] The estimates suggest that households reduce total land allocated to rice by 12% as salinity increases by one SD. This contraction may reflect adjustments along two margins: the number of planting seasons and land allocated per season. Column 2 shows that higher salinity reduces the number of rice seasons by 4% of the outcome mean. In column 3, we condition on the number of seasons to capture variation at the intensive margin. The estimates reveal that, even holding the number of seasons fixed, salinity is predicted to decrease land use by 8% within season. Taken together, these results show that households respond to salinity by both cultivating fewer seasons and reducing land per season, with hardly any evidence of offsetting expansion in less-affected periods. This adjustment helps explain why output and revenue fall more sharply than yields, and suggests that contractions in cultivated area—rather than yield losses alone—are the primary driver.

Because rice-producing households may reallocate land to other crops, land displaced from rice may be repurposed within agriculture. If so, we would expect total agricultural land use to remain unchanged. However, column 4 shows that this is unlikely: total agricultural land use—measured as the absolute land area reported by the household—declines at a similar rate to rice land, implying little reallocation toward other crops.[24] This pattern also provides a plausible mechanism underlying the decline in total agricultural revenue documented in Table 1. Our findings complement Aragón et al. (2021) by highlighting the importance of accounting for land-use adjustments when evaluating the total impacts of weather shocks. While they show that farmers may mitigate heat-induced losses by expanding cultivated land, we find land contraction following saline shocks that amplifies productivity declines.[25]

Do land transfers then occur among different groups of producers, who are heterogeneously

[23] Households report rice production for plain (main), glutinous, and specialty cultivars. Plain rice is recorded by season (Winter–Spring, Summer–Autumn, Autumn–Winter), while glutinous and specialty cultivars lack seasonal information. As the main cultivar typically spans up to three seasons in the MKD and the other cultivars are minor, we assign glutinous and specialty crops to the first reported main season and count the number of distinct planting seasons. Results are unchanged when the variable is alternatively defined as the simple count of reported categories (main Winter–Spring, main Summer–Autumn, main Autumn–Winter, glutinous, specialty).

[24] We note that while total absolute area used for all agriculture is directly reported, breaking down land use by crop type to quantify land reallocation is challenging due to differences in measurement units. For example, rice and other staple crops are measured in square meters, whereas fruit production is reported in number of trees.

[25] There are several possible explanations for the reduction in land use. Elevated salinity in water supplies may likely degrade soil quality, thus directly decreasing the productivity of land. If other inputs are fixed and the marginal cost of keeping land unchanged, profit-maximizing households might then reduce land use. Besides, the costs of holding land may actually rise, as saltwater intrusion limits the supply of freshwater essential for tending land. Finally, households may contract land due to risk aversion, anticipating more intense saline shocks in the future. Yet available data does not allow us to empirically test these underlying mechanisms.

affected by salinity? To answer this question, we extend the analysis to all agricultural producers in columns 5-6 (Table 2). Column 5 considers the probability of holding land for rice cultivation. Unlike the economically significant negative effect along the intensive margin in column 4, the estimates reveal only a negligible one on the extensive margin, as a one-SD increase in salinity is predicted to reduce the probability of using land for rice among all agricultural producers by 0.7 percentage points (1.7% the mean outcome). This result is in line with rice being a dominant source of income, thus representing a sticky production choice. Additionally, it offers a hint that between-producer transfer might be limited. Results in column 6 supports this notion: non-rice producers do not expand their agricultural land use in response, suggesting that land released from rice cultivation is not absorbed elsewhere.

In sum, Table 2 documents a substantial contraction in land used for rice cultivation, which helps elucidate the larger declines in output and revenue relative to yields. At the same time, we find little evidence of land reallocation either within rice production or across producers. Together, these results point to limited short-run adaptation to salinity shocks and align with the lack of productive crop switching, which we discuss next.

Crop switch

Results in Table 1 uncover a sizable reduction in rice-producers' total agricultural revenue. This implies that short-run adaptation to recover losses from rice is imperfect, consistent with the contraction of total agricultural land use previously documented. To gain insight into other adjustments, we turn to analyze how farmers alter their crop mix in reaction to salinity. To this end, we examine changes in their probability of reporting revenue from non-rice crops and in the shares of these crops in total agricultural revenue. Based on the agronomic guidelines on salt tolerance by Tanji and Kielen (2002) and Blom-Zandstra et al. (2017), we group the crops into salt-resistant (aquaculture, industrial crops), salt-sensitive (livestock, fruits), and mixture (non-rice staple crops, forestry). Appendix E.1 provides details on crop classification, while Appendix Table E.2 presents our estimates.

Three main findings emerge. First, we do not observe that households shift to salt-resistant aquaculture and industrial crops in the short run. Second, the chances of having revenue and revenue shares are estimated to decrease with extreme salinity for salt-sensitive livestock farming and fruit crops. Third, the only productive shifts we observe are toward non-rice staple crops, as farmers' probability of earning any revenue and revenue share together rise. These crops include mainly vegetables and herbs, likely the most feasible short-term substitutes for rice. However, they generally represent the lower-value choices of production, e.g., compared to salt-resistant alternatives. Therefore, their increases alone are probably not sufficient to compensate for losses from rice and other productions. Two factors likely explain the limited switching to salt-resistant, higher-value activities such as aquaculture. First, these options require capital and specialized skills that rice-producing households may lack, particularly in the short run. Second, high salinity levels can undermine even salt-tolerant production. While moderate salinity may benefit aquaculture, levels beyond certain thresholds are harmful, and managing salinity in ponds is often complex and demanding. As a result, severe salinity intrusion can substantially reduce expected returns.

Overall, the results indicate limited crop switching in response to salinity shocks. Rather than shifting to salt-resistant production, households appear only able to partially offset losses by moving into non-rice staple crops in the short run. This provides an explanation for why total agricultural revenue also decreases for the rice-producers. Furthermore, these results are consistent with the takeaway from land use estimates, in that they both indicate that productive input adjustments in response to extreme salinity are limited.

5.4 Medium-run associations

The results we document so far are estimated over the short run. An immediate question is whether they translate to longer-run changes. As discussed in Section 2, hydrological saline shocks are typically transitory, as increases in upstream freshwater and local precipitation in the rainy season tend to revert the salinity concentration in the hydrological network. Yet, these shocks can also add to soil salinization and cause unprecedented disruption in coastal wetland ecology, effects that may persist much longer (Tully et al., 2019a,b; Chau et al., 2021). The question about long-term impacts of hydrological saline shocks is thus of central importance. Although we lack panel data over a sufficiently long period to estimate long-run effects, we adopt a supporting approach to answer this question. Specifically, we estimate the relationship between accumulative local hydrological salinity exposure and changes in commune-level outcomes over the six years between the first and last survey waves in our data. Appendix E.1 describes the data construction and estimation equation. Coefficient estimates for rice production outcomes in Appendix Table E.3 highlight two patterns. First, we find suggestive evidence that persistent exposure to elevated hydrological salinity, while does not affect rice yields, is associated with substantial declines in total output and revenue. Second, echoing the short-run results, total land under rice cultivation decreases over this period. These findings suggest land downsizing as a response to cumulative salinity exposure and a mechanism underlying the reduction in total production. At the same time, the most affected, least productive plots may be taken out of cultivation, which could explain the absence of changes in measured yields. Together, the results suggest that hydrological salinity shocks adversely affect rice production in the medium run, with reductions in cultivated land likely amplifying revenue losses beyond what is implied by productivity.

6 Labor reallocation

We proceed to examine labor reallocation as a reaction to local saline shocks.[26] Changes in labor supply from farmer households as an input factor in rice production could further elucidate why household revenues decline more pronouncedly than rice yields. At the same time, labor reallocation may represent a second-order reaction to farm production losses induced by local salinity shocks. This section provides our results on the employment of individuals from the rice-producing households in our sample. We further draw on firm census data from the Vietnam Enterprise Survey to discern the general patterns in local labor shifts to non-agriculture sectors.

6.1 Labor from rice-producer households

Table 3 presents our estimates on the labor reallocation of individuals from rice-producer households. In columns 1-5, we restrict the sample to working-age members, i.e., aged 15-64. To begin, we explore whether people leave agriculture in reaction to higher salinity. Column 1 indicates that a one-SD salinity increase is predicted to decrease the probability of the individual working in self-employed agriculture by 3.7 percentage points, a 5% reduction compared to the mean at 69 percent. The result implies that members leave household farming in response to higher salinity conditions. We next see if this is accompanied by reallocation to off-farm work. In column 2, we do not find evidence that individuals switch to non-agricultural self-employed jobs. Another conjecture is that farmers switch to paid jobs in large farms or agricultural firms, which may be better hedged against salinity-related productivity risks (see e.g., Aragón et al., 2022). Alternatively, people may move to paid jobs in non-agriculture firms as these are less directly affected by salinity shocks. However, column 3 does not find support for these hypotheses: the probability of household members finding a wage job is precisely estimated to decrease by 3.2 percentage points with one SD higher salinity, accounting for 10% of the mean outcome. In column 4, we analyze whether

[26] Empirical evidence often indicates imperfect inter-sectoral shifts due to limitations in requisite conditions: (i) farmers need skills, physical-, and social capital to switch to off-farm jobs (see e.g., Emerick, 2018; Albert et al., 2021), (ii) there should exist sufficient market integration to facilitate labor movements (Jayachandran, 2006; Brooks and Donovan, 2020; Allen and Atkin, 2022), and (iii) the local tradable non-agriculture sector—manufacturing—must be developed enough to absorb workers displaced from agriculture (Henderson et al., 2017; Blakeslee et al., 2020).

Table 3: Household labor reallocation

	Self employment (y/n) Agriculture	Self employment (y/n) Non-agri.	Wage work (y/n)	Multiple jobs (y/n)	Employed (y/n)	No. of working-age members	Log total population
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Salinity index (SD)	–0.037	–0.007	–0.032	0.022	–0.054	–0.075	–0.002
	(0.013)***	(0.008)	(0.012)***	(0.032)	(0.011)***	(0.035)**	(0.001)*
	[0.013]***	[0.007]	[0.013]**	[0.028]	[0.012]***	[0.038]*	[0.001]**
Sample	Rice hh individuals	Rice hh individuals	Rice hh individuals	Rice hh individuals	Rice hh individuals	Rice hh	Rice hh communes
Commune FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Survey month FE	✓	✓	✓	✓	✓	✓	–
Weather controls	✓	✓	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓	✓	–
Mean dep. var.	0.691	0.112	0.329	0.756	0.837	2.866	11,186
Observations	2,923	2,923	2,923	2,001	2,923	1,020	1,591

Notes: 'Self employment (y/n)' in col. 1 is an indicator variable equal to one if the person reports to be self-employed in agriculture in the past 12 months, and zero otherwise. In col. 2, it is an indicator variable equal to one if the person reports to be self-employed in a non-agriculture job in the past 12 months, and zero otherwise. 'Wage work (y/n)' is an indicator equal to one if the person reports to be employed in a wage/paid work in the past 12 months, and zero otherwise. 'Multiple jobs (y/n)' is an indicator equal to one if the person reports to work more than one job in the past 12 months, and zero otherwise. 'Employed (y/n)' is an indicator equal to one if the person reports to have any employment in the past 12 months, and zero otherwise. 'No. of working-age members' is the number of present household members aged 15-64. 'Log total population' is the logarithmized commune population estimated by WorldPop (2018). Sample includes working-age individuals from rice-producer households (columns 1–5), the households (column 6), and their communes (column 7). 'Salinity index' is standardized in all regressions. Commune and year fixed effects are included in all estimations; survey-month fixed effects are included in cols. 1-6. Weather control vector includes the average temperature, precipitation, and potential evapotranspiration measured for the commune. Demographic controls include person's gender, age, and education level in cols. 1-5 and household head's age and education level in col. 6. Commune-level clustered robust standard errors are reported in the parentheses and Conley-robust standard errors (at 20km cutoff) are in the brackets. *p<0.1; **p<0.05; ***p<0.01.

salinity increases farmers' likelihood to work multiple jobs—a strategy to diversify income sources. Although the point estimate is positive, we can not reject the null hypothesis that there are no changes in their number of jobs.[27] Combined, results in columns 2-4 of Table 3 do not signal the reallocation of household labor to take jobs outside own farming. By and large, higher salinity is estimated to decrease their probability of working at all. In column 5, a one-SD increase in salinity is predicted to reduce the chance of having any employment in the past 12 months by 5.4 percent points. Together, our results suggest that at least in the short run, saline shocks generate unemployment for individuals from rice-producer households.

A natural question then is whether people react by outmigrating. Such response is well documented in the literature studying weather shocks (e.g., Feng et al., 2012; Dallmann and Millock, 2017) and particularly salinization (Chen and Mueller, 2018). While it is not feasible for us to observe migration consistently as this question differs between the survey wave in

[27]One caveat is that there are missing answers to this survey question on additional jobs, which reduces our sample size.

Table 4: Labor changes of local firms

	Labor change		
	Agricultural firms	Manufacturing firms	Service firms
	(1)	(2)	(3)
Salinity index$_t$ (SD)	0.333	1.33	–0.008
	(0.320)	(1.19)	(0.052)
Salinity index$_{t-1}$ (SD)	–0.287	–0.318	–0.066*
	(0.397)	(1.30)	(0.035)
Firm FE	✓	✓	✓
Year FE	✓	✓	✓
Weather controls	✓	✓	✓
Mean dependent variable	0.588	4.47	0.163
Observations	3,099	26,696	42,098

Notes: 'Labor change' is the within-year change in the firm's reported number of employees. 'Salinity index' is standardized in all regressions. All estimations control for firm and year fixed effects. Weather controls are the average temperature, precipitation, and potential evapotranspiration measured for the commune in the contemporaneous and previous years. Robust standard errors, adjusting for clustering at the firm level, are reported in the parentheses. *p<0.1; **p<0.05; ***p<0.01.

2012 and subsequent ones, we take two approaches to resolve this. First, analogous to Aragón et al. (2021), we capture outmigration by changes in the number of working-age household members present.[28] Column 6 of Table 3 shows that a one-SD increase in salinity in the past year reduces the number of present working-age members by about 2.6%. Second, we zoom out to examine changes in total population using pixel-level population estimates from WorldPop (2018) for communes where our rice-producing households reside. This allows us to build a commune-year panel across 2012-2018. The estimate (column 7) suggests that, as local saline level increases by one SD, total commune population decreases by about 0.2%. Taken together, the results provides suggestive evidence that people outmigrate in reaction to higher salinity.

6.2 Labor at the local firm level

To complement the household results, we estimate the changes in labor at the firm level using data from the annual Vietnamese Enterprise Survey, which covers all formally registered firms.[29] This helps us in two ways. First, this higher-frequency census data allows us to

[28] In the survey, household members whose information is present are those still living within the family or having been away no more than 6 months.

[29] For firm data, we estimate the following regression model:

$$\Delta labor_{i,c,t} = \alpha SI_{c,t} + \sigma SI_{c,t-1} + f(w_{c,t},\ w_{c,t-1}) + \pi_i + \tau_t + \varepsilon_{i,c,t},$$

in which $\Delta labor_{i,c,t}$ captures the within-year change in the number of people employed by firm i located in commune c reported for year t. SI is the salinity index measured for the commune at contemporaneous tease out more generalizable patterns in local labor shifts. Second, firms' reported industrial codes make the identification of inter-sectoral labor reallocation more accurate.[30] Table 4 presents the estimated effects of local hydrological saline shocks on firms' within-year change in the number of people employed. Column 1 indicates that salinity does not induce changes in the amount of labor employed by local agricultural firms.[31] In column 2 for manufacturing firms, the effects are likewise not precisely estimated, suggesting that any labor displaced from household farming may not smoothly transit to the local manufacturing sector. In column 3, we observe that while a contemporaneous increase in salinity does not generate changes in the amount of labor employed by local service firms, a negative delayed effect is precisely estimated. Specifically, a one-SD increase in salinity in the past year is associated with a 0.066 decrease in labor change. This is a sizable effect compared to the mean change at 0.163, amounting to a 40% decrease.

Results from the estimations using firm data align with those estimated for household labor presented in Table 3. While people leave household farming in reaction to higher salinity, our estimates do not suggest labor absorption by local agricultural or manufacturing firms. The latter is especially at odds with the theoretical prediction that manufacturing, as the other tradable sector in a small open economy, takes up labor from agriculture following negative productivity shocks (cf. Corden and Neary, 1982) and with more optimistic empirical findings (e.g., Blakeslee et al., 2020; Colmer, 2021b). We further find that the local service sector, as non-tradable, contracts following salinity shocks, likely because of lower local demands—this is in line with theory and recent empirical evidence (Santangelo, 2019; Albert et al., 2021; Liu et al., 2023).[32] Although we do not observe informal firms, if labor reallocation in fact occurs among these, that should be reflected in the household results.[33] To sum up, we find that households' propensity to work on farms decreases in response to salinity shock. This sheds further light on mechanisms underlying the larger agricultural revenue losses relative to rice yields. Beyond farming, we find little evidence that labor reallocates to local outside options in the short run.

year t and previous year $t-1$. $f(w)$ is a linear function of weather variables w including temperature, precipitation, and potential evapotranspiration. π_i and τ_t are the firm and year fixed effects respectively. In all estimations, standard errors are clustered at the firm level.

[30]We use the Vietnam Standard Industrial Classification 2007 (VSIC) to categorize firms into agriculture, manufacturing, and service sectors. VSIC 2007 is applicable to VES from 2008 to 2018, thus covering all the data used in our analysis. Appendix Table B.6 provides details on the VSIC industry classification.

[31]Over 60% of agricultural firms in the sample operate in the aquaculture and fishery industries while about 20% are seed- and agricultural service providers.

[32]Within the sample, more than one-third of service firms are retailers and around 5% are directly linked to local tourism.

[33]The question on wage work in VHLSS, i.e., capturing outcome in Table 3 (column 3), does not differentiate between formal and informal employers.

7 Living conditions, resource allocation, and schooling

The previous sections document the adverse impacts of hydrological salinity shocks on rice-farming households' production and employment. Furthermore, salinity may affect households through reduced access to freshwater and environmental degradation, with potential repercussions for health and well-being. These combined constraints could prompt families to reallocate their living resources and spending in particular. While these responses may operate primarily through income effects, we also explore if saline shocks directly alter resource allocation. Such salinity-specific link may arise through three channels. First, as worsening living conditions under high salinity could generate immediate needs such as healthcare, households may redirect spending accordingly. Second, salinity could potentially affect resource allocation via psychological pathways. For example, biased projected utility under idiosyncratic weather shocks may shape purchasing decisions (Busse et al., 2015; Chang et al., 2018). Third, salient environmental changes may lead people to update their beliefs about longer-term climate risks, thereby influencing forward-looking investments (e.g., Choi et al., 2020; Nguyen et al., 2025).

