Drought and Agricultural Adaptation: Land Reallocation and Labor Dynamics in Vietnam

Lifeng Ren[1], Giang Thai[1], Khoa Vu[2], and Nguyen Dinh Tuan Vuong[3]

[1]*University of Minnesota*

[2]*Charles River Associates*

[3]*University of Tsukuba*

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Abstract

Climate change increases the frequency and intensity of droughts, posing major risks to agricultural production in developing economies such as Vietnam. We study how droughts reshape land allocation and input choices that underpin both short-run adaptation and long-run structural change. We find that droughts reduce rice cultivation, reallocating land away from rice toward other crops and aquaculture in the long term. In response to droughts, households intensify rice production on smaller plots, diversify into non-rice crops, and expand aquaculture in the short run. At the same time, droughts have relatively more adverse effects on local manufacturing sectors, pulling workers out of non-agriculture into agriculture. The additional agricultural labor is absorbed primarily into rice intensification and crop diversification, whereas aquaculture expansion is entirely driven by mechanization adoption. The results highlight various adjustment margins to droughts in interaction with local labor market conditions in shaping adaptation pathways.

Keywords: drought, adaptation, land use, labor reallocation

JEL Codes: O13, Q12, Q15, Q54

1 Introduction

Climate change intensifies the frequency and severity of extreme weather events (Gebrechorkos et al., 2025). Among these, drought is considered as one of the most damaging events for global agriculture and food security (Zhao and Running, 2010; Lesk et al., 2016). In developing countries where markets are incomplete and coping mechanisms are limited, farming households relying on land productivity face particular vulnerability in sustaining their livelihoods. Understanding how farmers adjust land allocation across different input choices, such as land, labor and capital within agriculture in response to drought is important for policymakers to identify binding constraints or incentives farmers face and design effective policies to strengthen their climate resilience.

The adaptation strategies on land use farmers choose to do depend on local economic or geographic factors such as non-agricultural labor market conditions or water availability. On the one hand, the size of the non-agricultural sector determines the extent to which it can absorb reallocation from agriculture to manufacturing and services. On the other hand, the non-agricultural sector can also be directly affected by droughts. If the non-agricultural sector is affected relatively more than the agricultural sector, the labor reallocation adaptation strategy is limited, forcing farmers to adjust on different margins. Despite the importance of the non-agricultural sectors in (i) absorbing agricultural workers and (ii) being directly driven by climate change, there is limited empirical evidence on how (i) and (ii) jointly shape farmers' adaptation decisions.

This paper examines how drought drives land use change in Vietnam and how drought interact with local non-agricultural labor markets in shaping heterogeneous adaptation strategies. Vietnam offers a unique opportunity to answer these questions. It is a major rice exporter, and yet highly vulnerable to climate risks. Over the past decade, droughts have become more frequent and intense. At the same time, Vietnam's large manufacturing sector is itself vulnerable to drought shocks. We leverage nationally representative data to study how drought reallocates land among rice, other crops, and aquaculture, and how these land responses depend on local non-farm labor demand outside agriculture, shedding light on how households allocate land, labor, and capital to reduce the adverse effects of droughts.

We first analyze both contemporaneous and long-run impacts of drought on agricultural land use using comprehensive satellite data from 2000 to 2020 aggregated at the commune level, covering land use, drought exposure, rice productivity, water use, and quality. We complement this with household-level Agricultural Census data and firm-level Enterprise Census data to study labor shifts across sectors and the allocation of machinery and labor within agriculture. In the climate change literature, fixed effects panel estimation has become the standard approach for identifying causal climatic impacts by exploiting within-location temporal variation while controlling for time-invariant local characteristics (Schlenker and Roberts, 2009; Deschênes and Greenstone, 2007). Building on this foundation, we employ two complementary specifications: a panel fixed effects model with commune and region-by-year fixed effects to capture short-run responses (Deschênes and Greenstone, 2007; Cui, 2020b), and a long difference model (Burke and Emerick, 2016; Cui and Zhong, 2024) to identify long-run adaptation. This dual strategy allows us to distinguish immediate adjustments to annual drought shocks from persistent land use reallocations in response to sustained climate change.

Our study has four main findings. First, we find that droughts significantly decrease rice productivity and cultivation in the long term despite rice intensification as an adaptation strategy. In the short run, we actually find a modest but significant 0.43 percent increase in rice yield with a significant 0.47 percent drop in concentrated rice area, pointing to intensifying rice production on smaller plots. In the long run, however, droughts exert large adverse effects with a 27 percent fall in rice yield and a 55 percent shrinkage in concentrated rice area.

Second, droughts significantly reallocate land away from rice toward alternatives. The effects in the short run are modest but statistically significant. We document a

1.2 percent decrease in rice paddy areas but, in turn, a 1.2 percent increase in other crops, and 2.7 percent expansion into aquaculture. In the long run, we find no average change in rice paddy area, but the shift toward alternatives strengthens, with a 53 percent increase in other crops and a 16 percent increase in aquaculture.

Third, the effects of droughts vary by region and initial ecological conditions. The North and South – Vietnam's main agricultural production regions – are most exposed to drought risks. They both experience a significant reduction in rice paddy but adjust along different margins. The North focuses more on crop diversification, while the South expands aquaculture. However, in the long run, the North regains rice cultivation areas, possibly through government-intervened water management, whereas the South continues scaling aquacultural operations amid persistent salinity intrusion. In addition, communes with high baseline water supply, higher salinity, and greater irrigation are most exposed to droughts and move furthest away from rice. All three settings adopt both crop diversification and aquaculture, but high-salinity and heavily irrigated communes exhibit the largest long-run reallocations, especially toward aquaculture.

Lastly, we show that droughts interact with local labor markets to determine labor allocation and drive different adaptation responses. Our results suggest that droughts actually affect non-agricultural sectors relatively more than agriculture, moving non-agricultural labor into agriculture. This increase in agricultural workers is absorbed primarily in crop cultivation, supporting rice intensification on smaller plots and/or diversification into other crops. Strikingly, despite a sizable expansion of aquaculture land, we detect no corresponding rise in aquaculture labor, indicating a different adjustment margin. Consistent with a capital-intensive response, aquaculture growth is tied to machinery adoption, such as water pumps and aerators, rather than additional workers.

We contribute to three related literatures. First, our paper adds to growing empirical evidence on the broad impacts of climate change on agriculture. Previous work documents large and nonlinear yield losses from heat and water stress but is limited to on-farm adaptation (Schlenker and Roberts, 2009; Kuwayama et al., 2019; Cui, 2020a; Aragón et al., 2021; Wang et al., 2022). Several studies combine variations in temperature and precipitation to delineate the changing weather conditions (Welch et al., 2010; Nguyen and Scrimgeour, 2022; Chen et al., 2023). Our findings show opposite directions for short- and long-run effects on rice with short-run intensification on smaller plots but large long-run yield and area shrinkage, which is consistent with cumulative drought damage that short-run adaptation is not able to offset. We complement yield results with harvest areas similar to recent land-allocation papers (Cui, 2020b; Cai et al., 2022) but situate them in a developing country context that is vulnerable to climate crises.

Second, we extend the work on adaptation strategies through land reallocation. Several studies have documented crop diversification as a common adaptation strategy in response to extreme heat (Cui and Tang, 2024; Schmitt et al., 2024). Related evidence shows that farmers often adapt along both the yield and acreage margins: Sumner et al. (2026) demonstrate that drought-induced acreage adjustments account for a substantial share of U.S. production losses, while Cui (2020b) find that climate change explains 10–35 percent of recent corn and soybean expansion through land reallocations. In other settings, extreme weather has driven cropland expansion and deforestation, particularly among households lacking alternative coping strategies (He and Chen, 2022; Ramsey et al., 2021). While we show similar response toward non-rice crops in Vietnam, which is consistent with these broader patterns, we also document the shift into aquaculture as another durable adjustment. This change is consistent with Vietnam's documented salinity trends and drought–salinity compounding in the Mekong Delta (Binh et al., 2025; Mills et al., 2025), and highlights an adaptation pathway less visible in the existing land-allocation literature. These aggregate reallocations are reinforced by household-level decisions, as Nguyen Chau and Scrimgeour (2023) show that families under climate stress reallocate land away from rice, a mechanism consistent with our findings on diversification and aquaculture expansion.

Third, our study connects to a large body of evidence that documents labor reallocation response to climate change's effects on agricultural outputs (Colmer, 2021; Blakeslee et al., 2020; Grabrucker and Grimm, 2021). Within this literature, a small number of studies examine how the conditions of the local labor markets interact with the labor reallocation in response to climate change (Liu et al., 2023; Pham, 2025).[1] Liu et al. (2023) argue that the local labor market adjustment is an important mechanism of the labor reallocation response, while Pham (2025) shows that local labor market conditions, specifically trade openness, drive the heterogeneity in labor reallocation responses. Albert et al. (2021), on the other hand, show that capital reallocation response to climate change is limited; as a result, labor reallocation to non-agricultural sectors tends to be at small firms outside of the manufacturing sector. We extend this by bringing in direct measures of local non-agricultural labor demand, particularly manufacturing industries, and show that droughts hit non-agricultural sectors relatively harder in our context, pulling workers back into agriculture. In addition, we show the labor–capital dynamics behind the adaptation strategies. Specifically, rice intensification and crop diversification absorb agricultural labor, whereas the expansion of aquaculture is driven by machinery adoption rather than labor inflows.

The rest of the paper proceeds as follows. Section 2 introduces the conceptual model. Section 3 describes the data and spatial distribution of land use and drought. Section 4 discusses the empirical strategy. Section 5 reports results, including both average and heterogeneous treatment effects. Section 6 presents mechanism analysis and Section 7 concludes.

[1] Relatedly, Afridi et al. (2022) find that social norms may serve as an additional labor friction preventing women from switching to non-farm sectors.

2 Conceptual Model

We present a stylized framework to guide the empirical analysis. Consider a representative price-taking farmer in commune i and district d at time t. The farmer allocates land and labor across three agricultural activities, $s \in \mathcal{S} \equiv \{r, c, a\}$, where r denotes rice, c denotes other crops, and a denotes aquaculture. Let A_s, L_s, and K_s denote land, labor, and capital (machinery) used in activity s. Drought intensity is denoted by D. Drought tightens the freshwater constraint such that available water declines with drought intensity, $W(D) = \bar{W} - \phi D$, where $\bar{W}$ denotes baseline water availability and $\phi > 0$ measures the sensitivity of water availability to drought exposure. Activities also differ in freshwater intensity, with $\omega_r > \omega_c \geq \omega_a \geq 0$, where ω_j denotes the freshwater requirement of activity j. Thus, rice production is the most freshwater-intensive activity, while aquaculture is relatively less dependent on freshwater. The farmer takes the district wage as given. To summarize the local labor-market channel, let $B(D)$ denote local non-agricultural labor demand, with $B_D < 0$ when drought reduces non-agricultural activity. The district wage is written as $w(D, B(D))$, where $w_B > 0$.

For a given drought intensity D, the farmer chooses land, labor, and capital allocations across activities $s \in \mathcal{S}$ to solve

$$\max_{\{A_s, L_s, K_s\}_{s \in \mathcal{S}}} \pi = \sum_{s \in \mathcal{S}} \left[p_s Y_s(A_s, L_s, K_s; D) - w(D, B(D)) L_s - r_s K_s \right]. \tag{1}$$

The maximization is subject to the aggregate land and water constraints, $\sum_{s \in \mathcal{S}} A_s \leq \bar{A}$ and $\sum_{s \in \mathcal{S}} \omega_s A_s \leq W(D)$, respectively. The solution defines drought-dependent allocation rules $A_s^*(D)$, $L_s^*(D)$, and $K_s^*(D)$.

Assume that, for each activity $s \in \mathcal{S}$, the production function $Y_s(A_s, L_s, K_s; D)$ is increasing and concave in own inputs: $Y_{sA} > 0$, $Y_{sL} > 0$, $Y_{sK} > 0$, and $Y_{sAA} < 0$, $Y_{sLL} < 0$, $Y_{sKK} < 0$. Drought affects production both directly, through activity-specific productivity effects, and indirectly, by tightening the freshwater constraint. We assume that drought reduces the marginal productivity of rice land and rice labor more than it reduces those of the alternative activities, so that $Y_{rAD} < Y_{jAD}$ and $Y_{rLD} < Y_{jLD}$ for $j \in \{c, a\}$. Aquaculture is less labor-intensive and more capital-intensive than crop cultivation, so reallocation toward aquaculture tends to reduce labor demand while increasing demand for machinery or other capital inputs.

Let μ and λ denote the shadow values of the aggregate land and freshwater constraints, respectively. For an interior allocation, the first-order conditions imply that the marginal returns to land, labor, and capital are equated to their respective shadow costs. Comparing an alternative activity $j \in \{c, a\}$ with rice, define the marginal profitability gap as $\Delta_{jr} \equiv [p_j Y_{jA} - \lambda \omega_j] - [p_r Y_{rA} - \lambda \omega_r]$, where the common land shadow value μ cancels across activities. The model delivers three main comparative-static implications:

$$\frac{dA_j^*(D)}{dD} = -\frac{\partial \Delta_{jr}/\partial D}{\partial \Delta_{jr}/\partial A_j} > 0, \qquad j \in \{c, a\}, \tag{2}$$

$$\frac{dL_s^*(D)}{dD} = \frac{w_D + w_B B_D - p_s Y_{sLD}}{p_s Y_{sLL}} \gtrless 0, \qquad s \in \mathcal{S}, \tag{3}$$

$$\frac{dK_a^*(D)}{dD} = -\frac{p_a Y_{aKD} + p_a Y_{aKA} \frac{dA_a^*(D)}{dD} + p_a Y_{aKL} \frac{dL_a^*(D)}{dD}}{p_a Y_{aKK}} > 0. \tag{4}$$

Drought first changes the relative profitability of land across agricultural activities. When the freshwater constraint binds, a marginal increase in drought raises the shadow value of freshwater, so $\lambda_D > 0$. Since rice is more freshwater-intensive than other crops and aquaculture, $\omega_r > \omega_j$, the water-scarcity component of $\partial \Delta_{jr}/\partial D$ is positive. Drought also reduces the marginal productivity of rice land more than that of the alternative activities, so the direct productivity component is positive as well. Thus, $\partial \Delta_{jr}/\partial D > 0$. Because diminishing marginal returns imply $\partial \Delta_{jr}/\partial A_j < 0$, drought increases the optimal land allocated to other crops and aquaculture relative to rice.

The labor response is less direct because drought affects both farm productivity and the local outside option. On the production side, drought lowers the marginal productivity of labor, so $Y_{sLD} < 0$; together with $Y_{sLL} < 0$, this reduces optimal farm labor demand. On the labor-market side, drought may also reduce non-agricultural labor demand. When $B_D < 0$ and $w_B > 0$, the district wage falls through the local labor-market channel, so $w_D + w_B B_D < 0$. Since $Y_{sLL} < 0$, this wage effect increases agricultural labor demand by lowering the opportunity cost of farm work. The net effect on agricultural labor is therefore ambiguous and depends on whether the local wage effect dominates the direct productivity loss.

The capital margin is most relevant for aquaculture, where production is relatively capital-intensive. Since $Y_{aKK} < 0$, aquaculture capital increases when drought raises the marginal return to aquaculture capital. This can occur directly if drought increases the relative productivity of aquaculture capital, so $Y_{aKD} \geq 0$, and indirectly if drought expands aquaculture land, so $dA_a^*(D)/dD > 0$, with land and capital acting as complements, $Y_{aKA} > 0$. If the labor-capital complementarity term is small or positive, the numerator in (4) is positive, implying $dK_a^*(D)/dD > 0$. Thus, drought-induced aquaculture expansion is expected to be accompanied by greater machinery or capital use rather than by a proportional increase in aquaculture labor.

The conceptual model has several empirical implications. First, drought should reduce land allocated to freshwater intensive rice and increase land allocated to less freshwater intensive activities such as other crops and aquaculture. Second, the labor response need not follow the direct productivity effect. When drought weakens local non agricultural labor demand, especially in more manufacturing intensive districts, lower wages may draw workers back into agriculture. Because aquaculture is less labor intensive than crop cultivation, this labor response should be stronger for rice and other crops than for aquaculture. Third, drought induced movement toward aquaculture should be accompanied by greater machinery use, particularly in saline or water constrained communes. More broadly, the same drought shock can generate different adjustment margins depending on local water scarcity, salinity, baseline production patterns, and non agricultural labor market conditions.

3 Data

We construct a nationally comprehensive dataset for Vietnam by merging land use, climate, hydrological, and other socioeconomic data from multiple sources covering the period 2000–2020. The resulting dataset is aggregated at the commune–year level to analyze the impact of drought on land use change. In addition, we aggregate Vietnam's Agricultural Census data for 2006, 2011, and 2016 at the commune–year level to conduct the mechanism analysis.

3.1 Land Use

We use the Vietnam-wide Land Use/Cover Data (VLUCD) series to measure annual land use and land cover from 2000–2020 across mainland Vietnam (Duong et al., 2018; Phan et al., 2021, 2022). VLUCD provides 30 m products with a Level-1 scheme of ten primary land use classes, produced from Landsat and Sentinel-1/-2 imagery using random-forest classification with post-classification optimization and independently validated reference data. We use the Level-1 classes instead of the Level-2 data with 18 land use types for higher accuracy. According to Phan et al. (2021), the overall accuracy of Level-1 ranges from roughly 86–92%, while the Level-2 products range from 78% to 85%. The ten Level-1 land use categories and their average commune-level areas in 2000 and 2020 are summarized in Table A1. Forest remains by far the dominant land use type, averaging more than half of commune area in both 2000 and 2020, though it declined modestly over time. By contrast, residential and aquaculture land uses expanded sharply, with average commune-level aquaculture area more than tripling from 0.27 km^2 in 2000 to 0.86 km^2 in 2020. Rice paddies, which occupied over 4.2 km^2 per commune in 2000, declined to 3.7 km^2 in 2020, reflecting the broader land use reallocation described in the following sections.