In this section, we first document the negative impacts of saltwater intrusion on household living conditions. We then explore whether salinity affects resource allocation beyond income effects. Finally, we provide suggestive evidence that salinity increases spending on children's schooling and raises school attendance in the short run.

7.1 Living conditions

We start by examining how salinity affects social outcomes beyond production. Specifically, we consider three indicators of household well-being: hospitalizations, the propensity to incur debt, and subjective assessments of living conditions. Estimates are reported in Table 5. Column 1 reveals that the total number of household hospitalizations rises by 0.242 as salinity goes up by one SD. The estimate is large, accounting for roughly 65% of the outcome mean. Estimations at the individual level offer a similar pattern (Appendix Table E.4). This result underscores adverse health effects from salinization of water supplies, consistent with nascent empirical evidence at local and global scales (Chakraborty et al., 2019; Phung et al., 2021; Mueller et al., 2024). In column 2, a one-SD increase in salinity is estimated to raise the probability that household incurred debt in the past year by 6.6 percent points (26% of the outcome mean). Beginning in 2014, the survey records the purpose of borrowing, allowing further breakdown. While constrained by data limitations, the estimates provide suggestive evidence that salinity shocks increase borrowing for agricultural and health-related reasons

Table 5: Measures of household living conditions

	No. of hospitalizations	Incurring debt (y/n)	Worse living conditions
	(1)	(2)	(3)
Salinity index (SD)	0.242	0.066	0.177
	(0.053)***	(0.034)*	(0.033)***
	[0.055]***	[0.036]*	[0.033]***
Commune FE	✓	✓	✓
Time FE	✓	✓	✓
Weather controls	✓	✓	✓
Household controls	✓	✓	✓
Mean dependent variable	0.371	0.253	1.843
Observations	1,020	1,020	1,020

Notes: 'No. of hospitalizations' is the total number of hospitalizations among all household members in the past 12 months. 'Incurring debt (y/n)' is an indicator variable equal to one if household reports to incur debt (in goods or money) in the past 12 months, and zero otherwise. 'Worse living condition' measures household perception of the contemporaneous living conditions compared to 5 years ago; it is an ordinal variable going from 1 to 4 with 4 indicating a perception of living conditions becoming worse. 'Salinity index' is standardized in all regressions. Commune and time (year and survey-month) fixed effects are included in all estimations. Weather control vector includes the average temperature, precipitation, and potential evapotranspiration measured for the commune. Household control vector includes household size, household head's age and years of education. Commune-level clustered robust standard errors are reported in the parentheses and Conley-robust standard errors (at 20km cutoff) are in the brackets. *p<0.1; **p<0.05; ***p<0.01.

(Appendix Table E.5). Together, results in columns 1 and 2 indicate that households face greater constraints as local salinity intensifies. In column 3, we directly examine households' own assessments of their living conditions. The estimates indicate that extreme salinity leads households to view their living conditions more negatively.[34] This result aligns with evidence that water insecurity negatively affects farmers' self-reported physical and mental health in the region (Vuong et al., 2022).

7.2 Resource allocation

The previous results suggest that living conditions deteriorate as local salinity intensifies. Combined with the documented revenue and employment losses, these socioeconomic constraints may prompt changes in household resource allocation as a form of adjustment. Specifically, under idiosyncratic salient weather events, adjusted spending patterns may arise from increased immediate needs (e.g., healthcare), biased utility projection as behavioral responses to shocks, or revised expectations about longer-term climate risks that shape forward-looking investments (Busse et al., 2015; Chang et al., 2018; Choi et al., 2020).

[34] The survey question asks households how they think about their current living conditions compared to 5 years ago. The answer is coded to be: 1-substantially better; 2-slightly better; 3-the same; 4-worse. For a more straightforward interpretation, we alternatively code the outcome into an indicator equal to one if the household answers that their living conditions are worse than 5 years ago. The point estimate is similarly precisely estimated and shows that a one-SD higher salinity increases households' propensity to view their lives negatively by about 12.9 percentage points.

In this section, we hence explore if households reprioritize their living budgets in response to salient salinity, focusing on how relative demand for different goods—measured by expenditure shares—varies with exposure to hydrological salinity. We isolate these salinity-specific associations by accounting for Engel curves, since demand depends principally on household income. To estimate Engel curves, we apply the functional form introduced by Deaton and Muellbauer (1980), using the logarithm of total expenditures as a proxy for disposable income. Since disposable income reflects resources available for spending—including savings and borrowing, net of taxes and fixed costs—our earlier finding that debt increases suggests that using up savings or borrowing may play an important role. However, the survey does not directly observe savings, taxes, or fixed costs, total expenditures thus serve as a practical proxy (see e.g., Engel and Kneip, 1996). Our outcome variables are the budget shares of spending categories reported over the past 12 months, consistent with the outcomes analyzed in the preceding sections. We exclude expenditures on daily food consumption, as this data is available only for the past 30 days. The resulting categories are festive food, soft (non-durable) goods, durable goods, housing, healthcare, adult skill training, children's schooling. Total expenditures also include a reported residual 'other' category—covering items such as administrative fees, donations, and ceremonial expenses. Because this category's composition is heterogeneous and not clearly defined, we do not report it in the main table, though we give its estimate in footnote 36. Table 6 presents the results for the main categories.

In column 1, budget share allocated to festive food decreases as total expenditures rise, consistent with Engel's law. Holding this income effect constant, the estimates imply that households direct spending away from this category when exposed to higher local salinity at the rate of about 4% the outcome mean. For non-durable goods in column 2, the results indicate patterns of inferior goods. Budget share for this category, however, is estimated to increase with salinity, potentially reflecting short-run essential demands. Because a substantial portion of these soft goods consists of small household repairs, the increase may also hint at crowding out of durable goods purchases. This interpretation is supported by the results in column 3. Keeping total expenditures fixed, households shift a substantial share of spending away from this category when faced with intense salinity, signaling lower relative demands for long-term material investments.[35] Estimates in column 4 reinforce this notion. While budget share for housing appears largely orthogonal to total spending, it is crowded out as households experience more severe saline conditions. Together, the salinity-associated declines in budget shares for durables and housing may reflect reduced expected utility in response to salient negative weather shocks (e.g., Busse et al., 2015; Chang et al., 2018).

[35]The income elasticity of spending on durable goods is estimated to be 1.36, healthcare 0.83, and children's schooling 0.61 (Appendix Table E.7).

Table 6: Household budget reallocation

	Shares in total expenditures							Log total	Log total exp.
	Festive food	Soft goods	Durable goods	Housing	Health	Adult training	Children schooling	expenditures	excl. health & schooling
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Salinity index (SD)	–0.004	0.023	–0.028	–0.014	0.035	–0.0004	0.015	0.033	–0.043
	(0.002)**	(0.010)**	(0.006)***	(0.004)***	(0.009)***	(0.0005)	(0.006)**	(0.039)	(0.034)
	[0.002]*	[0.008]***	[0.005]***	[0.004]***	[0.007]***	[0.0004]	[0.006]**	[0.038]	[0.034]
Log total expenditures	–0.045	–0.061	0.099	0.014	0.029	0.001	0.008		
	(0.002)***	(0.006)***	(0.011)***	(0.013)	(0.011)***	(0.0005)**	(0.007)		
	[0.001]***	[0.007]***	[0.007]***	[0.017]	[0.008]***	[0.0005]**	[0.007]		
Commune FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean dep. var.	0.098	0.204	0.113	0.118	0.136	0.002	0.078	34,445	26,728
Observations	1,020	1,020	1,020	1,020	1,020	1,020	1,020	1,020	1,020

Notes: Dependent variables in columns (1) to (7) are the shares of expenditures on the corresponding category in the household's total living expenditures over the past 12 months, defined as the sum of all spending categories recorded in the survey. This includes a residual 'other' category, which enters total expenditures but is not reported separately. 'Festive food' is expenditure share on food for festive occasions. 'Soft goods' is expenditure share on non-durable goods. 'Durable goods' is expenditure share on durable goods. 'Housing' is expenditure share on housing and energy. 'Health' is expenditure share on medicines, medical services and hospitalizations. 'Adult training' is expenditure share on adults' skill training. 'Children schooling' is expenditure share on all children's schooling costs (tuition, books, uniforms, extra classes). 'Log total expenditures' is the logarithmized total living expenditures in the past 12 months, defined as the sum of all spending categories plus a residual 'other' category (e.g., administrative fees, donations, ceremonial expenses). 'Log total exp. excl. heath & schooling' is the logarithmized total living expenditures excluding health and children schooling expenses in the past 12 months. 'Salinity index' is standardized in all regressions. Commune, year, and survey-month fixed effects are included in all estimations. Weather control vector includes the average temperature, precipitation, and potential evapotranspiration measured for the commune. Household control vector includes household size, household head's age and years of education. Commune-level clustered robust standard errors are reported in the parentheses and Conley-robust standard errors (at 20km cutoff) are in the brackets. *p<0.1; **p<0.05; ***p<0.01.

In column 5, we estimate the effects on spending share distributed to healthcare. Baseline income estimates indicate that healthcare is a necessary good, with its share rising moderately in total expenditures. Importantly, consistent with our earlier findings on adverse health effects of salinity shocks (see also Phung et al., 2021; Mueller et al., 2024), households respond by reallocating resources toward healthcare to meet these immediate demands. Columns 6-7 proceed to inspect spending reallocation toward human capital development. Estimates in column 6 suggest that the budget share allotted to adult skill training increases slightly with household income, but does not vary with exposure to salinity. In column 7, the outcome measures household budget shares for enrolling children in schools, including tuition, textbooks, uniforms, compulsory extra classes, and fees. Engel-curve estimates indicate that the share of spending on children's schooling rises slightly with total household expenditure, though the estimate is not statistically significant at conventional levels. However, beyond this income effect, we find that families reallocate resources toward children's schooling as local salinity intensifies. We revisit this pattern in the next section.[36]

In the last two columns of Table 6, we estimate the effects of salinity on total household expenditures. In column 8, the coefficient is positive, yet not statistically different from zero. Several mechanisms can reconcile the negative farm-income effect with this neutral expenditure response. First, households may smooth consumption through savings or borrowing in the short run. For example, Newman and Tarp (2020) find that smallholder households in Vietnam respond to weather shocks by depleting savings or increasing borrowing. While we do not observe savings in the data, our earlier results show that salinity increases households' propensity to incur debt, which may help stable spending. Second, the total expenditures we capture are summed across categories reported over the preceding 12 months and exclude frequently purchased items such as daily food, which are reported over the past 30 days. If households reduce this spending in response to shocks, the decline in overall consumption may be understated.[37] Together, these reasons may explain why total expenditures remain unaffected under income losses. One central result of Table 6 is that expenditures on healthcare and children's schooling increase with salinity exposure. A reallocation toward these

[36]For completeness, we also estimate the effect on the share of household spending in the residual 'other' category (including e.g., administrative fees, donations, and ceremonial expenses). The estimate indicates that its share falls by about 11% of the outcome mean and the spending itself decreases by about 18% as the salinity index rises by one SD.

[37]Beyond the spending reported for the past 12 months, the VHLSS separately records two frequently-purchased categories of daily food and other daily expenses, which are reported for the past 30 days. We estimate salinity's association with these items over a matched exposure horizon. All coefficients are negative. But only the one for other daily expenses is statistically significant, while those for daily food and the two combined are not. These estimates directionally suggest a decline in daily spending under more intense salinity, though the short reporting window limits what we can firmly conclude. The results can be obtained from the authors and are included in the replication package.

categories can offset reductions in other types of spending, leaving total expenditures largely unchanged. To assess this directly, column 9 excludes health and schooling expenditures from total household spending. Once these components are removed, the estimated effect of salinity turns negative and increases in absolute magnitude.

Combined, the results in Table 6 suggest that, holding income effects constant, households reallocate their living budgets in response to local salinity shocks. Expenditures on material consumption decline, while spending on healthcare and children's schooling increases. The latter is probably striking for a region with relatively low level of human capital.[38] Evidence from time-use studies shows that school attendance may rise following negative agricultural shocks, as the opportunity cost of schooling relative to farm work declines (Kruger, 2007; Shah and Steinberg, 2017). Our results, however, capture direct monetary costs, suggesting that farmer households might actively invest in children's schooling.

7.3 Children's schooling

Table 6 shows that as salinity intensifies, households shift their budgets toward children's schooling while curtail spending on non-essential and luxury goods. This raises two questions. What mechanisms drive this adjustment, and what implications does it have for children's human capital? To answer these questions, we move beyond the household and conduct an analysis at the household-child level by constructing a sample comprising all school-aged children from rice-producing households.

Table 7 reports our results. First, we replicate the household-level analysis of budget shares devoted to children's schooling. The estimates in column 1 shows that, constant household and child-level characteristics, household budget share on a child's schooling increases with local salinity. This result is consistent with the household-level estimates in Table 6 (column 7), albeit more precisely estimated. The implied effect is meaningful, approximating 18% of the outcome mean. While the finding provides evidence of a positive adjustment, we next explore what motivates it. One possibility is short-run substitution: as saline shocks reduce farm productivity, the opportunity cost of schooling relative to farm work falls (Kruger, 2007; Shah and Steinberg, 2017), leading more children to attend school and thereby increasing associated expenditures. Alternatively, the response may reflect forward-looking investment. As repeated seawater intrusion signals declining agricultural viability, parents may invest in children's human capital to prepare them for non-farm, education-intensive

[38] The MKD's literacy rate is below average, while its share of people working informal jobs in the labor force is the second-highest and share of skilled labor—10.4% between 2009 and 2018—is the lowest nationwide (GSOV, 2024).

Table 7: Schooling investment and enrollment

	Schooling expenditure share	Schooling expenditures (y/n)	School attendance (y/n)
	(1)	(2)	(3)
Salinity index (SD)	0.011	0.086	0.084
	(0.002)***	(0.008)***	(0.010)***
	[0.001]***	[0.011]***	[0.013]***
Log total expenditures	–0.022	0.019	0.024
	(0.004)***	(0.023)	(0.023)
	[0.004]***	[0.027]	[0.027]
Age	0.004	–0.031	–0.033
	(0.0008)***	(0.004)***	(0.004)***
	[0.0008]***	[0.003]***	[0.003]***
Female	0.010	0.022	0.030
	(0.004)**	(0.025)	(0.024)
	[0.004]**	[0.030]	[0.027]
Commune FE	✓	✓	✓
Time FE	✓	✓	✓
Weather controls	✓	✓	✓
Household controls	✓	✓	✓
Mean dependent variable	0.059	0.888	0.881
Observations	858	858	858

Notes: Estimation sample includes all children aged 5-18 from rice-producer households in the main sample. 'Schooling expenditure share' is the share of the child's schooling expenses in total household living expenditures over the past 12 months. 'Schooling expenditures (y/n)' is an indicator variable equal to one if any schooling expenses in the past 12 months is reported for the child. 'School attendance (y/n)' is an indicator variable equal to one if the child is reported to attend school at the time of the survey, and zero otherwise. 'Salinity index' is standardized in all regressions. 'Log total expenditures' is the logarithmized total household living expenditures in the past 12 months. Commune and time (year and survey-month) fixed effects are included in all estimations. Weather control vector includes the average temperature, precipitation, and potential evapotranspiration measured for the commune in the past year. Household control vector includes household size, household head's age and years of education. Commune-level clustered robust standard errors are reported in the parentheses and Conley-robust standard errors (at 20km cutoff) are in the brackets. *p<0.1; **p<0.05; ***p<0.01.

opportunities (e.g., Nguyen et al., 2025). The two mechanisms, however, are not mutually exclusive and may operate simultaneously. To probe these dynamics, column 2 shows that the rise in schooling budget share is driven primarily by expansion on the extensive margin: the probability that parents spend on a child's schooling at all increases with salinity. Although this pattern is consistent with substitution, schooling still entails direct monetary costs. Specifically, even if children are less needed on the farm, sending them to school requires non-trivial expenses for these agricultural households. Per-child schooling on average accounts for 5.9% of the household budget, while spending on all children's schooling is on par with expenditures distributed to housing or healthcare needs (Appendix Table E.7).

Taken together, our results suggest that rice-farming households respond to salinity shocks by directing resources toward children's schooling. The final column of Table 7 shows an increase in children's school enrollment in the short run, closely aligning with households' spending decisions.[39] This represents a tangible outcome of parental investment for children's human capital development.

8 Conclusion

Saltwater intrusion, intensified by climate extremes, poses overarching threats to agricultural deltas around the world. Focusing on the coastal Vietnamese Mekong Delta—a major rice-exporting region—we examine how rising salinity affects smallholder rice farmers' production and adaptive responses. Our results show that salinity shocks reduce rice yields, but total agricultural revenues decline even more sharply. This discrepancy is driven by pronounced contractions in agricultural land, highlighting a crucial input margin under regional salinization. Despite the relative diversity of agricultural activities in the coastal Delta, households show limited short-run adaptation through land conversion or crop switching. Extreme salinity also disrupts household labor: own-farm work declines, but shifts to local alternative employment are minimal. Beyond production, we document negative effects on household well-being and that they reallocate living budgets in reaction. Notably, households shift spending toward children's schooling, potentially driven by short-run substitution for farm work and simultaneously a forward-looking response to invest in human capital. This in turn raises school attendance. Although our estimates capture short-run effects, they point to intergenerational investment as an important adaptation strategy. The long-term trajectory of these changes remains uncertain and warrants further study.

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[39] Possible responses to the VHLSS question asking whether the child is attending school include: 1-Yes, 2-Having summer break, 3-No. Our outcome variable is coded to be one if the recorded response is either 1 or 2, and zero otherwise. The results stay consistent when we recode the outcome to measure non-attendance, i.e., it is set to one if the response is 3, and zero otherwise.