Building on these descriptive patterns, our analysis focuses on the two land use categories most relevant for agricultural adaptation: rice paddies and aquaculture. The dependent variables are defined as commune-level land use areas (in km^2) for these categories. We collapse all other crop types, including woody crops and in-house crops, into a general cropland category (*other_cropland*). We define total agricultural land as the sum of rice paddies, aquaculture, and other cropland. As reported in Table 1, the average agricultural land area is about 9.69 km^2 per commune, of which 47.80% is rice paddies and 4.16% is aquaculture, across all communes from 2000 to 2020. Figure 1 shows that the rice share of total agricultural land increased from 2000 to 2008, peaking at 46.78%, and then declined steadily to 37.38% in 2020. By contrast, the aquaculture share of total agricultural land rose gradually over the same period, from below 2.80% in 2000 to around 8.64% in 2020.

The spatial distribution of changes is illustrated in Figure 2, which maps the difference in land use shares between the 2000–2005 and 2015–2020 six-year averages. Panel (a, left) shows that rice shares declined substantially in many communes, particularly across the Mekong Delta and parts of the Red River Delta, while increases were observed in selected upland areas in the north. Across all communes, the rice share decreased on average by 3.5 percentage points, with considerable variation ranging from losses of more than 70 percentage points to gains of over 50 percentage points. A small number of communes experienced complete abandonment of rice (19 communes) or new adoption where rice was previously absent (18 communes). Panel (a, right) presents changes in aquaculture shares over the same period. Expansion was widespread, especially in coastal communes of the Mekong Delta and along parts of the central and northern coastlines. On average, aquaculture shares increased by 2.3 percentage points, with observed changes spanning from reductions of about 33 percentage points to expansions of nearly 87 percentage points. Importantly, aquaculture appeared in 820 communes where it had not been present in the early 2000s, and no commune fully abandoned aquaculture. Together, these maps highlight a spatial reallocation of agricultural land: rice shares contracted in major delta regions, while aquaculture expanded in low-lying coastal areas, consistent with observed national trends in Figure 1.

3.2 Drought

Our main climate inputs come from the TerraClimate product (Abatzoglou et al., 2018), a global monthly dataset at 4 km (1/24°) resolution spanning 1958–present. Beyond temperature and precipitation, TerraClimate provides derived hydro-climate variables computed with a modified Thornthwaite–Mather water-balance model and reference evapotranspiration from the ASCE Penman–Monteith method; these include soil moisture, runoff, climatic water deficit, and the Palmer Drought Severity Index (PDSI) (Palmer, 1965). We use PDSI as our drought metric. We transform the series into a non-negative drought index by zeroing positive values and taking the absolute value of negatives so that larger numbers indicate greater drought severity:

$$D_{it} = \begin{cases} -\mathrm{PDSI}_{it}, & \text{if } \mathrm{PDSI}_{it} < 0 \\ 0, & \text{if } \mathrm{PDSI}_{it} \geq 0 \end{cases} \tag{5}$$

where D_{it} is the drought intensity for commune i in year t.

Figure 2 summarizes temporal and spatial patterns of drought intensity in Vietnam from 2000 to 2020. Panel (a) shows the national trend in average drought intensity, which increased from near zero in 2000 to 3.8 by 2020, representing a net rise of 2.5 points over the period. Droughts intensified particularly during the mid-2000s and again in the late 2010s. Panels (b) and (c) map the spatial distribution of average drought intensity and its variability, respectively. On average, communes experienced a drought intensity of 1.4, with observed values spanning from 0.5 to 7.5. The standard deviation of drought intensity averaged 1.7, with values between 1.0 and 5.3. The Mekong Delta and south-central coastal provinces experienced both higher average drought intensity and greater variability than northern and upland regions, underscoring their exposure to recurrent water stress.

3.3 Agricultural Census

We use Vietnam's Rural, Agricultural, and Fisheries Census (RAFC) to examine adaptation mechanisms, referred to as the Agricultural census. The data is nationally representative and administered in 2006, 2011, and 2016, enumerating all rural households and urban households that engaged in agriculture, forestry, or fisheries across all communes in 63 provinces. Each round follows a common design: a universal short form (household characteristics, labor, land use, livestock, and machinery/equipment) and a long form administered to approximately 0.5 percent of rural households with richer detail on inputs, credit markets, extension services, irrigation, and incomes. Taking advantage of this structure, we use the data from the universal household questionnaire, aggregate machinery and labor measures to the commune level and construct a three-wave commune panel spanning 2006–2016.

3.4 Other Datasets

Rice Production, Water Resources, and Population

To study the impact of drought on rice yield and harvested area, we use the gridded rice yield dataset from Wu et al. (2023) and the harvested area data from Xie et al. (2025) for the period 2000 to 2020, aggregated to the commune level. Because Vietnam cultivates rice in one, two, or three seasons, and yields differ across multi-cropping areas, we calculate yield ($tons/km^2$) as a weighted average across all cropping types, with weights given by the seasonal cropping areas. We measure total water area (km^2) using data from Pekel et al. (2016), which include both seasonal and permanent water pixels. As a proxy for water quality, we use salinity levels (mg/L) from Jones et al. (2023), which capture total dissolved solids in water from 2000 to 2019. We also incorporate irrigation classifications from Nagaraj et al. (2021), which distinguish irrigated from rainfed croplands. Finally, we use annual gridded population data from WorldPop (Tatem, 2017), at 100-meter resolution and aggregated to the commune level for 2000 to 2020, as a control variable in our analysis.

Manufacturing and Labor Market Data

We also examine whether adaptation strategies vary by the conditions of the local labor market. In particular, if non-farm labor demand is substantially high, the opportunity cost of switching crops or switching to other forms of farming may be very high. As a result, one would expect a stronger non-farm labor response and/or a weaker land use response. To measure non-farm labor demand, we use annual firm-level Vietnam Enterprise Census (VEC) data for 2006 to 2016. Specifically, we calculate the annual number of manufacturing firms at the district level for every year. Alternatively, we also use the manufacturing labor as a measure of labor demand.

4 Empirical Strategy

To identify the causal effect of drought on land use, we adopt a general empirical framework that accounts for unobserved time-invariant local characteristics. This framework can be specified as:

$$\bar{Y}_{ir\tau} = \alpha_i + f_r(\tau) + \beta \bar{D}_{ir\tau} + \gamma' \bar{\Omega}_{ir\tau} + \bar{\varepsilon}_{ir\tau} \tag{6}$$

where i indexes the commune in region r and τ indexes the time period, which can be a single year or a multi-year interval. $\bar{Y}_{ir\tau}$ is the average land use outcome (e.g., area of rice paddies, area of aquaculture, etc.) in commune i located in region r during period τ. $\bar{D}_{ir\tau}$ and $\bar{\Omega}_{ir\tau}$ are the period-averaged drought measure and control variable, respectively. The key independent variable, $D_{ir\tau}$, captures drought conditions, constructed from the PDSI measure as defined in equation (1). The vector of controls, $\Omega_{ir\tau}$, includes the population count of commune i of region r in year t. α_i represents the key time-invariant, commune-specific fixed effects, capturing unobserved characteristics like geography, soil quality, or deep-rooted farming culture. $f_r(\tau)$ is a general function for time-period effects, which captures shocks or trends common to all communes or specific regions within a given period. $\bar{\varepsilon}_{ir\tau}$ is the error term.

The goal is to estimate β, the effect of drought on land use, by eliminating the confounding influence of time $f_r(\tau)$ and location α_i (Schlenker and Roberts, 2009; Deschênes and Greenstone, 2007). Both our panel fixed-effect and long-difference models are specific applications of this general framework.

4.1 Panel Fixed Effect Specification

Our primary approach, the panel fixed-effect model, applies the general framework (2) to annual data from 2000 to 2020 to capture the comtemporous effect of drought. In this case, the time period τ is a single year t, so the period-averaged variables simply become their annual counterparts (e.g., $\bar{Y}_{ir\tau} = Y_{irt}$). The time effect $f_r(\tau)$ is specified as a combination of year fixed effects (τ_t) and region-by-year fixed effects (ξ_{rt}) to flexibly control for a wide range of time-varying shocks. This leads to the following specification:

$$Y_{irt} = \alpha_i + \tau_t + \xi_{rt} + \beta^{PD} D_{irt} + \gamma' \Omega_{irt} + \varepsilon_{irt} \tag{7}$$

This model identifies β^{PD} by using the within-commune variation over time, effectively differencing out the time-invariant α_i. The inclusion of ξ_{rt} ensures that our estimates are not biased by unobserved shocks that vary at the regional level, such as regional policy changes. We cluster standard errors at the commune level since it is the level of treatment assignment and allows for potential serial correlation over time within each commune (Abadie et al., 2023). The regression is estimated at the square-kilometer level, and we interpret the coefficient β^{PD} by comparing it with the mean of the dependent variable to express the drought effect on land use change in percentage terms following Chen and Roth (2023); Mullahy and Norton (2024).

4.2 Long-Difference Specification

To capture long-run adaptation and ensure our results are robust to short-term fluctuations, we also employ a long-difference approach. Following Burke and Emerick (2016), we define the starting period from 2000 to 2005 and the ending period from 2015 to 2020. For any variable Z, the long difference $\Delta\bar{Z}_i$ is calculated as the change between its average value in the ending period and its average value in the starting period for each commune i. This allows for the estimation of the following cross-sectional regression model:

$$\Delta\bar{Y}_{ir} = \beta^{LD}\Delta\overline{D}_{ir} + \Delta\overline{\Omega'_{ir}}\gamma + \delta_r + \Delta\bar{\varepsilon}_{ir}, \tag{8}$$

where $\Delta\bar{Y}_{ir} = \left(\frac{1}{6}\sum_{t=2015}^{2020} Y_{irt}\right) - \left(\frac{1}{6}\sum_{t=2000}^{2005} Y_{irt}\right)$. The differenced independent variable drought $\Delta\bar{D}_{ir}$, and the differenced control variable population $\bar{\Omega}_{ir}$, are constructed analogously by taking the change in the six-year average of the drought and control variables, respectively[2]. In this specification, the coefficient of interest, β^{LD}, captures the long-term land-use response to persistent changes in climate conditions. The model includes regional-level fixed effects, δ_r, which absorb any unobserved, regional-specific linear trends between the two periods, while $\Delta\bar{\varepsilon}_{ir}$ is the differenced error term. We also cluster standard errors at the commune level here.

We compare the magnitudes and signs of β^{PD} and β^{LD} to provide insights on whether there are short-run adaptation effects and whether there are any intensifying effects of drought over the long horizon, following Dell et al. (2014) and Burke and Emerick (2016).

[2] $\Delta\bar{D}_{ir} = \left(\frac{1}{6}\sum_{t=2015}^{2020} D_{irt}\right) - \left(\frac{1}{6}\sum_{t=2000}^{2005} D_{irt}\right)$ and $\Delta\bar{\Omega}_{ir} = \left(\frac{1}{6}\sum_{t=2015}^{2020} \Omega_{irt}\right) - \left(\frac{1}{6}\sum_{t=2000}^{2005} \Omega_{irt}\right)$

Specifically, if $\beta^{PD} = \beta^{LD}$, there is no adaptation. Suppose we find that $\beta^{PD} < \beta^{LD} < 0$, i.e. the magnitude of the coefficient in the short run is larger than the one in the long run, suggesting that despite the adverse effect of drought in the short run, households are able to adapt effectively to attenuate its effect in the long run. However, if we find $\beta^{LD} < \beta^{PD} < 0$, it suggests that the effect of drought intensifies over the long time horizon despite any short-run adaptation strategies.

5 Results

5.1 Main Effects

We begin with Table 2 by examining agricultural productivity responses. Since rice is Vietnam's primary crop, impacts on rice yield and harvest area shed light on short-run mitigation strategies and the potential for long-run productivity losses. This in turns motivates the land reallocation analysis for rice paddies, other crops, and aquaculture in subsequent tables.

Table 2 reports the effects of drought on rice yield and cultivation area using panel fixed effects and long-difference approaches. Both outcomes are weighted averages across single-, double-, and triple-cropping production areas, reflecting variation in the intensity of land use for rice. In the short run, column (1) shows that a one-unit increase in drought intensity leads to a statistically significant but modest increase in rice yield by 2.2 tons per km^2, equivalent to 0.4 percent of the commune-level average. At the same time, rice harvest area falls by 0.5 percent, as shown in column (3). These patterns are consistent with contemporaneous intensification as a mitigation strategy. Farmers appear to concentrate cultivation on smaller plots and achieve higher yields per unit area.

The long-difference estimates, however, reveal large adverse effects. Column (2) shows that for one unit increase in drought intensity in the long run, rice yield declines by 6.2 tons per km^2, equivalent to 27 percent of the commune-level average change in yield over the 20-year period. Harvest area contracts by 55 percent as in column (4). These estimates indicate that persistent drought reduces both the productivity and spatial concentration of rice cultivation. There are two possible explanations for the divergence between short- and long-run rice yield estimations. First, short-run rice intensification may be insufficient to offset the cumulative damage of repeated drought exposure. Second, the short-run mitigation strategies themselve, such as intensive input use or groundwater extraction, may degrade land qualty over time, contributing to the long-run decline in rice producitivity.

Next, table 3 examines how droughts reshape land allocation across rice paddy, other crops (annual and perennial), and aquaculture. The panel fixed effect estimates report a modest contemporaneous reallocation away from rice. Columns (1), (3), and (5) show that a one-unit increase in drought intensity reduces rice paddy area by 1.2 percent of the commune-level average, while other crop land and aquaculture land expand by 1.2 and 2.7 percent, respectively. These short-run shifts are consistent with farmers temporarily reallocating land at the margin in response to drought-induced reduction in rice production.

In the long run, however, rice paddy area shows statistically insignificant change on average, even as other crop and aquaculture land expand substantially by 53 and 16 percent of the commune-level average change over the 20-year period, respectively. The absence of long-run adjustment in rice paddy area likely reflects the constraints imposed by Vietnam's rice land protection policy. Since the late 1980s, Vietnam has maintained strict national targets for minimum rice cultivation area, currently set at 3.5 million hectares, as a cornerstone of its food security strategy. Under this framework, permanent conversion of designated rice paddy land to other uses requires explicit approval from local or provincial government authorities and is subject to land use plan constraints under the Land Law. These administrative and legal barriers make long-run conversion of rice paddy costly and slow, even when economic incentives favor a shift to alternative crops. The sizable long-run expansion in other crop and aquaculture land likely reflect extensification instead, bringing of previously non-agricultural or marginal land into production as a longer-run adaptation to persistent drought. This pattern suggests that while land use policy insulates the rice paddy stock from permanent reallocation, farmers do respond to persistent drought by expanding the agricultural frontier in other categories.

5.2 Heterogeneous Effects

The average effects mask key differences across areas with varying growing conditions, water limitations, and adaptation strategies. To clarify these patterns, we ask which places adjust the most and along which margins. In this section, we examine the effects of droughts by region and initial ecological conditions. Table 4 reports the panel fixed effects and long-difference estimates for three main regions of Vietnam, Central (used as the reference category), North and South. In the short run, compared to the Central and the South, the North exhibits a notably larger decline in rice paddy areas, shown in column (1) and a correspondingly larger increase in other crop land, as seen in column (3), indicating a shift away from rice toward alternative crops. The South shows a smaller additional decline in rice paddy but a pronounced expansion of aquaculture, shown in column (5). This is consistent with the reported increasing salinity intrusion and the region's taking advantage of brackish water conditions. The Central experiences only modest adjustments with a small reduction in rice paddy and a marginal rise in other crops. All together, these patterns suggest region -specific adaptation strategies, specifically crop diversification in the North, aquaculture expansion in the South, and limited adjustment in the Central.

In the long run, the North's pattern flips with increased rice paddy and reduced other crop land areas as a result of droughts, as presented in columns (2) and (4). In the South, there is a significant, albeit smaller, expansion of other crops, continued contraction of rice paddy, but sustained increase in aquacultural areas, as seen in column (6). The Central also follows the pattern of its short-run effects. A plausible explanation for these regional differences is government-intervened water management in the North. The Red River system in the North is fed by a cascade of large upstream reservoirs, in which the government can release water to partially offset drought shortfalls (cite). In the South, however, Vietnam lies at the end of the Mekong River with limited control over upstream flows in Laos and China. Thus, when river inflows are low, salinity intrusion pushes inland and makes freshwater supply for rice less reliable. This could explain the pivot toward brackish aquaculture as a durable adaptation strategy.

Next, we examine the heterogeneous treatment effects by baseline hydrological conditions. First, Panel A in Table 5 split communes by high and low initial water supply. In the short run, drought induces a larger reallocation out of rice and into aquaculture in high-water communes. Relative to low-water communes, rice paddy area falls by an additional 0.024 km^2 for one unit increase in drought intensity, while aquaculture expands by an additional 0.01 km^2. Long-run coefficients point in the same direction, which is continued rice contraction, limited crop diversification, and further aquaculture expansion in high-water communes, but the differences are not statistically distinguishable from those in low-water communes. This suggests that areas with high water supply ex-ante are exposed more to the adverse effect of droughts, leading to lessened rice and other crop cultivation and pivoting to aquaculture as the margin of adaptation. By contrast, crop diversification and expansion to aquaculture are both adopted in low water availability communes.

Second, Panel B in Table 5 reports the differential effects by baseline water quality for agricultural cultivation, proxied by water salinity level. In the short run, drought pushes both high- and low-salinity communes in the same direction: rice paddy contracts while other crop land and aquaculture expand. The reduction in rice planting and increase in other crops are larger in high-salinity communes. Aquaculture also rises in both groups, but the high–low differential is small and not statistically distinct in the short run. In the long run, high-salinity communes exhibit a significantly larger shift, including greater reductions in rice planting and substantially larger expansions in both other crops and aquaculture relative to low-salinity communes. This pattern suggests that droughts and water salinity could be complemetary stressors. In high-salinity settings, this compound stress nudges households to move away from rice toward non-rice crops and brackish-water aquaculture, while low-salinity communes move in the same directions but on a smaller margin.