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Appendices

Appendix A Agriculture and saltwater intrusion

Appendix A.1 Study area

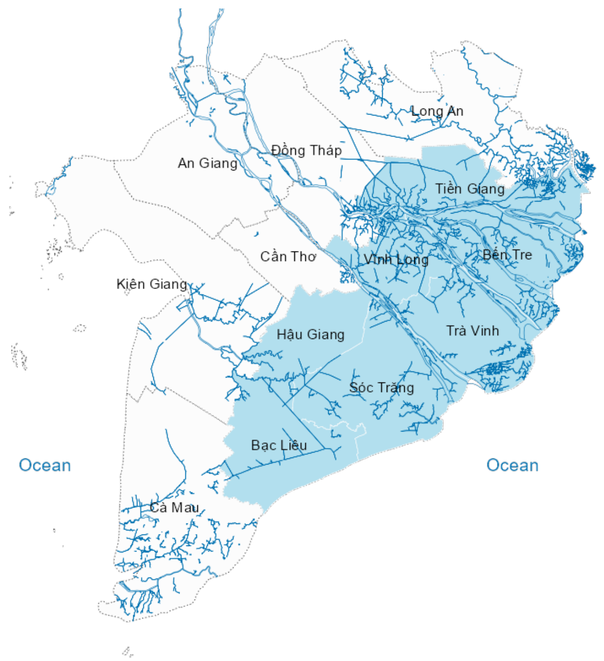


Figure A.1: Study area
Figure shows the entire Vietnamese Mekong Delta and its province boundaries (dotted and white lines), the Mekong river system (solid blue lines), and the study area (blue shaded).

Appendix A.2 Agricultural production

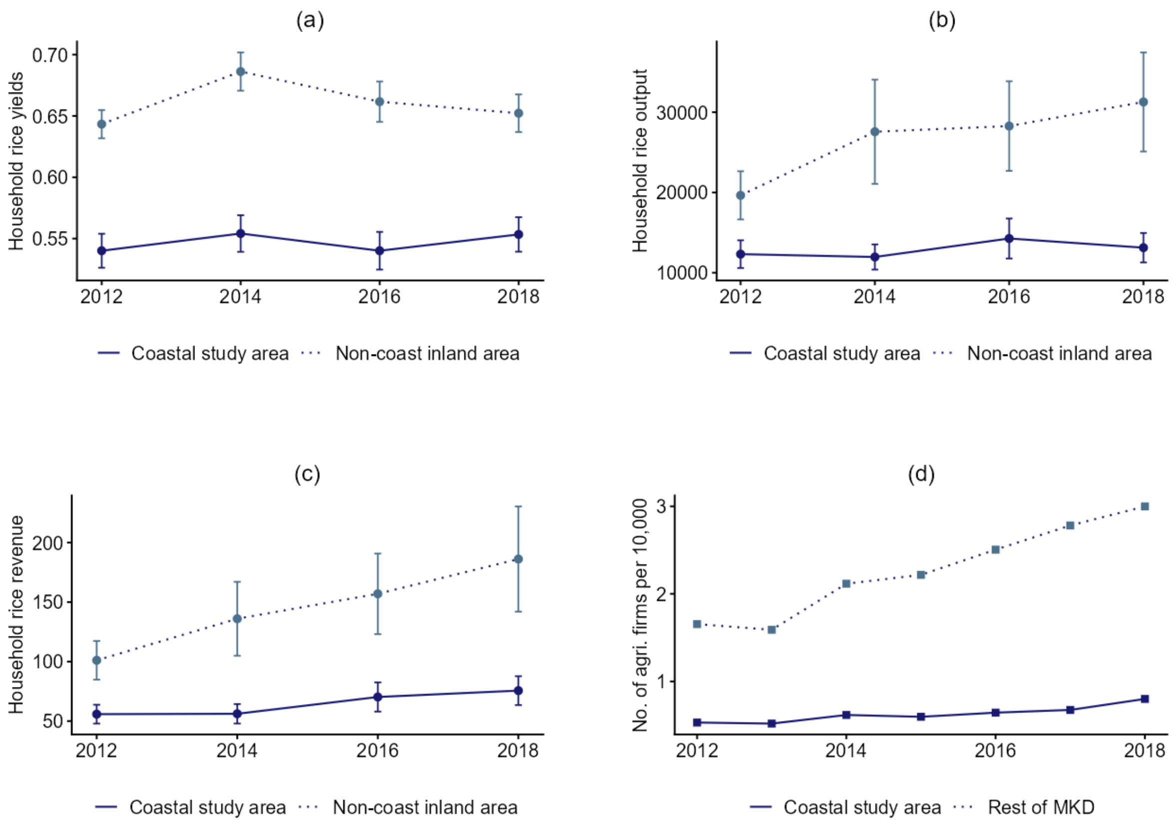


Figure A.2: Coastal-inland differences in rice production and agricultural firm presence over time
Figure depicts rice production and local agricultural firm presence trends between 2012 and 2018 in the coastal study area. Panels (a), (b), (c) illustrate the average rice yields (in kg/m^2), total rice output (in kg), and total rice revenue (in million VND) per household respectively, together with their 95% c.i. as bars. Panel (d) shows the number of registered agricultural firms per 10,000 inhabitants. For comparison, rice production trends for the non-coast, inland area of the Delta (consisting of An Giang, Can Tho, Dong Thap) are plotted in panels (a)-(c) and agricultural firm presence for all other provinces in the Vietnamese Mekong Delta outside the study area (An Giang, Can Tho, Dong Thap, Long An, Kien Giang, Ca Mau) is shown in panel (d).

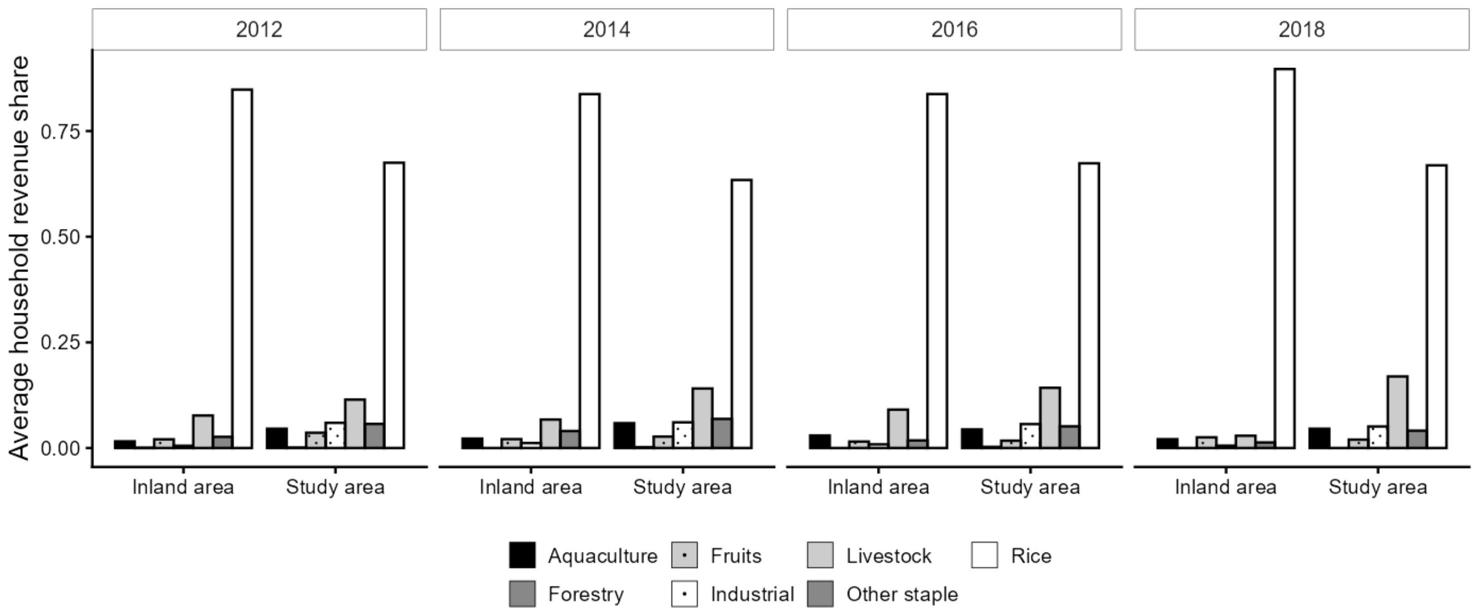


Figure A.3: Crop revenue shares
Figure illustrates the average household revenue shares of different crops between 2012 and 2018 in the study area and, for comparison, the non-coast, inland area of the Delta (consisting of An Giang, Can Tho, Dong Thap).

Appendix A.3 Saltwater intrusion

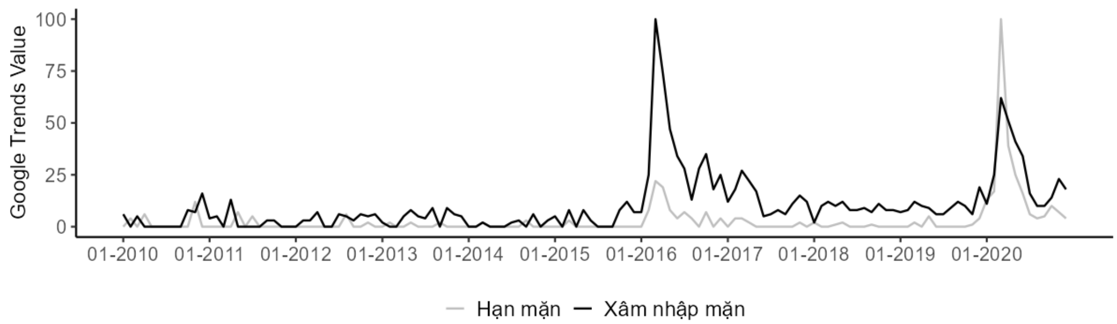


Figure A.4: Public attention on saltwater intrusion
Figure depicts the monthly Google Trends data capturing the relative internet search volume between 2010 and 2020 for search terms "xâm nhập mặn", meaning saltwater intrusion, and "hạn mặn", meaning salt drought.

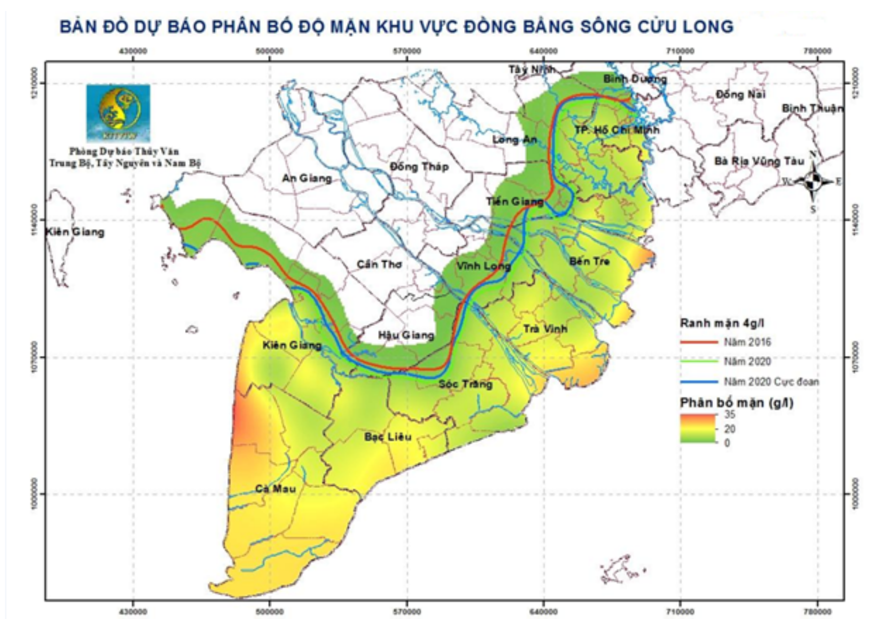


Figure A.5: Reported saltwater intrusion extent
Figure shows extent of saltwater intrusion (referred to as the "salinity border") officially reported by the Vietnam Meteorological and Hydrological Department. Colored lines indicate the extent in 2015 (red) and 2020 (green). Image retrieved from https://tnmttravinh.gov.vn/xem/xam-nhap-man-tai-dong-bang-song-cuu-long-nhung-ngay-dau-thang-52020 on February 18, 2026.

Appendix A.4 Saltwater intrusion impact on rice production

Rice cultivation is considered as highly freshwater-intensive. It generally requires more water than other grains, with 800–5,000 liters needed per kilogram of rough rice to account for combined losses from evapotranspiration, seepage, and percolation. Cultivation practice typically requires freshwater to be ponded for the crop to ensure adequate water uptake (Bouman, 2009). Rice is also classified as salt-sensitive. Its salinity-tolerance threshold is 3 dS/m for cultivation soil-water electrical conductivity, which is equivalent to about 1.9 g/L of salt in water. Salt-tolerance is lower during the crop's seedling stage (Tanji and Kielen, 2002, pp. 138, 147). Saltwater intrusion creates transitory, yet salient freshwater shortages for production. Tran et al. (2024) estimate that some sub-regions in the Mekong Delta could experience at least over 40 dry-season days without freshwater as a result of riverine saltwater intrusion, defined as periods when average salinity in freshwater supplies exceeds 1 g/L. For reference, the taste-acceptance threshold for drinking water is 0.25 g/L and higher salinity has been linked to negative health effects (WHO, 2008; Vineis et al., 2011). Saltwater intrusion also brings adverse consequences for agricultural production by increasing soil salinization and impairing longer-term soil quality (Tully et al., 2019a,b; Eswar et al., 2021; Chau et al., 2021). In Figure A.6, we provide preliminary evidence on the impacts of saltwater intrusion on rice production by comparing household-level outcomes between our coastal study area—exposed to seawater intrusion—and three inland provinces (An Giang, Dong Thap, and Can Tho) that remain unaffected by salinity even in peak years (Figure A.5). The results suggest that total rice production and revenue decline more sharply in the coastal region over time, particularly in 2018 following the high-salinity episode in 2016. We discuss these results in more detail in Section 2.

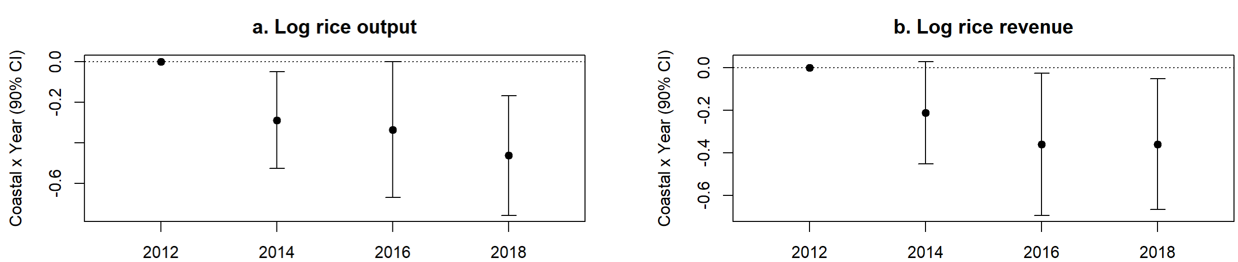


Figure A.6: Differential changes in rice production between coastal and inland regions
Figure reports dynamic estimates comparing the studied coastal region with the inland stretch (no saltwater intrusion) of the Vietnamese Mekong Delta, with 2012 as the reference year. Outcome is logarithmized household's total rice output (kg) in panel (a) and logarithmized household's total rice output in panel (b). Specifications partial out commune, year, and survey-month fixed effects and condition on weather and household-level covariates. Standard errors are clustered at the commune level. Bars denote 90% confidence intervals.

Appendix B Data

Appendix B.1 Salinity index construction

River salinity measured at hydrostations

We use river salinity data from 33 hydrological stations operated by the Vietnam Meteorological and Hydrological Department. The data and technical instruction were provided by the Research Institute for Climate Change at Can Tho University. The dataset covers 2011–2018 and consists of bi-hourly salinity readings (g/L) and daily means. For the main salinity index, we aggregate daily means from January up to the month preceding a household's survey month.[40] Salinity monitoring typically occurs during the dry season (until July), when upstream freshwater flows are limited and salinity rises in river water. Table B.1 and Figure B.1 report summary statistics and variation in river salinity.

Table B.1: River salinity summary statistics

River salinity	Mean	Std. Dev.	Min.	Max.	Obs.
2011	3.645	5.346	0	22.056	186
2012	2.599	4.138	0	21.778	186
2013	3.751	5.405	0	25.677	186
2014	2.773	4.605	0	25.549	186
2015	4.845	6.589	0	30.685	190
2016	6.150	7.070	0	31.473	186
2017	3.010	4.727	0	25.422	190
2018	2.946	4.750	0	26.385	186

Notes: River salinity is measured in g/L. Summary statistics are reported for station-month observations within a given year.

Canal distances

To measure household exposure to saltwater intrusion, we assign each commune to its nearest hydrostation and compute the shortest canal-path distance from the commune centroid. River water is the primary source for irrigation in the region, and the canal network channels it inland, making water way-distance a plausible proxy for exposure. The geodata on river and canal networks of the MKD is provided to us by the Research Institute for Climate Change at Can Tho University. It comprises only of the primary and secondary tiers of

[40] For example, for a household surveyed in June 2016, we aggregate salinity from January to May 2016 at the station matched to the household's commune.

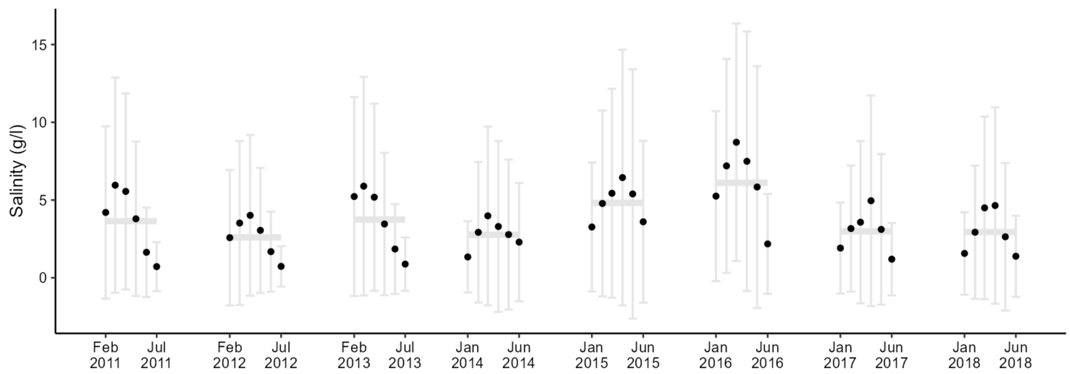


Figure B.1: River salinity 2011-2018
Figure shows the monthly average river salinity recorded across the 33 hydrostations used in our analysis (dots). Vertical bars show the variation of river salinity across these stations measured as $\overline{Salinity} \pm SD(Salinity)$. Horizontal lines indicate the yearly average river salinity across the stations for the given year.

the canal system, while leaves out the tertiary or on-farm segments. Figure B.2 presents a graphical illustration of the canal system.

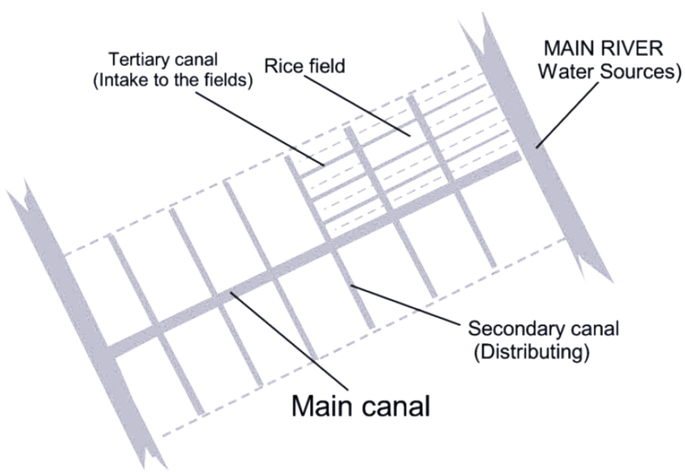
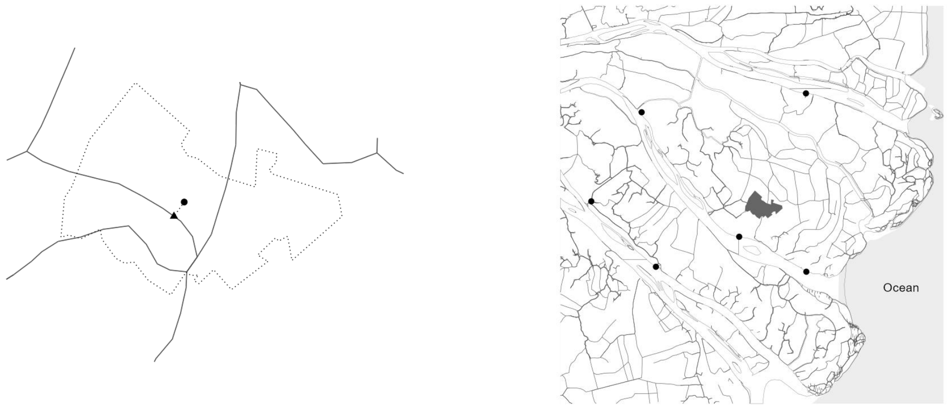


Figure B.2: Canal system
Figure shows the three-tier canal network in the Mekong Delta. Source: Tran and Weger, 2018.

To compute canal distances between a commune and hydrostations, we calculate distances along the combined canal–river network. First, we measure the Euclidean distance from the commune centroid to its nearest intersection with the network (Figure B.3, Panel a). Second, we trace the path from this intersection to hydrostations along the combined waterway network. The canal distance from commune to station is identified to be the sum of these two components. Panel (b) of Figure B.3 illustrates a commune's six nearest stations by canal distance. Table B.2 reports summary statistics of these distances for all communes in the estimation sample.



(a) (b)

Figure B.3: Example of commune-to-station canal distance calculation
Panel (a) shows a sample commune (dotted boundary), its centroid (dot), the canal network (solid lines), and the nearest point on the network by Euclidean distance (triangle). Panel (b) shows the same commune (gray), the river and canal network (solid lines), and the six closest hydrostations to the centroid based on canal distances (dots).

Table B.2: Canal distances between communes and hydrostations summary statistics

Canal distance	Mean	Std. Dev.	Min.	Max.	Obs.
Commune to nearest station	19,536	9,357	31	46,769	202
Commune to 2nd nearest station	27,950	9,981	7,129	57,677	201
Commune to 3rd nearest station	33,630	10,331	10,407	60,651	201
Commune to 4th nearest station	39,748	11,599	17,837	69,880	201
Commune to 5th nearest station	44,191	12,695	18,948	84,556	201
Commune to 6th nearest station	48,012	12,770	24,992	88,882	201
Commune to any station	89,362	46,089	31	236,552	6,232

Notes: Canal distances are measured in meters. Stations are ranked by canal distance from each commune centroid. "Commune to any station" refers to all commune–station pairs among the 33 hydrostations. The sample includes all communes in the main estimation sample (rice producer households). The different number of observations for the 2nd–6th nearest stations reflects one case in which the canal network does not connect the commune centroid to more distant stations.

Salinity index visualization

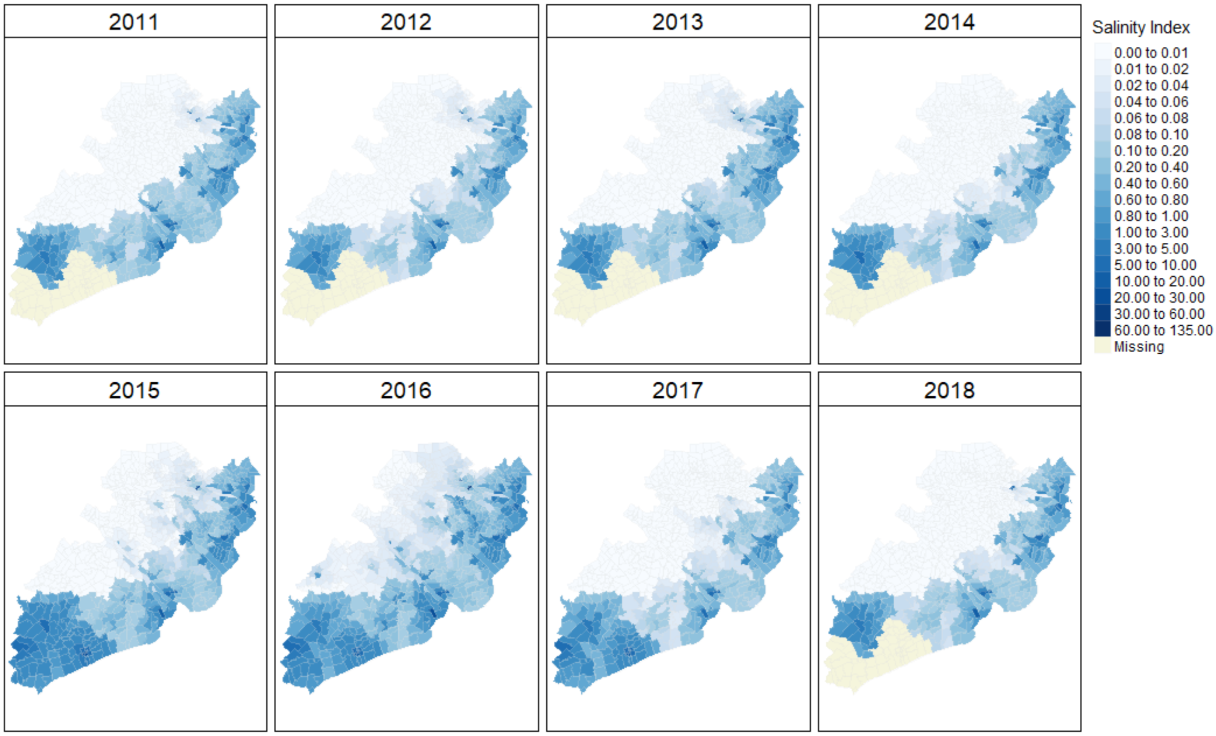


Figure B.4: Saltwater intrusion captured by the salinity index 2011-2018
Figure displays variation in seawater intrusion captured by yearly average salinity index for communes within the study area.

Appendix B.2 Household data

Our rice-producer sample is restricted to households in the study area participating in the VHLSS 2012-2018 who report rice output (all reported values are non-zero). For the land use estimation, we also draw on the agricultural producer sample to regress the probability of using land for rice. This sample is restricted to households who report output from any of the crops listed in the summary statistics of Table B.3. The non-rice producer household sample consists of agricultural producers who do not report rice output. Below is the definition of the outcome variables estimated for the sample of rice-producer households and the samples of working-aged individuals and children from these households.

Rice yields. Quantity of produced rice output divided by the total amount of land under rice cultivation (kilogram/square meter).
Rice output. Total quantity of produced rice (kilogram).
Rice revenue. Revenue received from selling or exchanging produced rice (thousand VND).
Agricultural revenue. Revenue received from selling or exchanging produces of all crops including rice, non-rice staple crops, fruits, industrial crops, aquaculture, livestock, and forestry (thousand VND).
Rice and crop revenue shares. Share of revenue received from the corresponding crop in the agricultural revenue.
Total land for rice. Total land area used for rice cultivation (square meter)—i.e., the sum of areas used for all rice planting seasons in the past 12 months.
Number of rice planting seasons. The number of planting seasons in which households cultivated rice in the past 12 months.
Land for agriculture. Total absolute land area used for all crops (square meter)—i.e., not adjusting for the number of cropping seasons, in the past 12 months.
Rice land. An indicator variable that equals one if household reports to have land used for rice in the past 12 months, and zero otherwise.
Is self-employed in agriculture. An indicator variable equal to one if the individual reports to be self-employed in agriculture in the past 12 months, and zero otherwise.
Is self-employed in non-agriculture. An indicator variable equal to one if the individual reports to be self-employed in a non-agriculture job in the past 12 months, and zero otherwise.
Is employed in wage work. An indicator equal to one if the individual reports to be employed in a wage/paid work in the past 12 months, and zero otherwise.
Have multiple jobs. An indicator equal to one if the individual reports to have more than one job in the past 12 months, and zero otherwise.
Is employed. An indicator variable equal to one if the individual reported to have any em-

ployment in the past 12 months.

Number of working-age members. The number of present household members aged 15-64.

Number of hospitalizations. The total number of hospitalizations among all household members in the past 12 months.

Incurring debt. An indicator variable equal to one if the household reports incurring debt (in goods or money) in the past 12 months, and zero otherwise.

Worse living conditions. Household perception of the contemporaneous living conditions compared to 5 years before. It is an ordinal variable ranging from 1 to 4 coded as 1-substantially better, 2-slightly better, 3-the same, 4-worse.

Shares in total expenditures. Share of spending on a category (among festive food, soft goods, durable goods, housing, healthcare, adult training, children schooling) in the total expenditures over the past 12 months.

Total expenditures. The sum of household spending over the past 12 months across festive food, soft (non-durable) goods, durable goods, housing, healthcare, adult skill training, and children's schooling, plus a residual 'other' category covering items such as administrative fees, donations, and ceremonial expenses.

Per-child schooling expenditures share. The share of the child's schooling expenses in total household living expenditures over the past 12 months.

Schooling expenditures y/n. An indicator variable equal to one if any schooling expenses in the past 12 months is reported for the child, and zero otherwise.

School attendance y/n. An indicator variable equal to one if the child is currently attending school or having summer break at the time of the survey, and zero otherwise.

Summary statistics of the household- and individual-level data are provided in Tables B.3 and B.4.

Table B.3: Summary statistics of rice-producing households

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Demographic characteristics					
Household size	1,020	4.028	1.534	1	11
Household head's age	1,020	51.777	12.218	21	90
Household head's years of education	1,020	5.921	3.435	0	12
Number of children (aged below 18)	1,020	1.074	0.945	0	5
Is of ethnicity Kinh	1,020	0.857	0.350	0	1
Residing in a rural region	1,020	0.935	0.246	0	1
Agricultural production					
Rice yields (kg/m^2)	1,020	0.547	0.119	0.140	1.141
Rice output (kg)	1,020	12,890	15,709	140	217,220
Rice revenue (thousand VND)	1,020	64,041	83,285	0	856,186
Agricultural revenue (thousand VND)	1,020	103,019	128,410	0	1,388,436
Land total land for rice (m^2)	1,020	22,357	24,979	400	288,600
No. of rice planting seasons	1,020	2.475	0.706	1	3
Land total land for agriculture (m^2)	1,020	11,258	10,797	675	100,100
Rice revenue share	1,020	0.663	0.339	0	1
Aquaculture revenue share	1,020	0.049	0.177	0	1
Industrial crop revenue share	1,020	0.057	0.159	0	1
Livestock revenue share	1,020	0.141	0.236	0	1
Fruits revenue share	1,020	0.025	0.091	0	0.876
Forestry revenue share	1,020	0.001	0.019	0	0.520
Other staple crops revenue share	1,020	0.055	0.181	0	1
Living conditions and expenditures					
No. of hospitalizations	1,020	0.371	1.031	0	16
Incurring debt	1,020	0.253	0.435	0	1
Worse living conditions	1,020	1.843	0.805	1	4
Spending share on festive food	1,020	0.098	0.059	0.005	0.547
Spending share on soft (non-durable) goods	1,020	0.204	0.113	0.007	0.698
Spending share on durable goods	1,020	0.113	0.172	0	0.844
Spending share on housing and energy	1,020	0.118	0.123	0	0.945
Spending share on healthcare	1,020	0.136	0.152	0	0.937
Spending share on adult training	1,020	0.002	0.013	0	0.276
Spending share on children schooling	1,020	0.078	0.125	0	0.717
Total living expenditures	1,020	34,445	34,950	2,117	380,105

Table B.4: Summary statistics of individuals from rice-producing households

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Panel A: Individuals from rice-producer households					
Employment					
Age	2,923	38.790	14.129	15	64
Is female	2,923	0.496	0.500	0	1
Years of education	2,923	6.821	3.522	0	12
Is self-employed in agriculture	2,923	0.691	0.462	0	1
Is self-employed in non-agriculture	2,923	0.112	0.315	0	1
Is employed in wage work	2,923	0.329	0.470	0	1
Have multiple jobs	2,001	0.756	0.430	0	1
Is employed	2,923	0.837	0.369	0	1
Health					
Hospitalization	2,003	0.122	0.328	0	1
Number of hospitalizations	2,003	0.189	0.640	0	10
Panel B: Children from rice-producer households					
Age	858	11.823	3.913	5	18
Is female	858	0.500	0.500	0	1
Household spending share on schooling	858	0.059	0.070	0	0.717
Schooling expenditures (y/n)	858	0.888	0.315	0	1
School attendance (y/n)	858	0.881	0.324	0	1

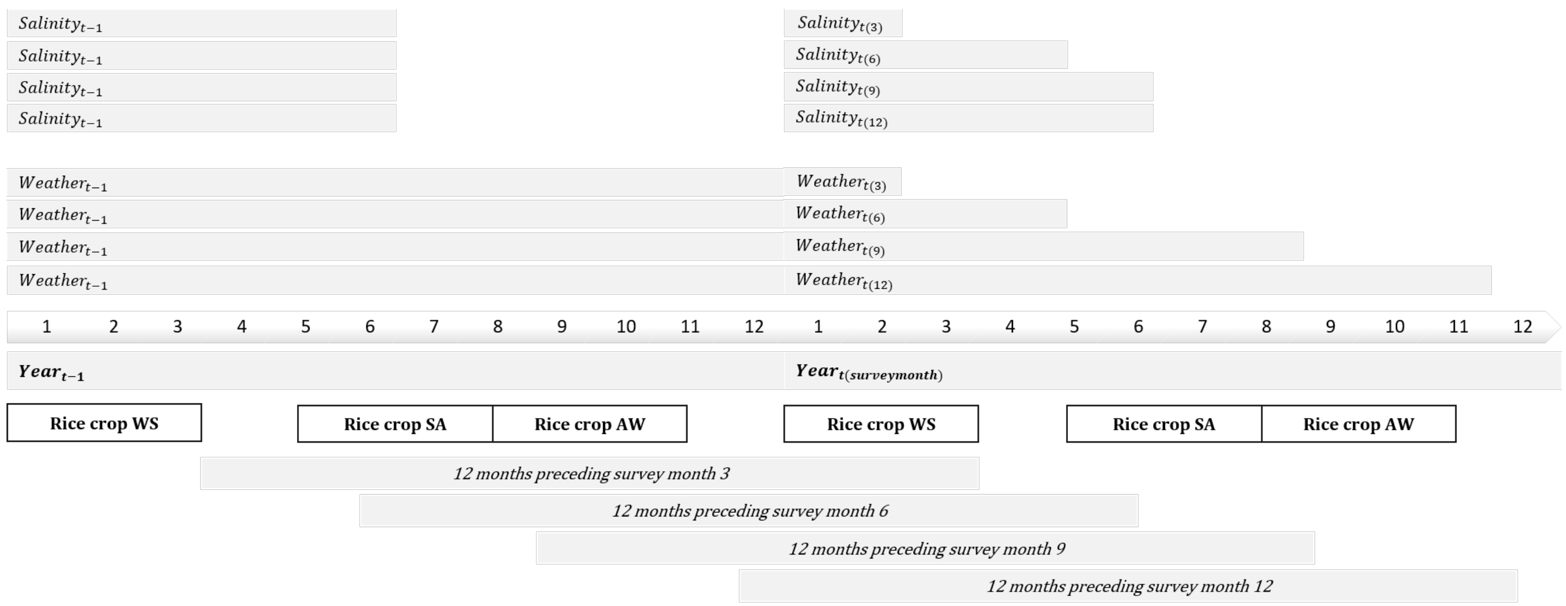


Figure B.5: **Matching survey sub-wave and weather variables** Figure illustrates how we match the household outcomes with the weather variables between the contemporaneous year t and past year $t-1$. In Equation 2, because outcomes from the VHLSS capture data in the 12 months preceding the survey wave (month m in year t), we take the average of the weather variables across the previous year and the contemporaneous year up to the survey month. For the salinity index, because our data is recorded until the end of the dry season in June/July, we incorporate the data up to this last reporting point. The typical cropping seasons (from seeding to harvest) for the main cultivar of plain rice in the MKD are also plotted in the timeline: WS is winter-spring season, SA is summer-autumn season, and AW is autumn-winter season.