Lastly, Panel C in Table 5 examines heterogeneity by baseline water infrastructure, proxied by irrigated area. In the short run, highly irrigated communes show the largest contraction in rice paddy, but no differential uptick in other crops or aquaculture relative to no-irrigated communes. Over the long run, heavily irrigated communes undergo the strongest exit from rice, with reductions of about 0.33 km^2, alongside the largest aquaculture gains of 0.19 km^2. These results indicate that when drought undermines the effectiveness of irrigation, communes with historically rice-intensive systems transition toward uses less dependent on freshwater, while those with low-to-medium irrigation record small negative long-run effects for other crops and aquaculture.

Across regions and hydrological settings, drought shifts land out of rice and into other activities on average, but the direction and persistence of change depend on local water regimes. The South and high-salinity areas transition most clearly toward aquaculture and, to a lesser extent, other crops. Low water availability tilts adjustment toward field crops, while high irrigation systems show the strongest long-run exit from rice and reallocation to aquaculture. These heterogeneous responses are consistent with a rising shadow price of freshwater and the increasing relative profitability of activities adapted to saline or brackish conditions.

6 Mechanism

The main results point to very different adaptation strategies to drought shocks. Regions may switch to other crops or intensify rice production in smaller areas. An important factor driving such different adaptation responses is the local non-agricultural labor markets. If drought shocks only affect the agricultural sector, it may trigger labor reallocation into the non-farm sector. The existing conditions of the non-farm labor market, therefore, will determine whether it can absorb the labor reallocation response.

However, if the non-agricultural sector is directly affected by drought shocks, e.g., droughts negatively affect productivity of manufacturing firms and force firm exits, the demand in the non-agricultural labor market is also negatively affected. The general equilibrium effect of droughts is then determined by the extent to which the agricultural labor supply and non-agricultural labor demand are affected. In other words, the relative sensitivity of agricultural versus non-agricultural sectors to droughts determine the *direction* and *magnitude* of labor reallocation: If droughts affect agriculture relatively more, labor productivity in agriculture would decrease, leading to lower labor demand. As a result, agricultural workers would move to non-agricultural industries for alternative employment options. If droughts affect non-agricultural sectors relatively more, local demand for non-agricultural labor contracts. Agriculture would end up absorbing non-agricultural workers, leading to an increase in agricultural labor, as predicted in Section 2.

We assess this mechanism by examining the effect of droughts on number of manufacturing firms and total manufacturing labor at district level using the enterprise survey data from 2006 to 2016. The first two columns of Table 6 indeed show that a one-unit increase in drought intensity reduces the number of manufacturing firms by 1.5 in the short run, equivalent to three percent of commune-level average, and by 4.1 in the long run, equivalent to 20 percent of commune-level average change in the ten-year period. Columns (3) and (4) show analogous declines in manufacturing employment with five percent in the short term and 19 percent decline in the long term. These results are a strong indicator that the non-agricultural sector is affected by droughts.

To gauge the *relative* impact on non-agriculture versus agriculture, we study labor movements between the two sectors using the Agricultural Census (2006, 2011, 2016), aggregating to the commune level. We split communes by their district's baseline level of manufacturing firms: high-firm districts defined as having above the 2006 median number of firms, and low-firm districts defined as having below or at the 2006 median.

In high-firm districts, there is a significant decrease in number of non-agricultural workers and a significant increase in number of agricultural workers, as shown in panel A of columns (1) and (2) in Table 7 and Table 8. Although the percentage changes in the short and long run are modest (2.2 and 4.9 percent decline), they are notably larger in magnitude than in low-firm districts (0.9 and 1.3 percent decline). This pattern is consistent with the hypothesis that non-agricultural sector, particularly manufacturing industries, is more drought-sensitive.

Where do workers go when leaving manufacturing firms in high-firm districts? A small fraction shifts into commerce and retail services, as shown in panel A of columns (7) and (8) in Table 7. But the majority move into agricultural sector, predominantly crop cultivation for both high- and low-firm districts, as shown in columns (3) and (4) of Table 8. Surprisingly, we find no detectable effect on aquacultural labor, despite the documented expansion of aquacultural land areas in Table 3. It suggests that a different adaptation mechanism to increase aquacultural activities.

Besides labor reallocation across sectors, farms can also adjust along the machinery-labor allocation within agriculture. Farming households can buffer drought shocks by intensifying crops on smaller areas and/or diversifying into other crops and aquaculture, using labor and mechanization as substitutes or complements. We assess this dimension of adjustment by examining the effect of droughts on the use of agricultural machinery in Table 9 across high- and low-firm districts. The first two columns indicate no average change in total agricultural machinerys in high-firm districts and a marginally significant increase in low-firm districts. We break down the effects further by rice-related machineries (including rice threshing, rice seeding, and rice harvesting machines), aquacultural machineries (including water pump, aquacultural processing, and aerator) and other machineries (including cargo cars, generators, drying machines, food processing, motorized insecticide, and livestock processing machines). Farmers in both high- and low-firm districts use a significantly higher quantity of rice machineries with 13.9 and 6.9 percent increases respectively. However, for aquacultural machinery, there is no detectable change within high-firm districts but sizable and statistically significant 6.6 and 14.7 percent increases in low-firm districts in the short and long term.

Overall, the labor and machinery results point to different adaptation strategies. In high-firm districts, droughts primarily contract non-agricultural labor demand, agriculture absorbs workers, and the dominant adaptation strategy leans more toward rice intensification rather crop diversification or expansion into aquaculture. In low-firm districts, there is a smaller increase in agricultural workers, most of them focus on crop cultivation as well. Different from high-firm districts, in response to droughts, farmers pivot toward aquaculture via a higher level of aquacultural mechanization.

7 Discussion and Conclusion

Our study provides nationally representative evidence on how Vietnam's agricultural landscape changes in response to drought along three margins, including land use, labor reallocation, and capital investment. While rice intensification serves as a short-run coping strategy, long-run drought exposure reverses the productivity gains and compresses rice area, with land reallocating toward diversified non-rice crops and especially aquaculture. These land responses are intertwined with local labor markets, in which drought contracts manufacturing activities and pulls workers back into farming.

Agricultural labor are mainly allocated to rice intensification and crop diversification, whereas aquaculture expansion relies primarily on mechanization. This reflects the high sensitivity of manufacturing sector to drought risks and highlights capital–labor substitution in adaptation, as high-firm districts displace workers into rice intensification, whereas low-firm districts expand aquaculture through greater capital investment.

While our study provides strong evidence on climate-adaptation patterns, it has limitations we aim to address next. First, our outcomes rely on aggregate satellite land use measures that can mask micro-level variation in smallholders' seasonal crop rotations and input choices. In ongoing work, we will leverage the Agricultural Census data to unpack these household measures to provide more insights into the decisions underlying observed land shifts. Second, our treatment uses annual average drought intensity, which may not align with crop calendars. We will add robustness checks using growing season-specific drought indices, month-level exposures, and placebo months to ensure the estimated effects map tightly to agronomic timing.

Our findings suggest several important policy directions for strengthening climate resilience. First, the short-run coping strategies may not offset the intensifying effects of extreme weather events such as droughts over the long horizon. It indicates that farming households' adaptation alone may be insufficient and entail more government interventions and support. Governments should facilitate a transition toward more sustainable production systems, including adoption of drought-resistant rice varieties, better water-saving practices where rice remains an important crop, access to other non-rice crops and aquaculture. As an extension of this implication, the variation in adaptation pathways across regions and local hydrological conditions highlights that uniform policies are unlikely to be effective. In salinity-exposed deltas, support should prioritize brackish aquaculture as a durable margin. Promoting capital investment is essential for the transition to the high-value mechanized aquacultural sector. Where freshwater control is feasible, such as in the Red River delta, coordinated reservoir operations and irrigation can help stabilize rice in drought years and even expand rice cultivation in the long run. Finally, the vulnerability of local manufacturing industries relative to agriculture highlights the need for climate policy to extend beyond agriculture. It calls for infrastructure investment toward providing reliable access to power, strengthening water supplies for manufacturing industries, preventing mass labor displacement during climate crises.