Appendix B.3 Firm data

Table B.5: Firm data summary statistics

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Agriculture firms					
Number of employees at year-end	3,099	24.183	36.935	1	625
Within-year change in number of employees	3,099	0.588	11.275	-98	449
Manufacturing firms					
Number of employees at year-end	26,696	83.854	667.660	0	29,132
Within-year change in number of employees	26,696	4.469	216.549	-28,103	6,999
Service firms					
Number of employees at year-end	42,098	7.910	17.560	0	443
Within-year change in number of employees	42,098	0.163	5.029	-197	312

Table B.6: VSIC 2007 Industry classification

Agriculture		
Agriculture & related services	Forestry & related services	Fishing, operation of fish hatcheries & fish farms
Manufacturing		
Other quarrying	Manufacture of food	Manufacture of beverages
Manufacture of tobacco products	Weaving	Manufacture of wearing apparel
Manufacture of leather and related products	Manufacture of wood	Manufacture of paper
Printing and reproduction of recorded media	Manufacture of refined petroleum products	Manufacture of other chemical products
Manufacture of drug and medical products	Manufacture of rubber and plastics products	Manufacture of non-metallic mineral products
Manufacture of metals	Manufacture of fabricated metal products	Manufacture of electronic, computer and optical products
Manufacture of electrical appliances	Manufacture of other electrical	Manufacture of motor vehicles
Manufacture of other transport equipment	Manufacture of furniture	Other processing and producing
Repairing and maintaining	Manufacture and distribution of electricity, gas, hot water	Collection, purification and distribution of water
Escaping and processing of water disposal	Collecting, processing, recycling of disposals	Housing construction
Construction of public-used projects	Specialized constructing activities	
Service		
Sale &repair of motor vehicles	Wholesale except motor vehicles	Retail trade (except motor vehicles)
Land transport & transport via railways & pipelines	Sea transport	Warehouse; supporting transport activities
Post and courier activities	Resident service	Dining service

Appendix B.4 Weather data

Table B.7: Summary statistics of weather variables

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Salinity index	0.343	1.271	0.000	19.626	575
Temperature	27.364	0.438	26.071	28.558	575
Precipitation	130.641	32.820	64.875	188.699	575
Potential evapotranspiration	155.713	7.929	132.844	180.880	575

Notes: Table reports summary statistics for weather variables at the commune–year–survey-month level in the main estimation sample of rice-producing households. Each variable is constructed as the average of the previous-year mean and the current-year mean up to the survey month (see Figure B.5 for details on the matching procedure). Salinity index is defined in Equation 1. Temperature, precipitation, and potential evapotranspiration are obtained from CHELSA monthly data version 2.1 (Karger et al., 2017, 2025). Temperature is measured in degrees Celsius, precipitation and potential evapotranspiration in kg/m^2.

Table B.8: Correlation among weather variables

	Salinity index	Temperature	Precipitation
Temperature	0.007		
Precipitation	-0.001	0.380	
Potential evapotranspiration	0.132	0.523	-0.213

Notes: Table reports Pearson correlation coefficients between pairs of weather variables shown in Table B.7.

Appendix C In situ and machine learning prediction

Appendix C.1 In situ data

Overview

To examine the validity of the constructed salinity index in capturing spatial variation in saltwater intrusion shocks, we compare it with salinity measurements from more than 180 in situ samples. These samples were collected in April 2016 by the Soil Sciences Department at Can Tho University. The data cover five provinces within our study area: Ben Tre, Tra Vinh, Vinh Long, Soc Trang, and Bac Lieu. Figure C.1 presents the geographic distribution of the sampling locations.

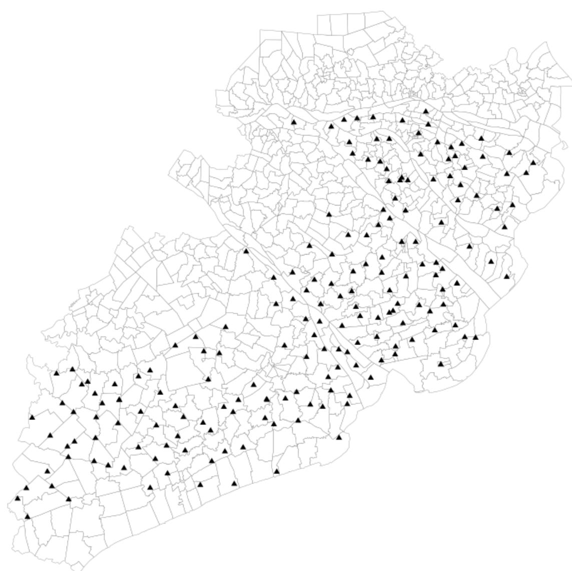


Figure C.1: Location of in situ samples
Figure maps locations of in situ samples across the study area. Gray lines show the commune border. Locations of in situ samples are marked as triangles

At each site, salinity information is available for one water sample, one soil sample at a depth of 0–20 cm, and another soil sample at 20–50 cm. Water salinity is measured in grams per liter (g/L), while soil salinity is measured as the electrical conductivity of the soil saturation extract (ECe), expressed in dS/m. Table C.1 reports summary statistics for the sampling locations and salinity measurements. All water samples were collected from on-farm irrigation systems. Notably, the observed in situ salinity levels are relatively high for both water and soil samples. The mean salinity of water samples is 7.38 g/L, substantially exceeding the 2 g/L threshold classified as severe salinity by Scianna et al.

(2007). Similarly, soil samples at both depths show average ECe values of 8–9 dS/m, which fall within the range classified as moderately saline soils by USDA (2011). The high salinity levels observed in the in situ data are likely driven by the timing of sample collection. Since the samples were collected in April 2016, a period of intense salinity intrusion, all locations exhibited measurable salinity. Consequently, the dataset contains no zero (non-saline) observations. Finally, Table C.2 reports the correlation coefficients between in situ water and soil salinity measures. Water salinity exhibits a strong positive correlation with soil salinity, with coefficients of 0.79 for the 0–20 cm layer and 0.75 for the 20–50 cm layer. These high correlations suggest a close linkage between contemporaneous water salinity and longer-term soil salinization processes.

Table C.1: Summary statistics of in situ salinity

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Panel A. In situ water salinity					
Salinity (g/L)	7.376	9.073	0.310	43.100	181
Water sample from on-farm canal	0.376	0.486	0.000	1.000	181
Water sample from on-farm ditch	0.425	0.496	0.000	1.000	181
Water sample from rice field	0.022	0.147	0.000	1.000	181
Water sample from aquaculture pond	0.177	0.383	0.000	1.000	181
Panel B. In situ soil salinity (depth 0-20cm)					
ECe (dS/m)	9.104	9.165	1.050	54.500	180
Panel C. In situ soil salinity (depth 20-50cm)					
ECe (dS/m)	8.220	7.150	1.110	45.600	122

Notes: Table reports the summary statistics of in situ salinity from the samples shown in Figure C.1. Panel A presents information from water samples, including their salinity level and source. Salinity (g/L) is the measure of salt content in water samples. Panel B and C present information from soil samples at 0-20cm and 20-50cm, respectively. ECe, denoting electrical conductivity of the soil saturation extract (dS/m), is the measure of salinity in soil samples.

Table C.2: Correlation among in situ salinity measures

	Water salinity	Soil ECe (0–20cm)
Soil ECe (0–20cm)	0.794	
Soil ECe (20–50cm)	0.745	0.859

Notes: Table reports Pearson correlation coefficients computed using pairwise complete observations.

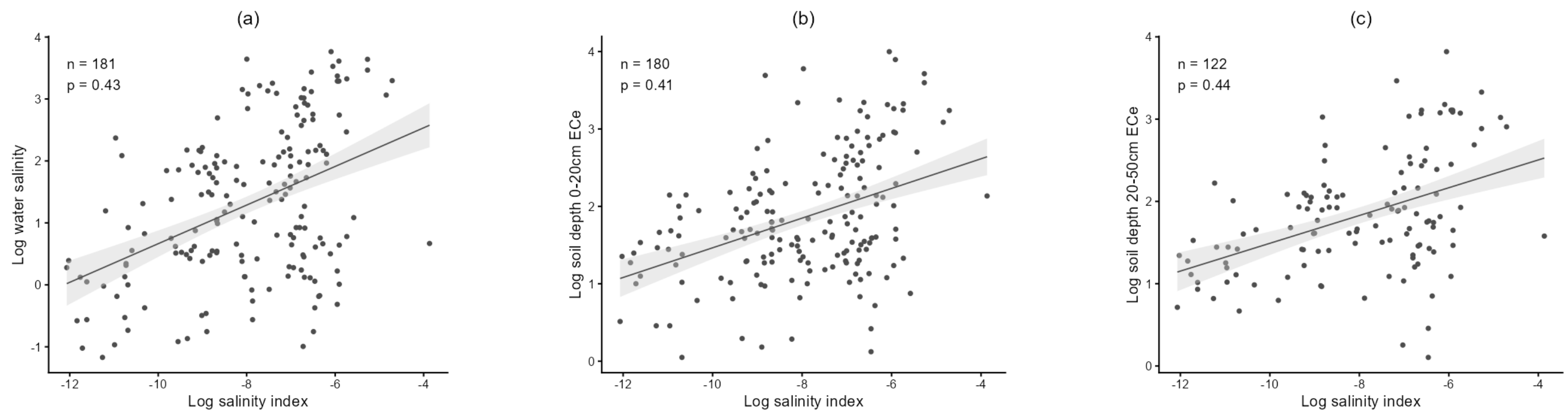


Figure C.2: Correlation between in situ samples' salinity and the constructed salinity index
Figure shows plots of in situ samples' data and constructed SI in logarithm. In each panel, the fitted regression line together with the 90% c.i. interval are displayed. Further shown on the top left corner of each panel are the number of observations and the Pearson correlation coefficient between in situ salinity measure and the salinity index in logarithm. Panel (a) reports water-sample salinity (g/l) and the salinity index constructed from canal distance to the nearest station and river salinity in April 2016. Panel (b) reports soil-sample (at depth 0–20cm) salinity (ECe) and the salinity index constructed from canal distance to the nearest station and river salinity in April 2016. Panel (c) reports soil-sample (at depth 20–50cm) salinity (ECe) and the salinity index constructed from canal distance to the nearest station and river salinity in April 2016.

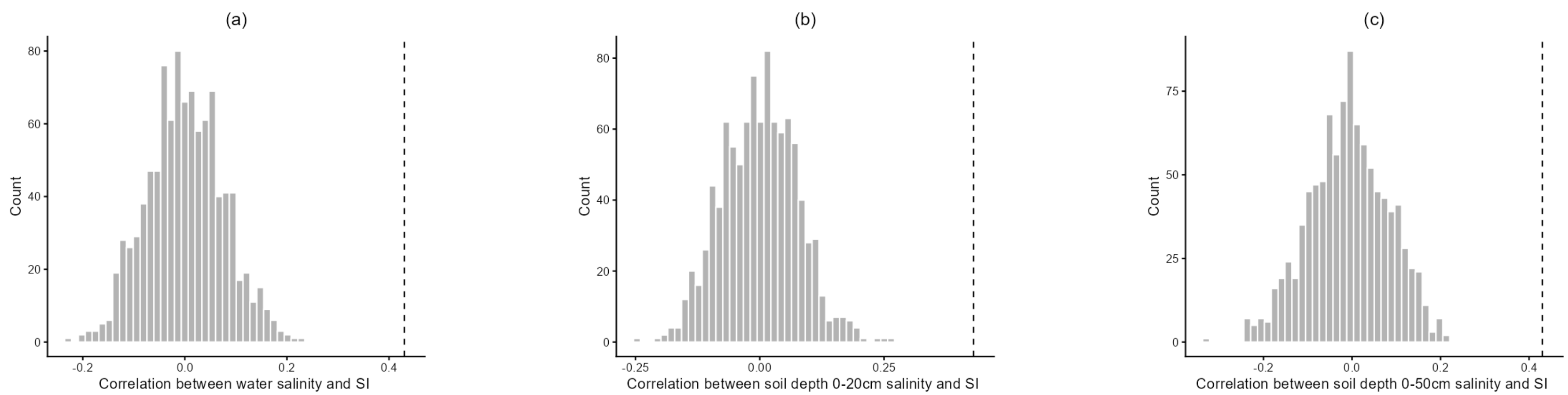


Figure C.3: Distributions of correlation between in situ samples' salinity and randomized salinity index
Figure shows distributions of the Pearson correlation coefficients calculated between in situ samples' data and randomized constructed SI obtained from 1,000 permutations. In each panel, the vertical dashed line shows the correlation coefficient between in situ data and the actual SI as reported in Figure C.2. Panel (a) reports the distribution of correlation between water-sample salinity (g/l) and permuted SI which is constructed from canal distance to the nearest station and river salinity in April 2016. Panel (b) reports the distribution of correlation between soil-sample (at depth 0-20cm) salinity (ECe) and permuted SI which is constructed from canal distance to the nearest station and river salinity in April 2016. Panel (c) reports the distribution of correlation between soil-sample (at depth 20-50cm) salinity (ECe) andpermuted SI which is constructed from canal distance to the nearest station and river salinity in April 2016.

Goodness-of-fit assessment

In this section, we assess how accurately the salinity index predicts the spatial variation of true salinity levels by examining the goodness-of-fit measure R^2 of the following model:

$$ln(in\ situ)_{i,c,d,l} = \pi ln(SI)_c + f(w_c) + \delta_d + \kappa_l + \varepsilon_{i,c,d,l}, \tag{C.1}$$

in which $ln(in\ situ)_{i,c,d,l}$ is the logarithimized water or soil salinity measured for sample i located at commune c and district d. Subscript l denotes the specific location where the in situ sample was collected, e.g., whether it is an on-farm canal, ditch, or field. $ln(SI)_c$ is the logarithimized salinity index measured for commune c in April 2016. $f(w_c)$ is a linear function of the commune's temperature, precipitation, and potential evapotranspiration in April 2016. We successively add district fixed effects δ_d and location characteristic fixed effects κ_l to account for unobserved geographic conditions influencing the baseline differences in in situ salinity.[41] Table C.3 presents our results.

Table C.3: R^2 from models predicting in situ salinity using SI

	(1)	(2)	(3)
Panel A. In situ water salinity			
R^2	0.546	0.579	0.748
Observations	181	181	181
Panel B. In situ soil salinity (depth 0-20cm)			
R^2	0.541	0.549	0.698
Observations	180	180	180
Panel C. In situ soil salinity (depth 20-50cm)			
R^2	0.523	0.558	0.762
Observations	122	122	122
District fixed effects	✓	✓	✓
Location characteristic fixed effects	–	–	✓
Weather controls	–	✓	✓

Notes: Table reports the R^2 obtained from the estimation of Eq. C.1. The estimated outcomes are log water salinity (panel A), log soil salinity at depth 0-20 cm (panel B), and log salinity at depth 20-50 cm (panel C) of the in situ sample.

[41] Controlling for commune fixed effects is not feasible because the samples are spread out rather evenly across communes, i.e., the number of communes where these samples are located is 157.

Appendix C.2 Machine learning prediction of in situ salinity

A key constraint in using the in situ samples to validate the constructed salinity index is their limited sample size and spatial coverage. To overcome this, we apply machine learning methods to generate spatial predictions of water salinity for all communes in the study area.[42] To characterize exposure to salinity shocks induced by saltwater intrusion, we focus on prediction of water salinity levels. This section describes the model selection process, out-of-sample prediction procedure, and results on the alignment between predicted salinity and the salinity index.

Model calibration and selection

To predict water salinity, we compile a set of geomorphological and hydrological predictors for each in situ sampling location. Guided by the hydrology machine learning literature (e.g., Sahour et al., 2020; Jeong et al., 2024; Mahmoud et al., 2025), these predictors include geographic coordinates, elevation, distance to the coast, and weather-related characteristics. To more directly capture salinity driven by seawater intrusion, we additionally incorporate upstream river freshwater discharge, analogous to the approach of Duc et al. (2025) in the context of the Mekong Delta. In detail, we let upstream freshwater flow interact with proximity to the coast to characterize saltwater intrusion dynamics. The predictor variables are constructed from multiple data sources with varying spatial resolutions and acquisition methods, including remote sensing and reanalysis products. In total, 26 predictors are assembled as inputs for model calibration. Table C.5 summarizes their definitions, sources, and aggregation procedures. Excluding observations with incomplete predictor information—primarily due to cloud cover in remote sensing data—yields a final sample of 174 observations as input for model selection.

We evaluate four candidate methods—Lasso, Gaussian Process (GP), XGBoost (XGB), and Random Forest (RF)—using nested cross-validation (CV) to generate out-of-sample predictions. The dataset is split into five outer folds, with four folds for training and one for testing. Within each outer fold, the training set is further divided into three inner folds for hyperparameter tuning.[43] The same seed is used for each method's data splitting to ensure identical training and test splits. This nested CV prevents data leakage, i.e., by omitting outer test fold information in hyperparameter tuning, and provides unbiased estimates of predictive performance. We obtain 174 predicted values of the in situ water salinity from each model.

[42] Since the in situ data was collected only in April 2016—a period characterized by uniformly high salinity and no non-saline observations—the predictions are performed spatially rather than over time.

[43] Hyperparameters are tuned via grid search to minimize CV mean squared error. The tuned parameters are λ (Lasso), σ (GP), *max depth* (XGB), *mtry* (RF).

To compare performance, we compute mean squared error (MSE), Pearson correlation with observed values, and R^2. Table C.4 reports the results. Among the candidate methods, Random Forest predictions have the lowest MSE and the highest correlation with observed water salinity (Pearson 0.79). We then fit a final RF model on all 174 in situ observations using the selected hyperparameter, which is subsequently applied to generate out-of-sample spatial predictions across the study area.[44]

Table C.4: Nested cross-validation performance comparison

Method	*MSE*	*Corr. (Pearson)*	R^2
Lasso	43.796	0.722	0.521
Gaussian Process	41.564	0.758	0.575
XGBoost	45.850	0.717	0.515
Random Forest	35.164	0.789	0.623

Spatial prediction of water salinity

To generate spatial estimates of water salinity for all communes in the study area, we apply the trained RF model at the 1km pixel level. Because the average commune area in the study region is approximately 20km^2, each commune contains around 20 pixels. Figure C.5, Panel (a), shows the template raster used for prediction. For each pixel, we compute the predictors listed in Table C.5 and use the model to obtain salinity values.[45] Panel (b) of Figure C.5 displays the resulting pixel-level estimates. The observed missing pixel predictions are resulted from cloud interference in the MODIS remote sensing data. To produce commune-level values, we then aggregate pixel estimates within each commune using a weighted mean, where weights correspond to the fraction of each pixel covered by the commune. The aggregation yields predicted values for 712 of 801 communes. Figure C.5, Panel (c), presents the final commune-level estimates.

Comparison of predicted water salinity and the salinity index

To evaluate the validity of the baseline salinity index, Figure C.4 contrasts model-based salinity estimates with both in situ measurements and the salinity index. Panel (a) plots log predicted salinity against log observed in situ salinity at the sampled locations. Panel (b) compares log predicted salinity—aggregated to the commune level—with the log salinity index constructed for each commune. The correlation between the two measures is 0.64. This

[44]The final RF model grows 500 trees, using 4 randomly selected variables at each split ($mtry = 4$).

[45]Predictor data at resolution finer than 1km are aggregated to the pixel level, while coordinate- or distance-based variables are computed using the pixel centroid.

is higher than the correlation of 0.43 between the salinity index and in situ water salinity at the sampled points reported in Figure C.2, Panel (a). This result is consistent with the salinity index capturing spatial variation in water salinity at broader geographic scales.