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Tables

Table 1: Summary Statistics for Drought Condition

Variable	Mean	Std. Dev.	Min	Max	Obs
Panel A. Land Use					
All Agricultural Land Area (km^2)	9.694	11.191	0.000	168.879	231,987
Rice Paddy Area (km^2)	4.122	5.984	0.000	111.406	231,987
Aquaculture Area (km^2)	0.572	3.992	0.000	86.682	231,987
Rice Paddy Share of All Agricultural Land (%)	47.802	29.226	0.000	100.000	231,159
Aquaculture Share of All Agricultural Land (%)	4.155	13.524	0.000	100.000	231,159
Panel B. Climate					
Historical Drought Conditions (Adjusted PDSI)	1.400	1.895	0.000	19.039	232,344
Average Water Salinity (mg/L)	1,172.454	5,388.647	0.000	411,848.200	219,410
Panel C. Socioeconomic					
Population Density (pop/km^2)	1,950.171	6,466.727	0.591	98,161.430	232,344

Table 2: Effects of Droughts on Land Productivity

	Rice yield (ton/km^2)		Rice cultivation area (km^2)	
	Panel FE	Long difference	Panel FE	Long difference
	(1)	(2)	(3)	(4)
Droughts	2.237***	-6.237***	-0.142***	-0.910***
	(0.225)	(0.633)	(0.005)	(0.042)
Dep. Var. mean	524.567	23.047	30.342	1.655
Effect Relative to mean (%)	0.426	-27.062	-0.468	-54.977
Commune FE	Y	N	Y	N
Year FE	Y	N	Y	N
Region-Year FE	Y	N	Y	N
Region FE	N	Y	N	Y
Including controls	Y	Y	Y	Y
Observations	88,905	11,064	232,344	11,064
R-squared	0.939	0.030	0.998	0.253

Notes: All regressions control for population count but the coefficient of the control variable is not shown here. Standard errors are clustered at the commune level and reported in parentheses. Stars denote statistical significance as follows: * p < 0.1, ** p < .05, *** p < 0.01.

Table 3: Effects of Droughts on Land Use Allocation

	Rice paddy land area (km^2)		Other crop land area (km^2)		Aquaculture land area (km^2)	
	Panel FE	Long difference	Panel FE	Long difference	Panel FE	Long difference
	(1)	(2)	(3)	(4)	(5)	(6)
Droughts	-0.048***	-0.008	0.060***	0.104**	0.015***	0.049***
	(0.004)	(0.015)	(0.007)	(0.035)	(0.002)	(0.010)
Dep. Var. mean	4.122	-0.201	5.001	0.197	0.572	0.306
Effect Relative to mean (%)	-1.175	4.186	1.210	52.967	2.654	16.084
Commune FE	Y	N	Y	N	Y	N
Year FE	Y	N	Y	N	Y	N
Region-Year FE	Y	N	Y	N	Y	N
Region FE	N	Y	N	Y	N	Y
Including controls	Y	Y	Y	Y	Y	Y
Observations	231,987	11,064	231,987	11,064	231,987	11,064
R-squared	0.946	0.024	0.905	0.125	0.947	0.081

Notes: The regressions control for population count but the coefficient of the control variable is not shown here. Standard errors are clustered at the commune level and reported in parentheses. Stars denote statistical significance as follows: * p < 0.1, ** p < .05, *** p < 0.01.

Table 4: Effects of Droughts on Land Use Allocation by Region

	Rice paddy land area (km^2)		Other crop land area (km^2)		Aquaculture land area (km^2)	
	Panel FE	Long difference	Panel FE	Long difference	Panel FE	Long difference
	(1)	(2)	(3)	(4)	(5)	(6)
Droughts (Central)	-0.013***	-0.010	0.038*	0.167*	0.000	0.006*
	(0.003)	(0.012)	(0.016)	(0.071)	(0.001)	(0.003)
Droughts × Northern region	-0.069***	0.491***	0.144***	-0.416***	0.003***	0.041***
	(0.009)	(0.075)	(0.019)	(0.083)	(0.001)	(0.007)
Droughts × Southern region	-0.049***	-0.077**	-0.015	-0.057	0.032***	0.080***
	(0.008)	(0.029)	(0.019)	(0.077)	(0.004)	(0.020)
Dep. Var. mean of Central	2.519	-0.170	8.177	1.083	0.119	0.075
P-value of North sum = 0	0.000	0.000	0.000	0.000	0.000	0.000
P-value of South sum = 0	0.000	0.001	0.020	0.001	0.000	0.000
P-value of North-South diff. = 0	0.063	0.000	0.000	0.000	0.000	0.048
Commune FE	Y	N	Y	N	Y	N
Year FE	Y	N	Y	N	Y	N
Region-Year FE	Y	N	Y	N	Y	N
Region FE	N	Y	N	Y	N	Y
Including controls	Y	Y	Y	Y	Y	Y
Observations	231,987	11,064	231,987	11,064	231,987	11,064
R-squared	0.946	0.028	0.905	0.125	0.947	0.082

Notes: The regressions control for population count but the coefficient of the control variable is not shown here. Standard errors are clustered at the commune level and reported in parentheses. Stars denote statistical significance as follows: * $p < 0.1$, ** $p < .05$, *** $p < 0.01$.

Table 5: Effects of Droughts on Land Use Allocation by Baseline Water Conditions and Infrastructure

	Rice paddy land area (km2)		Other crop land area (km2)		Aquaculture land area (km2)	
	Panel FE	Long difference	Panel FE	Long difference	Panel FE	Long difference
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Water Availability						
Droughts (Low)	-0.038***	0.017	0.059***	0.158***	0.011***	0.041***
	(0.003)	(0.014)	(0.008)	(0.043)	(0.001)	(0.006)
Droughts × High water availability	-0.024***	-0.058**	0.005	-0.122*	0.010***	0.008
	(0.003)	(0.022)	(0.007)	(0.058)	(0.001)	(0.015)
Dep. Var. mean of Low water availability	2.566	-0.151	4.756	0.511	0.033	0.038
P-value of sum for High water availabity = 0	0.000	0.000	0.000	0.388	0.000	0.000
Observations	231,987	11,064	231,987	11,064	231,987	11,064
R-squared	0.946	0.025	0.905	0.125	0.947	0.087
Panel B - Water Salinity						
Droughts (Low)	-0.041***	0.037*	0.045***	-0.010	0.015***	0.024***
	(0.004)	(0.018)	(0.009)	(0.046)	(0.002)	(0.006)
Droughts × High water salinity	-0.022***	-0.117***	0.041***	0.217***	0.002	0.040*
	(0.004)	(0.027)	(0.008)	(0.052)	(0.002)	(0.017)
Dep. Var. mean of Low water salinity	3.143	-0.208	6.266	0.823	0.476	0.167
P-value of sum for High water salinity = 0	0.000	0.002	0.000	0.000	0.000	0.001
Observations	230,433	10,973	230,433	10,973	230,433	10,973
R-squared	0.946	0.025	0.905	0.129	0.946	0.083
Panel C - Irrigation Areas						
Droughts (No to little)	-0.041***	0.044	0.105***	0.286**	0.014***	0.049*
	(0.004)	(0.022)	(0.013)	(0.087)	(0.002)	(0.023)
Droughts × Low-to-medium irrigation	0.000	-0.009	-0.067***	-0.361***	0.000	-0.056*
	(0.004)	(0.026)	(0.013)	(0.089)	(0.002)	(0.026)
Droughts × High irrigation	-0.049***	-0.369***	-0.019	-0.146	0.005	0.141**
	(0.006)	(0.053)	(0.012)	(0.100)	(0.003)	(0.045)
Dep. Var. mean of No-to-little irrigation	2.556	-0.110	7.447	2.469	0.427	0.227
P-value of sum for Low-to-medium irrigation = 0	0.000	0.365	0.000	0.000	0.000	0.033
P-value of sum for High irrigation = 0	0.000	0.000	0.000	0.000	0.000	0.000
Observations	231,987	11,064	231,987	11,064	231,987	11,064
R-squared	0.946	0.032	0.905	0.152	0.947	0.095
Commune FE	Y	N	Y	N	Y	N
Year FE	Y	N	Y	N	Y	N
Region-Year FE	Y	N	Y	N	Y	N
Region FE	N	Y	N	Y	N	Y
Including controls	Y	Y	Y	Y	Y	Y

Notes: The regressions control for population count but the coefficient of the control variable is not shown here. Standard errors are clustered at the commune level and reported in parentheses. Stars denote statistical significance as follows: * p < 0.1, ** p < .05, *** p < 0.01.

Table 6: Effects of Droughts on Manufacturing Firms and Labor

	Manufacturing firms (count)		Manufacturing labor (count)	
	Panel FE	Long difference	Panel FE	Long difference
	(1)	(2)	(3)	(4)
Droughts	-1.484*	-4.060**	-391.947**	-637.310**
	(0.663)	(1.345)	(118.936)	(207.604)
Dep. Var. mean	47.996	19.814	7805.111	3354.976
Effect Relative to mean (%)	-3.093	-20.490	-5.022	-18.996
Commune FE	Y	N	Y	N
Year FE	Y	N	Y	N
Region-Year FE	Y	N	Y	N
Region FE	N	Y	N	Y
Including controls	N	N	N	N
Observations	6,721	690	6,721	690
R-squared	0.962	0.175	0.963	0.105

Notes: The sample is from the enterprise survey from 2006 to 2016 at district level. Standard errors are clustered at the district level and reported in parentheses. Stars denote statistical significance as follows: * $p < 0.1$, ** $p < .05$, *** $p < 0.01$.