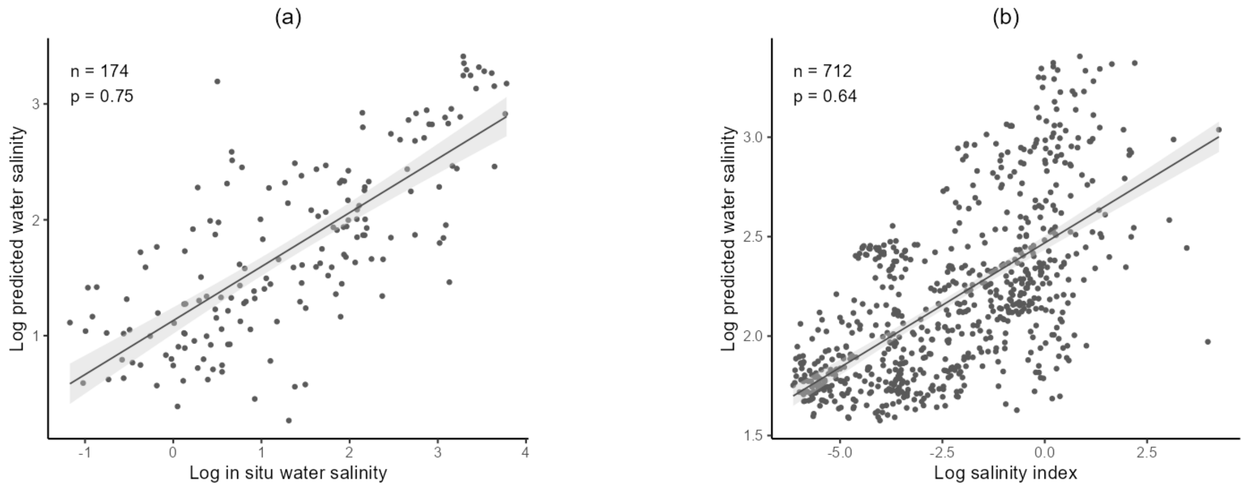
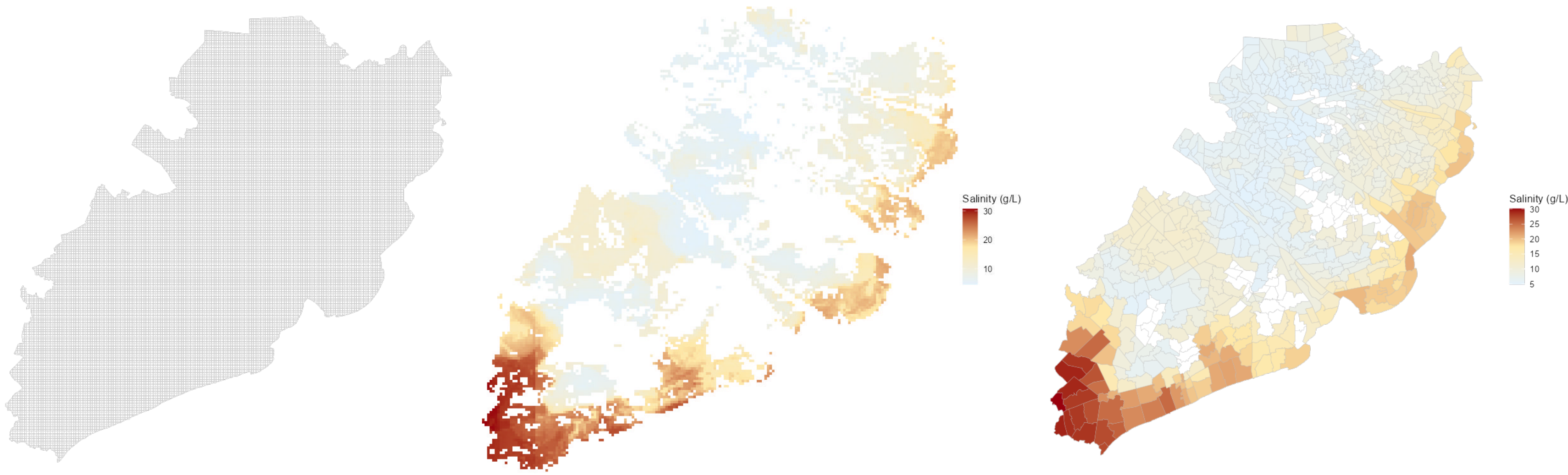


Figure C.4: Predicted water salinity, in situ measurements, and the salinity index.
Predicted salinity values are obtained from the selected Random Forest model. Panel (a) plots log predicted salinity against log observed in situ salinity at sampled locations. Panel (b) plots log predicted salinity aggregated to the commune level against the log salinity index. In both panels, the fitted linear regression line and corresponding 95% confidence interval are shown. The number of observations and the Pearson correlation coefficient are reported in the upper-left corner of each panel.

Table C.5: Predictors used in the spatial prediction of water salinity

Predictor	Definition	Data source and resolution	Aggregation and matching	Literature
Sample location	Geographic coordinates (longitude and latitude) of each sample location	Data by Can Tho University		
SRTM DEM	Elevation derived from the Shuttle Radar Topography Mission (2000)	NASA; 30m resolution	Pixel value assigned to sample location	Sahour et al. (2020) use topography as an input to predict salinity in the coastal aquifer of the Caspian Sea.
MERIT DEM	Error-corrected DEM combining SRTM and other products, suitable for flat regions	Google Earth Engine MERIT/DEM/v1_0_3; 90m resolution	Pixel value assigned to sample location	Sahour et al. (2020) use topography as an input to predict salinity in the coastal aquifer of the Caspian Sea.
MODIS LST	Day and night land surface temperature	Google Earth Engine MODIS/061/MOD11A2; 8-day composites, 1km resolution	8-day values averaged for April 2016; pixel value assigned to sample location	Mahmoud et al. (2025) include temperature to predict water salinity across the Colorado River Basin.
MODIS ET and PET	Evapotranspiration (ET) and potential evapotranspiration (PET) based on the Penman–Monteith equation and MODIS inputs, together with their difference ($= PET - ET$)	Google Earth Engine MODIS/061/MOD16A2GF; 8-day composites, 500m resolution	8-day values averaged for April 2016; pixel value assigned to sample location	Sahour et al. (2020) and Jeong et al. (2024) use evaporation as input in models predicting water salinity in aquifers of the Caspian Sea and the Mekong Delta, respectively.
CHELSA variables	Monthly climate variables: cmi, hurs, pet, pr, sfcWind, tas, tasmax, tasmin, vpd	CHELSA monthly data (v2.1) developed by Karger et al. (2017); 1 km spatial resolution	Pixel value assigned to sample location	Sahour et al. (2020) and Jeong et al. (2024) use rainfall in models predicting water salinity in aquifers of the Caspian Sea and the Mekong Delta. Mahmoud et al. (2025) include temperature to predict water salinity across the Colorado River Basin.
Distance to river	Euclidean distance to the nearest river segment	Local river system shapefile by Can Tho University	Distance calculated for each sample location	
Distance to coast	Euclidean distance to the nearest coastline point		Distance calculated for each sample location	Sahour et al. (2020) add distance to the sea in their prediction model.
Distance to estuary	Euclidean distance to the nearest estuary (defined as river–coast intersections)		Distance calculated for each sample location	Sahour et al. (2020) add distance to the sea in their prediction model.
Upstream discharge interactions	Interaction terms: $upstream^{-1} \times dist\,to\,river^{-1}$; $upstream^{-1} \times dist\,to\,coast^{-1}$; $upstream^{-1} \times dist\,to\,estuary^{-1}$; $upstream^{-1} \times dist\,to\,river^{-1} \times dist\,to\,coast^{-1}$; $upstream^{-1} \times dist\,to\,river^{-1} \times dist\,to\,estuary^{-1}$	Upstream freshwater discharge measured at Kratie, Cambodia (Mekong River Commission, 2025)	Calculated for each sample location	Duc et al. (2025) incorporate upstream water discharge to predict saltwater intrusion in the Mekong Delta.



(a) (b) (c)

Figure C.5: Prediction of water salinity in April 2016 using Random Forest

Figure shows the prediction procedure and results. Panel (a) presents the template raster at 1 km resolution that was used in the prediction. Panel (b) shows the predicted water salinity at the 1 km pixel level obtained using Random Forest model selected from cross-validation. Panel (c) depicts the predicted average water salinity aggregated at the commune level. White cells and communes in Panels (b) and (c) indicate missing values resulting from unavailable predictor data.

Appendix D Validity and Robustness

Appendix D.1 Salinity index and prediction discrepancies

To assess potential threats to identification arising from measurement error in the salinity index, we examine whether the baseline estimates are sensitive to discrepancies between the index and the water salinity predicted from in situ measurements (Appendix C.2). As shown in Figure C.4 (Panel b), some communes exhibit noticeable differences between the salinity index and the predicted salinity level. If these discrepancies reflect measurement error, and if such error is systematically related to the outcomes, the estimated effects of salinity exposure captured by the salinity index could be biased.

To investigate this, we successively exclude communes whose absolute differences between the salinity index and predicted water salinity in April 2016 fall within the top 5%, 10% and 25% of the distribution. Table D.1 reports the estimates. The estimated coefficients remain qualitatively and quantitatively similar to the baseline estimates when observations from communes with the largest discrepancies are sequentially dropped. This result suggests that the baseline estimates are unlikely driven by measurement discrepancies between the salinity index and predicted salinity, hence supporting the validity of the index in capturing variation of saltwater intrusion.

Table D.1: Robustness to salinity index and prediction discrepancies

	Log rice yields	Log rice output	Log rice revenue	Rice revenue share	Log agricultural revenue
	(1)	(2)	(3)	(4)	(5)
	Panel A. Excluding top 5% salinity index-prediction discrepancies				
Salinity index (SD)	-0.070	-0.209	-0.244	-0.043	-0.156
	(0.012)***	(0.046)***	(0.043)***	(0.010)***	(0.038)***
	[0.009]***	[0.032]***	[0.026]***	[0.010]***	[0.022]***
Commune FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓
Observations	891	891	828	891	882
	Panel B. Excluding top 10% salinity index-prediction discrepancies				
Salinity index (SD)	-0.070	-0.204	-0.240	-0.046	-0.142
	(0.012)***	(0.045)***	(0.045)***	(0.010)***	(0.036)***
	[0.009]***	[0.033]***	[0.028]***	[0.011]***	[0.019]***
Commune FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓
Observations	840	840	790	840	834
	Panel C. Excluding top 25% salinity index-prediction discrepancies				
Salinity index (SD)	-0.068	-0.213	-0.241	-0.047	-0.153
	(0.010)***	(0.047)***	(0.046)***	(0.011)***	(0.038)***
	[0.007]***	[0.030]***	[0.028]***	[0.013]***	[0.023]***
Commune FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓
Observations	717	717	681	717	711

Notes: 'Log rice yields' is the logarithmized amount of rice output per unit of land under rice cultivation (in kg/m^2). 'Log rice output' is the logarithmized total amount of produced rice (in kg). 'Log rice revenue' is the logarithmized revenue gained from selling or exchanging produced rice (in thousand VND). 'Rice revenue share' is the share of revenue received from rice production in total agricultural revenue. 'Log agricultural revenue' is the logarithmized total revenue from all crops including rice, non-rice staple crops, fruits, industrial crops, aquaculture, livestock, and forestry (in thousand VND). Panels A–C report estimates from samples that sequentially exclude communes in the top 5%, 10% and 25% of the absolute differences between the constructed salinity index and the predicted water salinity for April 2016 (see Appendix C.2). 'Salinity index' is standardized using the baseline full-sample mean and standard deviation in all specifications. Commune and time (year and survey-month) fixed effects are included in all estimations. Weather control vector includes the average temperature, precipitation, and potential evapotranspiration measured for the commune. Household control vector includes household size, household head's age and years of education. Commune-level clustered robust standard errors are reported in the parentheses and Conley-robust standard errors (at 20km cutoff) are in the brackets. *p<0.1; **p<0.05; ***p<0.01.

Appendix D.2 Multi-station salinity indices

We construct alternative measures of saltwater intrusion exposure to be the average inverse canal-distance weighting of salinity at the multiple nearest hydrostations for each commune. The indices are computed as follows.

$$SI^{(n)}_{c,t_m} = \frac{1}{n}\sum_{k=1}^{n} \frac{Salinity_{s_k,t_m}}{Distance_{c,s_k}}, \quad n \in \{2, ..., 6\}. \tag{D.1}$$

$SI^{(n)}_{c,t_m}$ denotes the salinity index measured for commune c in year t up to month m. Stations are ordered by increasing canal-network distance from the centroid of commune c, such that s_k denotes the k-th nearest station. *Distance* is the canal-network distance between the centroid of c and station s_k. *Salinity* is the average river salinity content recorded at station s_k in year t up to month m. Table D.2 presents the estimated effects on the main outcome variables on rice and agricultural production (Table 1) using these alternative indices.

Table D.2: Effects of salinity on agricultural production with nearest-stations indices

	Log rice yields	Log rice output	Log rice revenue	Rice revenue share	Log agricultural revenue
	(1)	(2)	(3)	(4)	(5)
	Panel A. Salinity index constructed based on 2 nearest hydrostations				
Salinity index (SD)	-0.069	-0.188	-0.220	-0.046	-0.123
	(0.017)***	(0.047)***	(0.052)***	(0.015)***	(0.071)*
	[0.019]***	[0.032]***	[0.045]***	[0.009]***	[0.048]**
	Panel B. Salinity index constructed based on 3 nearest hydrostations				
Salinity index (SD)	-0.072	-0.130	-0.153	-0.032	-0.074
	(0.020)***	(0.074)*	(0.090)*	(0.022)	(0.102)
	[0.021]***	[0.064]**	[0.092]*	[0.008]***	[0.064]
	Panel C. Salinity index constructed based on 4 nearest hydrostations				
Salinity index (SD)	-0.048	-0.160	-0.167	-0.048	-0.061
	(0.026)*	(0.072)**	(0.091)*	(0.017)***	(0.122)
	[0.025]*	[0.062]**	[0.092]*	[0.011]***	[0.094]
	Panel D. Salinity index constructed based on 5 nearest hydrostations				
Salinity index (SD)	-0.028	-0.131	-0.122	-0.047	-0.016
	(0.034)	(0.089)	(0.115)	(0.017)***	(0.144)
	[0.035]	[0.077]*	[0.116]	[0.013]***	[0.119]
	Panel E. Salinity index constructed based on 6 nearest hydrostations				
Salinity index (SD)	-0.016	–0.111	-0.102	-0.047	0.020
	(0.037)	(0.098)	(0.123)	(0.017)***	(0.156)
	[0.040]	[0.089]	[0.125]	[0.013]***	[0.137]
Commune FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓
Mean dependent variable	0.547	12,890	64,041	0.663	103,019
Observations	1,020	1,020	948	1,020	1,011

Notes: ‘Log rice yields’ is the logarithmized amount of rice output per unit of land under rice cultivation (in kg/m^2). ‘Log rice output’ is the logarithmized total amount of produced rice (in kg). ‘Log rice revenue’ is the logarithmized revenue gained from selling or exchanging produced rice (in thousand VND). ‘Rice revenue share’ is the share of revenue received from rice production in total agricultural revenue. ‘Log agricultural revenue’ is the logarithmized total revenue from all crops including rice, non-rice staple crops, fruits, industrial crops, aquaculture, livestock, and forestry (in thousand VND). Panels A–E report estimates using ‘Salinity index’ constructed from 2 to 6 nearest stations, respectively (Eq. D.1). ‘Salinity index’ is standardized in all regressions. Commune and time (year and survey-month) fixed effects are included in all estimations. Weather control vector includes the average temperature, precipitation, and potential evapotranspiration measured for the commune. Household control vector includes household size, household head’s age and years of education. Commune-level clustered robust standard errors are reported in the parentheses and Conley-robust standard errors (at 20km cutoff) are in the brackets. *p<0.1; **p<0.05; ***p<0.01.

Appendix D.3 Two-stage least squares estimation

This section outlines our construction of two instrumental variables to address potential endogeneity in the salinity index, particularly if observed river salinity or canal distances are correlated with agricultural production outcomes through unobserved or reverse causal links. This approach also helps us to further alleviate the concern that potential measurement error in the baseline salinity index may bias the main results.

Instrumental variable for river salinity

Among the main drivers of saltwater intrusion discussed in Section 2, upstream freshwater discharge (and associated sediment transport) along the Mekong River acts as a hydrological "push" factor, while tidal amplitude linked to sea-level rise operates as an external "intrusion" force. Both processes originate outside the local region and are plausibly exogenous to commune-level agricultural outcomes. In the first step, we thus instrument the salinity measured at local hydrostations using an interaction between (i) the inverse of upstream freshwater discharge and (ii) the inverse of the distance along rivers between each station and its nearest estuary. Intuitively, lower upstream discharge increases salinity level, and stations located closer to estuaries by river path are more exposed to seawater intrusion. The instrument variable for our salinity index at the commune level is constructed as:

$$\mathrm{IV1}_{c(s),t_m} = Distance_{c,s}{}^{-1} \times \underbrace{Upstream_{t_m}{}^{-1} \times DistEst_{s,e}{}^{-1}}_{\text{IV for river salinity at station}}. \tag{D.2}$$

$Distance_{c,s}$ is the canal distance between commune c and its closest station s. $Upstream_{t_m}$ is the average freshwater discharge rate (m^3/s) recorded upstream from January up to month m of year t. $DistEst_{s,e}$ is the river distance between station s and its nearest estuary e.

For upstream freshwater discharge, we use monthly data from the hydrological station located in Kratie, Cambodia. This is the first major upstream station outside the Vietnamese Mekong Delta with publicly available time series. We obtained the data from the portal of the Mekong River Commission (2025). The station's location is shown in Panel (a) of Figure D.1, while Panel (b) plots the average monthly discharge at Kratie during dry-season months. Upstream discharge are lower in 2015 and 2016, consistent with documented severe saltwater intrusion and the higher salinity levels observed in our hydrostation data for 2016. To calculate the distances along the river network between each local hydrostation and its nearest estuary, we integrate the local river network shapefile with the Global River Topology (GRIT) dataset developed by Wortmann et al. (2025). This enables us to construct a connected, consistent river network feasible for compute network distances.[46] Panel (a) of Figure D.2 illustrates the resulting combined network. River distances between each station and all estuaries are computed along the combined graph, and the shortest path is used in constructing the instrument.[47] As the final construction step, analogous to the salinity index, we average the IV over the previous and current year up to the survey month to match it with household data.

Table D.3 reports the two-stage least squares estimates using the instrument defined in Equation D.2. Panel B presents the first-stage results, demonstrating the relevance of the IV in predicting the baseline salinity index. Panel A reports the second-stage estimates for agricultural production outcomes. The IV coefficients are precisely estimated and comparable in magnitude to the OLS estimates shown in Table 1. This consistency alleviates concerns that the baseline estimates are biased by measurement error or endogeneity in the reported river salinity.