Table 7: Effects of Droughts on Non-Agricultural Labor Allocation

	All non-agricultural labor (count)		Manufacture labor (count)		Construction labor (count)		Commerce labor (count)		Transportation labor (count)	
	Panel FE	Long difference	Panel FE	Long difference	Panel FE	Long difference	Panel FE	Long difference	Panel FE	Long difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A - High-firm districts										
Droughts	-41.454***	-51.881***	-52.135***	-58.978***	1.705	1.833	7.125***	11.367***	-0.761	0.716
	(4.423)	(5.739)	(4.540)	(5.873)	(1.112)	(1.493)	(1.708)	(2.451)	(0.627)	(0.688)
Dep. Var. mean of High-firm districts	1855.882	1058.851	724.670	520.442	252.363	166.311	381.207	11.889	92.822	70.394
Effect Relative to mean (%)	-2.234	-4.900	-7.194	-11.332	0.676	1.102	1.869	95.613	-0.820	1.017
Observations	12,338	3,863	12,338	3,863	12,338	3,863	12,338	3,863	12,338	3,863
R-squared	0.985	0.919	0.941	0.744	0.918	0.493	0.930	0.411	0.923	0.693
Panel B - Low-firm districts										
Droughts	-8.699**	-6.929	-7.485**	-5.811	-0.781	-0.588	0.055	0.858	-0.422	-0.264
	(3.078)	(4.066)	(2.289)	(3.231)	(0.931)	(1.191)	(1.169)	(1.805)	(0.483)	(0.654)
Dep. Var. mean of Low-firm districts	967.630	553.704	253.047	189.231	141.253	130.602	252.914	13.249	53.536	46.415
Effect Relative to mean (%)	-0.899	-1.251	-2.958	-3.071	-0.553	-0.450	0.022	6.477	-0.788	-0.569
Observations	14,397	4,702	14,397	4,702	14,397	4,702	14,397	4,702	14,397	4,702
R-squared	0.963	0.595	0.890	0.338	0.894	0.385	0.927	0.366	0.850	0.289
Difference in pct. chg. A-B	-1.335	-10.775	-4.236	-15.781	1.229	-1.894	1.847	2.537	-0.032	-2.917
P-value of equality A = B	0.001	0.000	0.000	0.000	0.121	0.330	0.004	0.941	0.977	0.344
Commune FE	Y	N	Y	N	Y	N	Y	N	Y	N
Year FE	Y	N	Y	N	Y	N	Y	N	Y	N
Region-Year FE	Y	N	Y	N	Y	N	Y	N	Y	N
Region FE	N	Y	N	Y	N	Y	N	Y	N	Y
Including controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The regressions control for population count but the coefficient of the control variable is not shown here. Standard errors are clustered at the commune level and reported in parentheses. Stars denote statistical significance as follows: * $p < 0.1$, ** $p < .05$, *** $p < 0.01$.

Table 8: Effects of Droughts on Agricultural Labor Allocation

	All agricultural labor (count)		Agricultural labor (count)		Aquacultural labor (count)	
	Panel FE	Long difference	Panel FE	Long difference	Panel FE	Long difference
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - High-firm districts						
Droughts	33.581***	48.282***	33.763***	45.908***	-0.182	2.374
	(4.103)	(5.692)	(3.870)	(5.478)	(1.337)	(1.430)
Dep. Var. mean of High-firm districts	1930.229	-549.026	1834.470	-539.169	95.759	-9.857
Effect Relative to mean (%)	1.740	-8.794	1.840	-8.515	-0.190	-24.083
Observations	12,338	3,863	12,338	3,863	12,338	3,863
R-squared	0.954	0.267	0.955	0.262	0.958	0.049
Panel B - Low-firm districts						
Droughts	14.486***	16.605***	15.930***	18.627**	-1.445	-2.022
	(3.289)	(4.422)	(4.138)	(5.957)	(2.658)	(3.776)
Dep. Var. mean of Low-firm districts	2458.275	-264.887	2285.740	-253.399	172.535	-11.488
Effect Relative to mean (%)	0.589	-6.269	0.697	-7.351	-0.837	17.598
Observations	14,397	4,702	14,397	4,702	14,397	4,702
R-squared	0.978	0.673	0.971	0.587	0.969	0.071
Difference in pct. chg. A-B	1.150	8.100	1.144	9.087	0.648	-18.889
P-value of equality A = B	0.000	0.002	0.000	0.000	0.755	0.601
Commune FE	Y	N	Y	N	Y	N
Year FE	Y	N	Y	N	Y	N
Region-Year FE	Y	N	Y	N	Y	N
Region FE	N	Y	N	Y	N	Y
Including controls	Y	Y	Y	Y	Y	Y

Notes: The regressions control for population count but the coefficient of the control variable is not shown here. Standard errors are clustered at the commune level and reported in parentheses. Stars denote statistical significance as follows: * $p < 0.1$, ** $p < .05$, *** $p < 0.01$.

Table 9: Effects of Droughts on Agricultural Machinery Quantity

	Agric. machinery quantity		Rice machinery quantity		Aqua machinery quantity		Other agric. machinery quantity	
	Panel FE	Long difference	Panel FE	Long difference	Panel FE	Long difference	Panel FE	Long difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - High-firm districts								
Droughts	3.922	6.777	5.258***	6.762***	2.627	6.182	-3.963*	-6.167*
	(3.358)	(4.951)	(0.587)	(0.887)	(2.299)	(3.384)	(1.702)	(2.411)
Dep. Var. mean of High-firm districts	399.462	246.016	37.845	-50.959	238.183	141.575	123.434	155.400
Effect Relative to mean (%)	0.982	2.755	13.893	-13.269	1.103	4.366	-3.211	-3.968
Observations	12,338	3,863	12,338	3,863	12,338	3,863	12,338	3,863
R-squared	0.843	0.152	0.575	0.054	0.867	0.103	0.737	0.170
Panel B - Low-firm districts								
Droughts	9.377*	14.995**	3.045***	2.971*	18.736***	30.466***	-12.405***	-18.441***
	(4.076)	(5.746)	(0.839)	(1.302)	(3.410)	(5.042)	(2.003)	(2.557)
Dep. Var. mean of Low-firm districts	481.788	377.165	44.261	-21.335	283.904	207.881	153.623	190.620
Effect Relative to mean (%)	1.946	3.976	6.880	-13.925	6.600	14.655	-8.075	-9.674
Observations	14,397	4,702	14,397	4,702	14,397	4,702	14,397	4,702
R-squared	0.820	0.210	0.633	0.028	0.829	0.134	0.694	0.170
Difference in pct. chg. A-B	-0.964	1.428	7.012	1.286	-5.497	-8.382	4.864	8.376
P-value of equality A = B	0.418	0.569	0.004	0.839	0.000	0.013	0.010	0.000
Commune FE	Y	N	Y	N	Y	N	Y	N
Year FE	Y	N	Y	N	Y	N	Y	N
Region-Year FE	Y	N	Y	N	Y	N	Y	N
Region FE	N	Y	N	Y	N	Y	N	Y
Including controls	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The regressions control for population count but the coefficient of the control variable is not shown here. Standard errors are clustered at the commune level and reported in parentheses. Stars denote statistical significance as follows: * p < 0.1, ** p < .05, *** p < 0.01.