Instrumental variable for river salinity and canal distance

A potential limitation of our first instrument is that the canal distance between each commune and its nearest hydrostation remains part of the construction. If the canal network is endogenous—for instance, if its layout responds to local agricultural productivity—the instrument may not fully capture exogenous exposure to saltwater intrusion. To address this, we construct a second IV relying solely on (i) time-varying upstream freshwater discharge and (ii) the river-network distance directly from each commune to its nearest estuary:

$$\mathrm{IV2}_{c,t_m} = {Upstream_{t_m}}^{-1} \times {DistEst_{c,e}}^{-1}. \tag{D.3}$$

$Upstream_{t_m}$ is the average freshwater discharge (m^3/s) at Kratie from January through month m of year t, and $DistEst_{c,e}$ is the distance along the combined river network from commune c (centroid) to its nearest estuary.[48] As shown in Figure D.2, Panel (a), the river network used for the IV captures the region's main hydrological structure and is largely

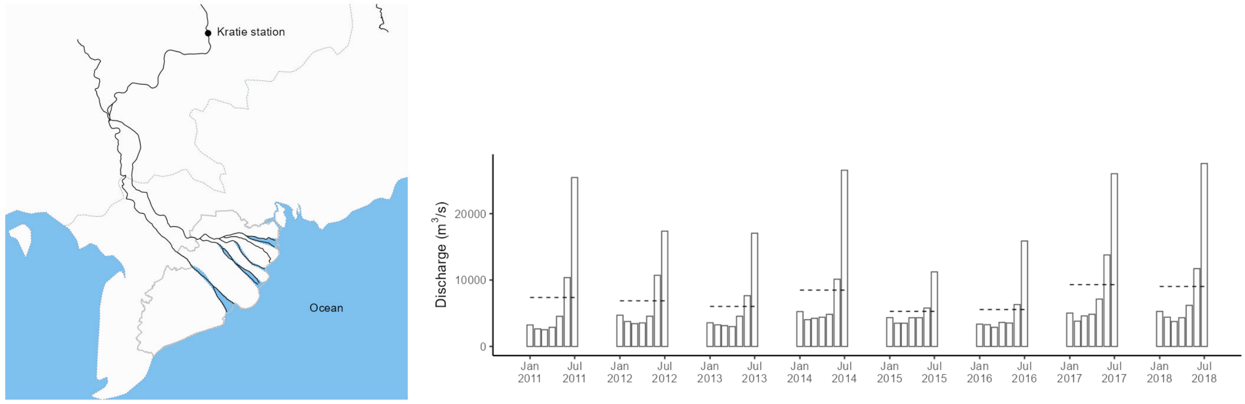
[46]GRIT provides high-resolution data on bifurcating river systems, particularly in floodplains and deltas. The dataset includes main stems, distributaries, and canals wider than 30 meters, allowing us to accurately connect segments in the local shapefile.

[47]We use the GRIT "network reaches" layer, which divides rivers into segments between nodes of length below 1 km. Hydrostations are snapped to their nearest network nodes. Estuary points are identified as intersections between the combined river network and the coastline, allowing a 20 m buffer to ensure connectivity; these are then added nodes.

[48]In the first step, we compute the shortest Euclidean (straight-line) distance between the commune centroid and the nearest point on the river network (Figure D.2, Panel a). Second, we calculate the distance along the river network from this nearest river point to the closest estuary. The total commune-to-estuary river distance is the sum of these two measures.

determined by natural processes. By contrast, the canal network underlying the baseline salinity index (Panel b) is more detailed, even though it includes only primary and secondary canals and excludes on-farm irrigation channels. Because the IV relies on distances along the major river network rather than commune-to-station canal distances, it reduces concerns about endogeneity in the baseline index. Moreover, the second IV does not require assigning communes to specific stations, thereby further limiting potential measurement error. To match the IV with the outcomes, we average it over the previous and contemporaneous year up to the survey month, similar to the salinity index.

Table D.4 reports 2SLS results using the second IV from Equation D.3. First-stage estimates in Panel B show the IV strongly predicts the baseline salinity index. Second-stage coefficients presented in Panel A largely mirror the OLS estimates (Table 1) in both magnitude and significance, providing additional evidence that measurement error or endogeneity in river salinity and canal distance is unlikely to bias the baseline OLS estimates. In all 2SLS estimations in Tables D.2 and D.3, we formally test for endogeneity by implementing Durbin-Wu-Hausman specification test. The reported test statistic's p-value is reported in the second-stage Panels. In only one out of ten cases is it below 0.05, while in all remaining cases the test's p-value is more than an order of magnitude larger, approaching unity in many estimations. The null hypothesis that the OLS estimator is consistent therefore cannot be rejected in the majority of specifications. These results provide the evidence supporting that potential endogeneity or measurement error in river salinity or canal distance is unlikely to bias the our baseline results in Table 1.



(a) (b)

Figure D.1: Mekong river's freshwater discharge at Kratie, Cambodia
Panel (a) shows the location of Kratie station in Cambodia, which records freshwater discharge (m^3/s) along the Mekong River (solid dot). The Mekong and its branches are shown as solid black lines, country borders as dashed gray lines, and the study area boundary in the Vietnamese Mekong Delta as a solid gray line. Panel (b) depicts average monthly freshwater discharge measured at the station during the dry season 2011-2018. The dashed lines represent the annual mean discharge calculated over these months.

(a) (b)

Figure D.2: River paths used in IV construction
Panel (a) displays the river network used to calculate river-path distances for IV construction in Eq. D.2 and D.3, combining the local shapefile and Global River Topology reaches. Further shown are hydrostations (dots) and estuaries (triangles). For reference, Panel (b) shows the combined river and canal network used in the baseline salinity index construction (Eq. 1), together with hydrostations (dots). Figures in both panels cover the study area.

Table D.3: Rice and agricultural production 2SLS IV1

	Panel A. Second stage				
	Log rice yields	Log rice output	Log rice revenue	Rice revenue share	Log agricultural revenue
	(1)	(2)	(3)	(4)	(5)
Salinity index (SD)	-0.059	-0.153	-0.217	-0.038	-0.154
	(0.007)***	(0.039)***	(0.034)***	(0.012)***	(0.034)***
	[0.010]***	[0.045]**	[0.034]***	[0.010]***	[0.009]***
Commune FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓
Mean dependent variable	0.547	12,890	68,904	0.663	103,936
Observations	1,020	1,020	948	1,020	1,011
Durbin-Wu-Hausman p-val	0.633	0.608	0.976	0.871	0.696
	Panel B. First stage				
	Salinity index (SD)				
	(1)	(2)	(3)	(4)	(5)
IV1 (SD)	1.37	1.37	1.38	1.37	1.37
	(0.071)***	(0.071)***	(0.070)***	(0.071)***	(0.071)***
	[0.073]***	[0.073]***	[0.070]***	[0.073]***	[0.073]***
Commune FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓
Observations	1,020	1,020	948	1,020	1,011
Kleibergen-Paap F-stat	134.2	134.2	133.6	134.2	133.8

Notes: Panel A reports second-stage estimates and Panel B reports first-stage estimates. 'Log rice yields' is the logarithmized amount of rice output per unit of land under rice cultivation (in kg/m^2). 'Log rice output' is the logarithmized total amount of produced rice (in kg). 'Log rice revenue' is the logarithmized revenue gained from selling or exchanging produced rice (in thousand VND). 'Rice revenue share' is the share of revenue received from rice production in total agricultural revenue. 'Log agricultural revenue' is the logarithmized total revenue from all crops including rice, non-rice staple crops, fruits, industrial crops, aquaculture, livestock, and forestry (in thousand VND). 'Salinity index' is standardized in all regressions. 'IV1' is the instrumental variable defined in Eq. D.2 and standardized in all regressions. Commune and time (year and survey-month) fixed effects are included in all estimations. Weather control vector includes the average temperature, precipitation, and potential evapotranspiration measured for the commune. Household control vector includes household size, household head's age and years of education. Commune-level clustered robust standard errors are reported in the parentheses and Conley-robust standard errors (at 20km cutoff) are in the brackets. *p<0.1; **p<0.05; ***p<0.01.

Table D.4: Rice and agricultural production 2SLS IV2

	Panel A. Second stage				
	Log rice yields	Log rice output	Log rice revenue	Rice revenue share	Log agricultural revenue
	(1)	(2)	(3)	(4)	(5)
Salinity index (SD)	-0.097	-0.220	-0.262	-0.044	-0.275
	(0.042)**	(0.072)***	(0.064)***	(0.025)*	(0.163)*
	[0.042]**	[0.090]**	[0.060]***	[0.029]	[0.109]**
Commune FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓
Mean dependent variable	0.547	12,890	68,904	0.663	103,936
Observations	1,020	1,020	948	1,020	1,011
Durbin-Wu-Hausman p-val	0.029	0.650	0.594	0.830	0.137
	Panel B. First stage				
	Salinity index (SD)				
	(1)	(2)	(3)	(4)	(5)
IV2 (SD)	0.935	0.935	1.00	0.935	0.944
	(0.287)***	(0.287)***	(0.271)***	(0.287)***	(0.285)***
	[0.211]***	[0.211]***	[0.172]***	[0.211]***	[0.207]***
Commune FEs	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓
Observations	1,020	1,020	948	1,020	1,011
Kleibergen-Paap F-stat	54.0	54.0	62.2	54.0	55.3

Notes: Panel A reports second-stage estimates and Panel B reports first-stage estimates. 'Log rice yields' is the logarithmized amount of rice output per unit of land under rice cultivation (in kg/m^2). 'Log rice output' is the logarithmized total amount of produced rice (in kg). 'Log rice revenue' is the logarithmized revenue gained from selling or exchanging produced rice (in thousand VND). 'Rice revenue share' is the share of revenue received from rice production in total agricultural revenue. 'Log agricultural revenue' is the logarithmized total revenue from all crops including rice, non-rice staple crops, fruits, industrial crops, aquaculture, livestock, and forestry (in thousand VND). 'Salinity index' is standardized in all regressions. 'IV2' is the instrumental variable defined in Eq. D.3 and standardized in all regressions. Commune and time (year and survey-month) fixed effects are included in all estimations. Weather control vector includes the average temperature, precipitation, and potential evapotranspiration measured for the commune. Household control vector includes household size, household head's age and years of education. Commune-level clustered robust standard errors are reported in the parentheses and Conley-robust standard errors (at 20km cutoff) are in the brackets. *p<0.1; **p<0.05; ***p<0.01.

Appendix D.4 Robustness

Table D.5: Robustness tests

	Excl. rivers-pass communes (1)	Excl. non-coastal provinces (2)	Excl. Bac Lieu province (3)	Excl. 5% observations randomly (4)	SI using only high-elevated stations (5)	SI using straight-line distances (6)	Adding more household controls (7)	Adding weather polynomials (8)	Adding district fixed effects (9)	Stand. error Conley 30km cut-off (10)
Panel A. Dependent variable is log rice yields										
SI (SD)	-0.054***	-0.052***	-0.053***	-0.052***	-0.065	-0.081***	-0.054***	-0.042***	-0.053***	-0.053***
	(0.011)	(0.012)	(0.009)	(0.008)	(0.067)	(0.026)	(0.011)	(0.012)	(0.011)	(0.005)
Obs	1,012	687	921	1,000	1,009	1,020	1,020	1,020	1,020	1,020
Panel B. Dependent variable is log rice output										
SI (SD)	-0.179***	-0.166***	-0.178***	-0.184***	-0.347**	-0.176***	-0.176***	-0.181***	-0.181***	-0.181***
	(0.036)	(0.037)	(0.037)	(0.029)	(0.174)	(0.045)	(0.036)	(0.037)	(0.038)	(0.016)
Obs	1,012	687	921	1,000	1,009	1,020	1,020	1,020	1,020	1,020
Panel C. Dependent variable is log rice revenue										
SI (SD)	-0.215***	-0.205***	-0.222***	-0.214***	-0.447**	-0.241***	-0.210***	-0.211***	-0.215***	-0.215***
	(0.038)	(0.037)	(0.039)	(0.036)	(0.201)	(0.048)	(0.038)	(0.038)	(0.039)	(0.023)
Obs	946	630	850	1,000	940	948	948	948	948	948
Panel D. Dependent variable is rice revenue share										
SI (SD)	-0.040***	-0.039***	-0.038***	-0.041***	-0.009	-0.040***	-0.040***	-0.044***	-0.041***	-0.041***
	(0.010)	(0.010)	(0.009)	(0.008)	(0.053)	(0.011)	(0.009)	(0.010)	(0.010)	(0.004)
Obs	1,012	687	921	921	1,009	1,020	1,020	1,020	1,020	1,020
Panel E. Dependent variable is log agricultural revenue										
SI (SD)	-0.131***	-0.124***	-0.132***	-0.125***	-0.406*	-0.127***	-0.124***	-0.128***	-0.129***	-0.129***
	(0.042)	(0.043)	(0.042)	(0.030)	(0.213)	(0.044)	(0.042)	(0.041)	(0.043)	(0.029)
Obs	1,005	680	912	1,000	1,000	1,011	1,011	1,011	1,011	1,011
Fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
HH controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Estimations in column (1) exclude communes through which more than one main river branches pass. Estimations in column (2) exclude non-coastal (inland) provinces of Hau Giang and Vinh Long. Estimations in column (3) exclude province Bac Lieu, which lies farthest from the main river branches. Column (4) reports point estimates and standard errors obtained from 1,000 estimations in each of which 5% of the observations are randomly excluded (the number of observations is reported as the number of iterations). Estimations in column (5) check salinity index constructed using data of stations at elevation higher than communes' mean elevations based on MERIT DEM data. Estimations in column (6) check salinity index constructed using straight-line- instead of canal distances between communes and stations. Estimations in column (7) further control for household's number of children, defined as those under 18 years old, and household ethnicity. Estimations in column (8) add second-order polynomials of the weather controls. Estimations in column (9) add district fixed effects. Column (10) reports Conley-robust standard errors at 30km cutoff. 'Salinity index' is standardized in all regressions. Commune, year, and survey-month fixed effects are included in all estimations. Weather control vector includes the average temperature, precipitation, and potential evapotranspiration measured for the commune. Household control vector includes household size, household head's age and years of education. Commune-level clustered robust standard errors are reported in the parentheses for columns (1) to (9). *p<0.1; **p<0.05; ***p<0.01.

Covariate balance check

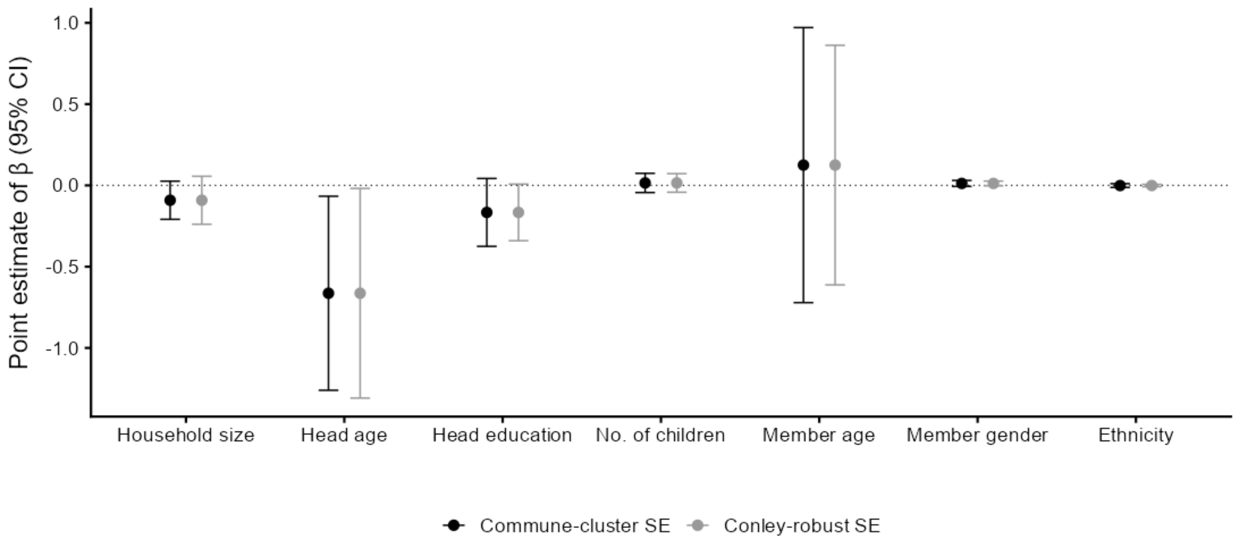


Figure D.3: Covariate balance check
Figure presents results from the balance check of household demographic covariates. The point estimates of parameter β from Equation 2, in which the outcomes are household characteristics, are shown (as dots) together with the 95% confidence intervals (as vertical lines) calculated using commune-cluster robust standard errors (black) and Conley spatial-correlation robust standard errors (gray). The tested outcomes listed on the x-axis include household size, household head's age, head's education, the number of children in the household (aged under 18), age and gender of household members, and whether household is of ethnicity Kinh. The balance check helps us assess the potential self-selection of households into locations of certain salinity levels. We discuss the results in Section 5.2.

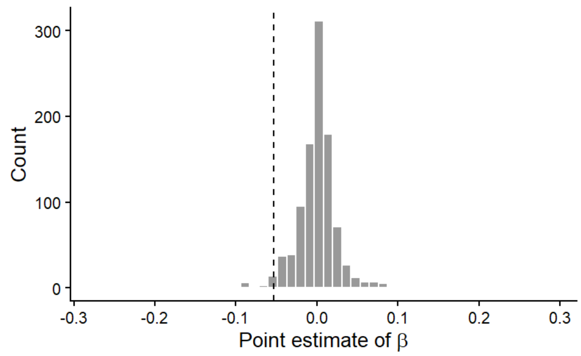


Figure D.4: Spatial permutation
Figure plots the distribution of the point estimates for parameter β in Eq. 2 which measures the relationship between the constructed SI and outcome log rice yields. The point estimates are obtained from 1,000 estimations in which communes' nearest hydro-stations and canal distances are permuted for each iteration. The vertical dashed line shows the estimate obtained from actual data (Table 1, column 1).

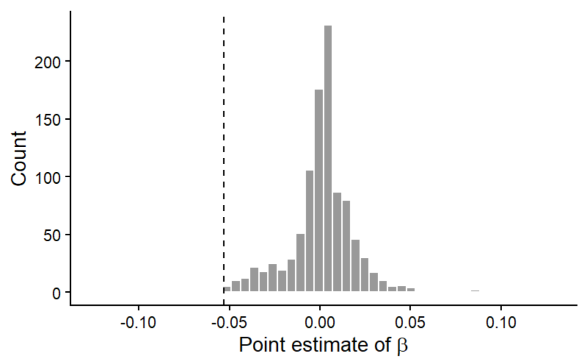


Figure D.5: Temporal permutation
Figure plots the distribution of the point estimates for parameter β in Eq. 2 which measures the relationship between the constructed SI and outcome log rice yields. The point estimates are obtained from 1,000 estimations in which each hydro-station's recorded river salinity levels are permuted across time for each iteration. The vertical dashed line shows the estimate obtained from actual data (Table 1, column 1).

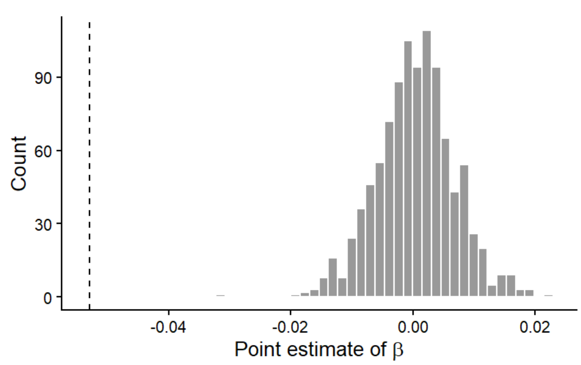


Figure D.6: Spatial and temporal permutation
Figure plots the distribution of the point estimates for parameter β in Eq. 2 which measures the relationship between the constructed SI and outcome log rice yields. The point estimates are obtained from 1,000 estimations in which SI's are permuted across space and time for each iteration. The vertical dashed line shows the estimate obtained from actual data (Table 1, column 1).

Appendix E Additional results

Appendix E.1 Agricultural production

Table E.1: Restricted sample estimates

	Log rice yields	Log rice output	Log rice revenue	Rice revenue share	Log agricultural revenue
	(1)	(2)	(3)	(4)	(5)
Salinity index (SD)	-0.054	-0.184	-0.215	-0.039	-0.126
	(0.011)***	(0.034)***	(0.038)***	(0.009)***	(0.042)***
	[0.008]***	[0.022]***	[0.031]***	[0.007]***	[0.022]***
Commune FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓
Mean dependent variable	0.558	13,763	68,904	0.713	105,688
Observations	948	948	948	948	948

Notes: 'Log rice yields' is the logarithmized amount of rice output per unit of land under rice cultivation (in kg/m^2). 'Log rice output' is the logarithmized total amount of produced rice (in kg). 'Log rice revenue' is the logarithmized revenue gained from selling or exchanging produced rice (in thousand VND). 'Rice revenue share' is the share of revenue received from rice production in total agricultural revenue. 'Log agricultural revenue' is the logarithmized total revenue from all crops including rice, non-rice staple crops, fruits, industrial crops, aquaculture, livestock, and forestry (in thousand VND). 'Salinity index' is standardized in all regressions. Commune and time (year and survey-month) fixed effects are included in all estimations. Weather control vector includes the average temperature, precipitation, and potential evapotranspiration measured for the commune. Household control vector includes household size, household head's age and years of education. Commune-level clustered robust standard errors are reported in the parentheses and Conley-robust standard errors (at 20km cutoff) are in the brackets. *p<0.1; **p<0.05; ***p<0.01.

Crop switch

To analyze potential shifts of farmers to alternative productions, we categorize non-rice crops into salt-resistant, salt-sensitive, and mixture, based on the agronomic literature studying salt sensitivity of crops in general (Tanji and Kielen, 2002) and in the Mekong Delta in particular (Blom-Zandstra et al., 2017). Specifically, salt-tolerant crops consist of aquaculture and industrial crops. As for the latter, more than 90% of the crops reported in the data are coconut—one of the most salt-resistant production choices in the region. Salt-sensitive crops are livestock, which crucially depends on freshwater, and fruits, the majority of which are banana and citrus—also classified as salt-sensitive (Tanji and Kielen, 2002). The mixture group includes forestry and non-rice staple crops. The former contains mainly bamboo, mangrove, and woody plants—while bamboo and mangrove are salt-resistant (Parida and Jha, 2010; Pulavarty and Sarangi, 2018), we lack information on the other wood plants. Similarly for non-rice staple crops, from the data, we only know that the majority are vegetables and herbs. These could include both salt-sensitive crops (e.g., bean or cabbage) and salt-tolerant ones (e.g., shallot) (Blom-Zandstra et al., 2017). For each of the reported crops, we focus on two outcomes: (i.) the probability that the household receives revenue from the respective production and (ii.) its share in household total agricultural revenue.

Appendix Table E.2 presents the estimated adjustments of rice farmers in choices of crops. Columns 1-4 report the estimated salinization-induced changes for salt-resistant production. Although aquaculture is well mentioned in the literature as a coping strategy for agricultural production in salt-affected coastal deltas (see e.g., Chen and Mueller, 2018; Costello et al., 2020) and for the MKD another focus beside rice (Brennan et al., 2002), estimates in columns 1-2 indicate no changes toward aquaculture for rice producers. Plausible reasons include households' limited capital and skills to switch to aquaculture, especially in the short run. Additionally, although a moderate level of salinity can benefit aquaculture, salinity above certain thresholds adversely affects production. Qualitative evidence suggests that aquaculture often requires tedious management of salinity levels in farming ponds. Therefore, saltwater intrusion in intense years can significantly reduce farmers' chance of receiving revenue. As for industrial crops—the other salt-resistant category, further contradicting the prediction that their relative importance would increase, we observe that both revenue indicator and share decrease with higher salinity. The next columns of Table E.2 show results for the salt-sensitive/freshwater-intensive productions of livestock farming (columns 5-6) and fruit crops (columns 7-8). Throughout, higher salinity is precisely estimated to lower both households' probability of having revenue and the revenue shares from these productions.

Columns 9-10 of Table E.2 present the estimated changes in revenue from forestry. The point estimates for both outcomes are minimal and not statistically different from zero, indicating that rice farmers do not switch to this production in the short run either (the mean outcomes are, however, also very modest). The last columns report the estimated shifts to non-rice staple crops, representing a mixture of salt-resistant and salt-sensitive grains, vegetables, and herbs. A one-SD increase in salinity is predicted to increase the probability of reporting revenue from this production by 12 p.p. (column 11) and its revenue share by about 8.7 p.p. (column 12). These effects account for 76% and 160% of the mean outcomes respectively. A possible explanation is that for farmers, non-rice staples are the most substitutable with rice in the short run. Nevertheless, as these crops likely reflect the lower-value choice of production, their increases—being the only productive crop switches observed—are probably not sufficient to offset losses from rice and other productions combined.

Table E.2: Crop switch

	Salt-resistant				Salt-sensitive				Mixture			
	Aquaculture		Industrial crops		Livestock		Fruits		Forestry		Other staple crops	
	Revenue (y/n)	Revenue share	Revenue (y/n)	Revenue share	Revenue (y/n)	Revenue share	Revenue (y/n)	Revenue share	Revenue (y/n)	Revenue share	Revenue (y/n)	Revenue share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Salinity index (SD)	0.009	0.006	-0.048	-0.016	-0.109	-0.030	-0.046	-0.006	0.011	-0.0003	0.119	0.087
	(0.014)	(0.008)	(0.016)***	(0.003)***	(0.023)***	(0.007)***	(0.015)***	(0.002)***	(0.009)	(0.0006)	(0.016)***	(0.010)***
	[0.012]	[0.007]	[0.016]***	[0.003]***	[0.019]***	[0.005]***	[0.017]***	[0.002]***	[0.009]	[0.0006]	[0.014]***	[0.008]***
Commune FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean dependent variable	0.118	0.049	0.367	0.057	0.494	0.141	0.232	0.025	0.020	0.001	0.156	0.055
Observations	1,020	1,020	1,020	1,020	1,020	1,020	1,020	1,020	1,020	1,020	1,020	1,020

Notes: 'Salt-resistant' refers to the group of agricultural production activities that are less dependent on freshwater and more tolerant to saltwater intrusion. 'Salt-sensitive' refers to the group of agricultural production activities that rely more on freshwater and are more sensitive to changes in salinity. 'Mixture' refers to the combination of both groups. 'Aquaculture' refers to aquaculture production. 'Industrial crops' refers to short-term and perennial crops produced for industrial uses. 'Livestock' refers to animal farming activities. 'Fruits' refers to fruit tree crops. 'Forestry' refers to forestry activities. 'Other staple crops' refers to production of non-rice short-term staple grains and vegetables. 'Revenue (y/n)' is an indicator variable equal to one if the household receives revenue from the respective production, and zero otherwise. 'Revenue share' is the share of revenue household receives from the respective production in the total agricultural revenue. 'Salinity index' is standardized in all regressions. Commune and time (year and survey-month) fixed effects are included in all estimations. Weather control vector includes the average temperature, precipitation, and potential evapotranspiration measured for the commune. Household control vector includes household size, household head's age and years of education. Commune-level clustered robust standard errors are reported in the parentheses and Conley-robust standard errors (at 20km cutoff) are in the brackets. *p<0.1; **p<0.05; ***p<0.01.

Cumulative salinity and medium-run production outcomes

To examine whether compounded exposure to saltwater intrusion prompts changes in production outcomes in the medium run, we compare the averaged outcomes between the first and last survey year in our data, i.e., 2012 and 2018 wave. We estimate the following commune-level regression equation.

$$y_{c,t} = \pi \left(D2018_t \times \sum_{m=2011}^{2018} SI_{c,m} \right) + \delta_t + \kappa_c + \varepsilon_{c,t}, \tag{E.1}$$

in which $y_{c,t}$ denotes the outcome of interest averaged for commune c in year t. $SI_{c,m}$ is the monthly salinity index for commune c in month s, summed over 2011-2018. $D_{2018,t}$ is a dummy variable equal to one for observations in 2018 and zero for those in 2012. δ_t and κ_c are year and commune fixed effects, respectively. $\varepsilon_{c,t}$ is the error term. The coefficient of interest, π, helps us gauge if exposure to saltwater intrusion accumulated over time translates to mid-run changes in production outcomes. Table E.3 presents the results.

Table E.3: Medium-run estimates

	Log rice yields	Log rice output	Log rice revenue	Log land area under rice cultivation
	(1)	(2)	(3)	(4)
D2018 × $\sum$ SI (SD)	-0.002	-0.072	-0.105	-0.071
	(0.004)	(0.023)***	(0.025)***	(0.023)***
	[0.004]	[0.016]***	[0.023]***	[0.018]***
Commune FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean dependent variable	0.551	12,749	66,241	22,402
Observations	268	268	268	268

Notes: 'Log rice yields' is the commune-averaged logarithmized amount of rice output per unit of land under rice cultivation (in kg/m^2). 'Log rice output' is the commune-averaged logarithmized total amount of produced rice (in kg). 'Log rice revenue' is the commune-averaged logarithmized revenue gained from selling or exchanging produced rice (in thousand VND). 'Log land area under rice cultivation' is the commune-averaged logarithmized total land area used for rice cultivation. D2018 equals one if the observation is in 2018. $\sum$ SI is the commune's accumulative salinity index over 2011-2018, standardized in all regressions. Commune and year fixed effects are included in all estimations. Commune-level clustered robust standard errors are reported in the parentheses and Conley-robust standard errors (at 20km cutoff) are in the brackets. *p<0.1; **p<0.05; ***p<0.01.

Appendix E.2 Living conditions indicators

Table E.4: Household member health outcomes

	Hospitalization (y/n)		No. of hospitalizations	
	(1)	(2)	(3)	(4)
Salinity index (SD)	0.062	0.051	0.121	0.096
	(0.012)***	(0.011)***	(0.023)***	(0.022)***
	[0.010]***	[0.008]***	[0.023]***	[0.021]***
Salinity index (SD) × Vulnerable age		0.024		0.055
		(0.008)***		(0.014)***
		[0.006]***		[0.012]***
Commune FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Household controls	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓
Mean dependent variable	0.122	0.122	0.189	0.189
Observations	2,003	2,003	2,003	2,003

Notes: 'Hospitalization (y/n)' is an indicator that equals one if the individual reports to be hospitalized for health check or treatment, which is not related to vaccination, pregnancy or birth, in the past 12 months. 'No. of hospitalizations' is the number of hospitalizations for health checks or treatments, which are not related to vaccination, pregnancy or birth, that the individual reports to have in the past 12 months. 'Salinity index' is standardized in all regressions. 'Vulnerable age' is an indicator that equals one if the individual is under 15 or above 60 years old. Commune and time (year and survey-month) fixed effects are included in all estimations. Weather control vector includes the average temperature, precipitation, and potential evapotranspiration measured for the commune. Household control vector includes household size, household head's age and years of education. Individual controls are gender and age. Commune-level clustered robust standard errors are reported in the parentheses and Conley-robust standard errors (at 20km cutoff) are in the brackets. *p<0.1; **p<0.05; ***p<0.01.

Table E.5: Household debts

	Log total debt amount	Agricultural debt (y/n)	Non-agri business debt (y/n)	Health-related debt (y/n)
	(1)	(2)	(3)	(4)
Salinity index (SD)	0.075	0.695	–0.112	0.231
	(0.864)	(0.543)	(0.135)	(0.186)
	[0.542]	[0.419]*	[0.108]	[0.127]*
Commune FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Household controls	✓	✓	✓	✓
Mean dependent variable	70,894	0.668	0.058	0.040
Observations	245	223	223	223

Notes: 'Log total debt' is the logarithmized total amount of debt that the household reports to have (in thousand VND). 'Agricultural debt (y/n)' is an indicator variable equal to one if the household reports to have any debt for agricultural production reasons. 'Non-agri business debt (y/n)' is an indicator variable equal to one if the household reports to have any debt for non-agricultural production or business reasons. 'Health-related debt (y/n)' is an indicator variable equal to one if the household reports to have any debt for health check or treatment reasons. Sample in column 1 includes all households reporting to incur debt in the past 12 months (Table 5, column 3), whose debt amount data is available. Sample in columns 2-3 includes all households reporting to incur debt in the past 12 months (Table 5, column 3) in survey waves 2014-2018, when data on debt purposes was collected. 'Salinity index' is standardized in all regressions. Commune and time (year and survey-month) fixed effects are included in all estimations. Weather control vector includes the average temperature, precipitation, and potential evapotranspiration measured for the commune. Household control vector includes household size, household head's age and years of education. Commune-level clustered robust standard errors are reported in the parentheses and Conley-robust standard errors (at 20km cutoff) are in the brackets. *p<0.1; **p<0.05; ***p<0.01.

Appendix E.3 Living expenditures

Table E.6: Extensive-margin estimates of living expenditures by category

	Expenditures (y/n)				
	Durable goods	Housing	Health	Adult training	Children schooling
	(1)	(2)	(3)	(4)	(5)
Salinity index (SD)	0.047	-0.001	0.003	0.004	0.126
	(0.044)	(0.003)	(0.003)	(0.005)	(0.021)***
	[0.040]	[0.003]	[0.002]	[0.006]	[0.024]***
Log total expenditures	0.229	0.005	0.013	0.035	0.039
	(0.023)***	(0.004)	(0.006)**	(0.013)***	(0.025)
	[0.026]***	[0.005]	[0.007]*	[0.016]**	[0.029]
Commune FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓
Household controls	✓	✓	✓	✓	✓
Mean dependent variable	0.526	0.995	0.992	0.043	0.595
Observations	1,020	1,020	1,020	1,020	1,020

Notes: 'Expenditures (y/n)' is an indicator equal to one if household reports any expenditure in the past 12 months in the given category. 'Durable goods' is expenditures on durable goods. 'Housing' is expenditures on housing and energy. 'Health' is expenditures on medicines, medical services and hospitalizations. 'Adult training' is expenditures on adults' skill training. 'Children schooling' is expenditures on all children's schooling costs (tuition, books, uniforms, extra classes). 'Log total expenditures' is the logarithmized total living expenditures in the past 12 months, defined as the sum of all spending categories plus a residual 'other' category (e.g., administrative fees, donations, ceremonial expenses). 'Salinity index' is standardized in all regressions. Commune and time (year and survey-month) fixed effects are included in all estimations. Weather controls include the average temperature, precipitation, and potential evapotranspiration measured for the commune. Household controls include household size, household head's age and years of education. Commune-level clustered robust standard errors are reported in the parentheses and Conley-robust standard errors (at 20km cutoff) are in the brackets. *p<0.1; **p<0.05; ***p<0.01.

Table E.7: Intensive-margin estimates of living expenditures by category

	Log expenditures						
	Festive food (1)	Soft goods (2)	Durable goods (3)	Housing (4)	Health (5)	Adult training (6)	Children schooling (7)
Salinity index (SD)	-0.009	0.114	-0.465	-0.078	0.183	-6.89	0.046
	(0.020)	(0.031)***	(0.080)***	(0.029)***	(0.064)***	(1.97)***	(0.409)
	[0.023]	[0.031]***	[0.052]***	[0.026]***	[0.050]***	[1.93]***	[0.407]
Log total expenditures	0.371	0.547	1.36	0.702	0.830	0.876	0.609
	(0.032)***	(0.039)***	(0.112)***	(0.072)***	(0.070)***	(0.082)***	(0.085)***
	[0.031]***	[0.055]***	[0.087]***	[0.085]***	[0.062]***	[0.080]***	[0.087]***
Commune FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Survey month FE	✓	✓	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓	✓	✓
Mean dependent variable	2,444	5,819	10,752	5,114	5,005	1,989	4,624
Observations	1,020	1,020	537	1,015	1,012	44	607

Notes: 'Log expenditures' is the logarithmized expenditures in the past 12 months that household reports for the given category. 'Festive food' is expenditures on food for festive occasions. 'Soft goods' are expenditures on non-durable goods. 'Durable goods' are expenditures on durable goods. 'Housing' is expenditures on housing and energy. 'Health' is expenditures on medicines, medical services and hospitalizations. 'Adult training' is expenditures on adults' skill training. 'Children schooling' is expenditures on all children's schooling costs (tuition, books, uniforms, extra classes). 'Log total expenditures' is the logarithmized total living expenditures in the past 12 months, defined as the sum of all spending categories plus a residual 'other' category (e.g., administrative fees, donations, ceremonial expenses). 'Salinity index' is standardized in all regressions. Commune and time (year and survey-month) fixed effects are included in all estimations. Weather control vector includes the average temperature, precipitation, and potential evapotranspiration measured for the commune. Household control vector includes household size, household head's age and years of education. Commune-level clustered robust standard errors are reported in the parentheses and Conley-robust standard errors (at 20km cutoff) are in the brackets. *p<0.1; **p<0.05; ***p<0.01.

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