Figures

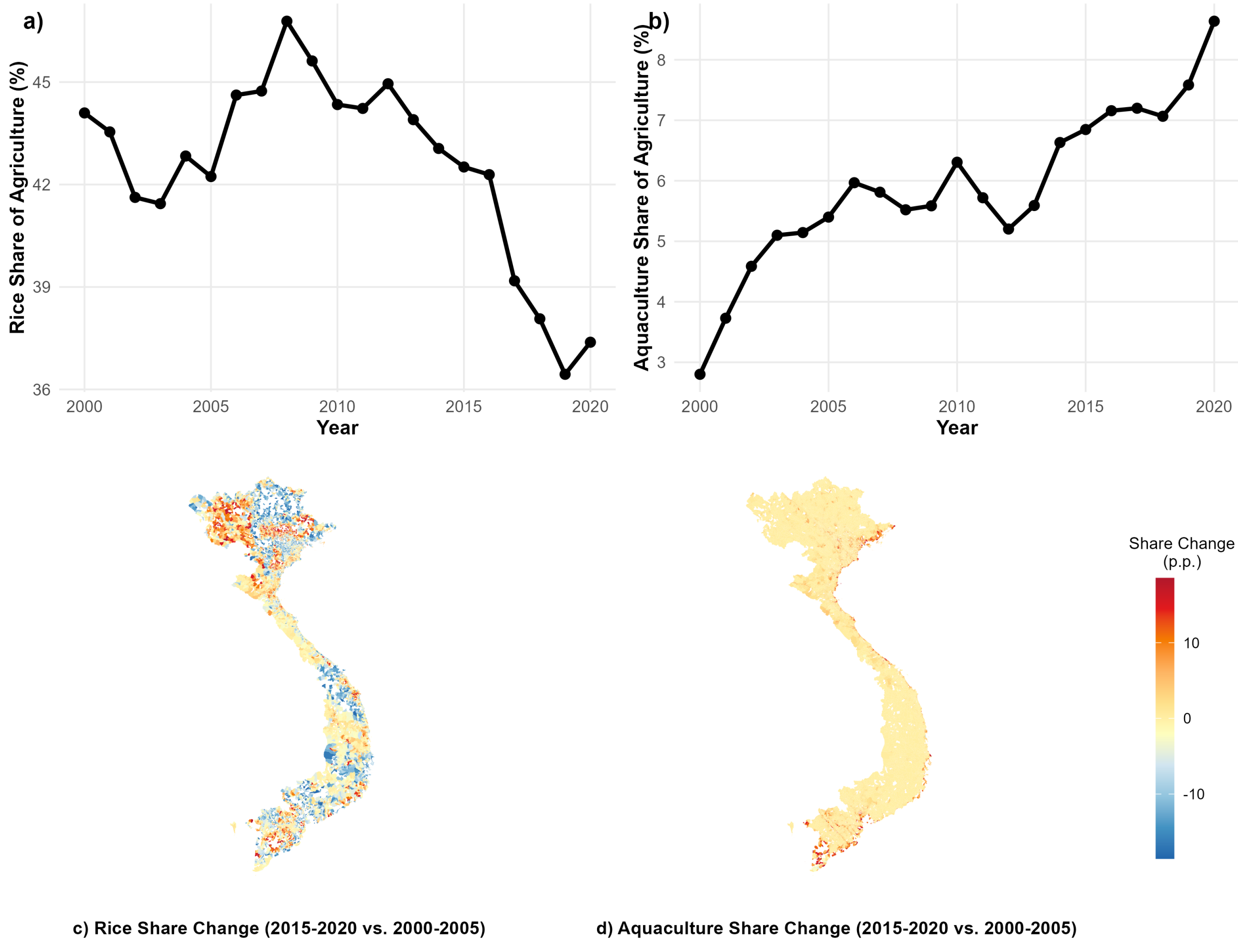

Figure 1: National shares of agricultural land in rice paddies and aquaculture, 2000–2020

Notes: Panel (a): share of total agricultural land area in rice paddies (%). Panel (b): share of total agricultural land area in aquaculture (%). Annual national series are computed as ratio-of-sums across communes: $\sum$ area $_{\text{type}}$ / $\sum$ all ag area $\times 100$. "All ag area" = rice paddies + aquaculture + other crop type. Values are percentages; years are calendar years. Panel (c) and (d) displays the change in the share of agricultural land dedicated to rice and aquaculture between two periods (2000–2005 vs. 2015–2020). The change is measured in percentage points (p.p.).

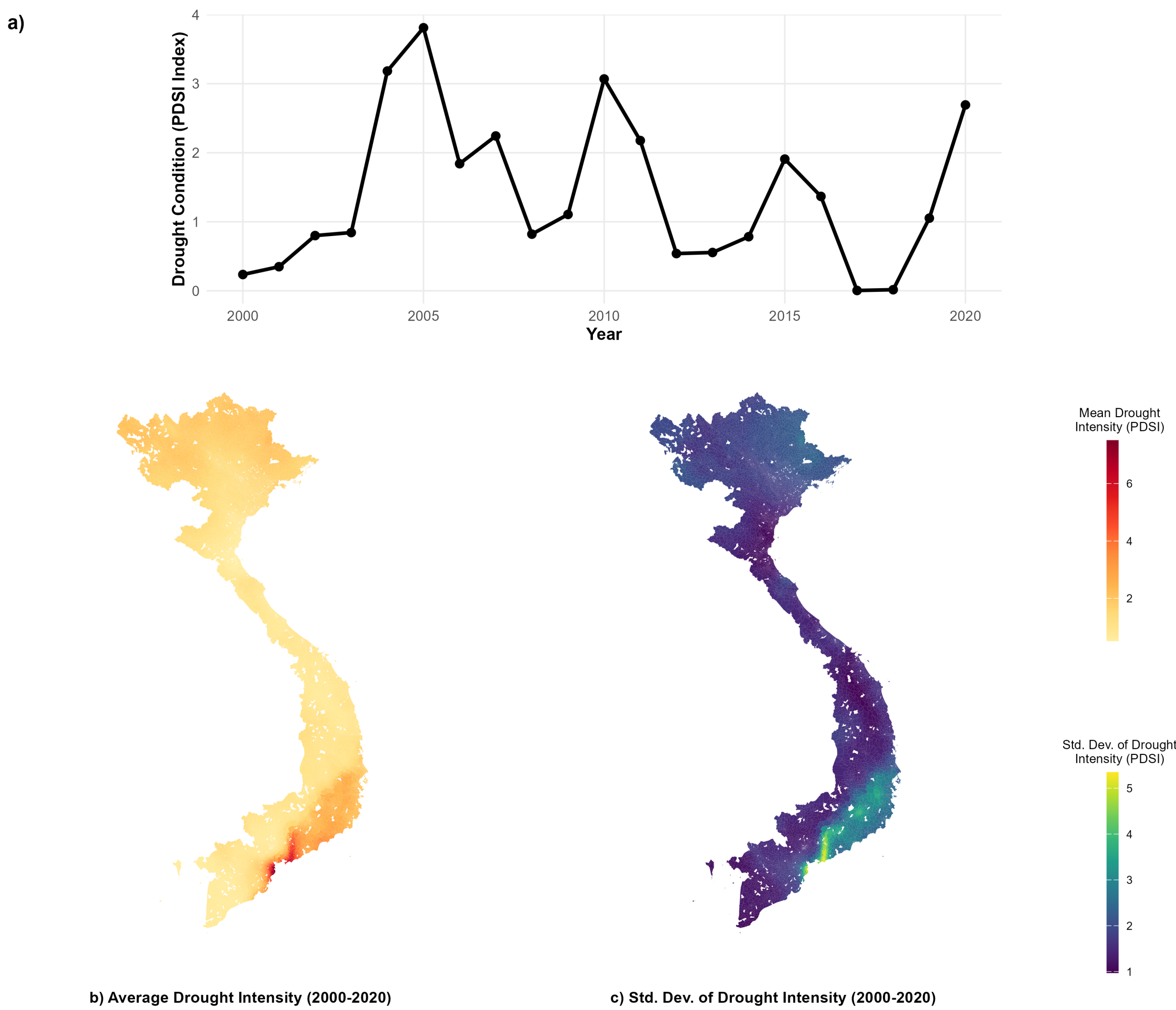

Figure 2: Drought in Vietnam, 2000–2020

Notes: Panel (a) shows the drought condition (PDSI) at commnue average from 2000 to 2020. Panel (b) and (c) shows the summary of drought conditions over the entire 2000–2020 period. The panel (b) displays the average drought intensity, while the right map shows its temporal volatility, measured by the standard deviation.

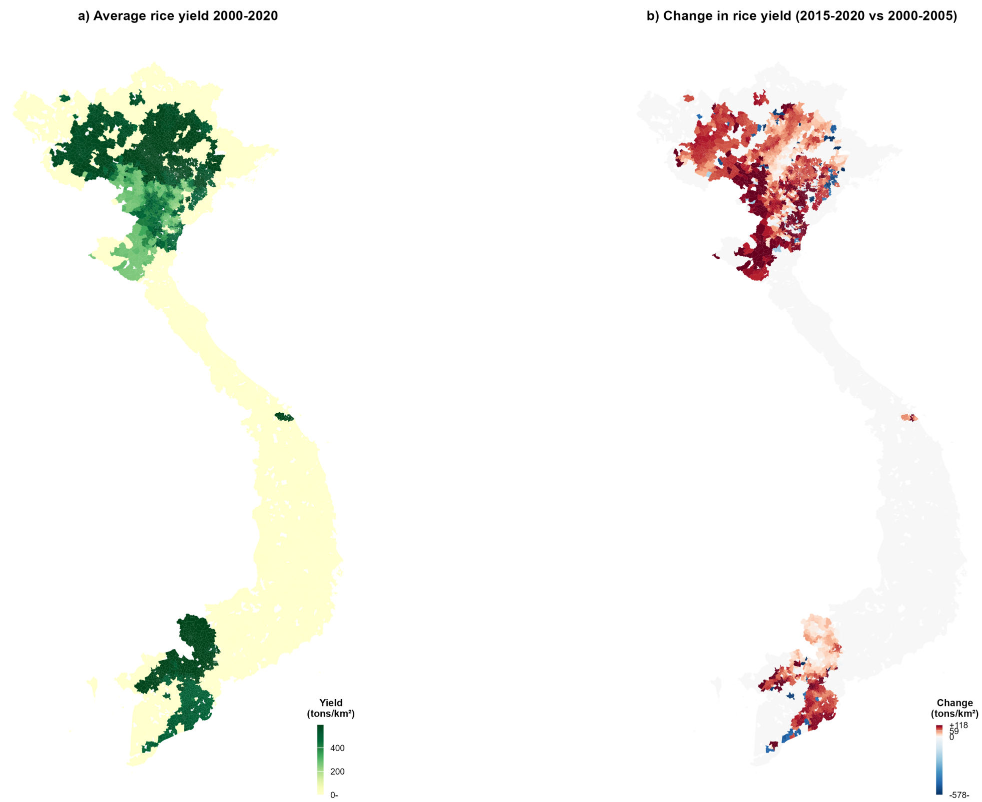

Figure 3: Spatial Patterns of Rice Yield in Vietnam, 2000–2020

Notes: Panel (a) shows the commune-level average rice yield ($tons/km^2$) over the period 2000–2020. Panel (b) shows the change in rice yield between the periods 2015–2020 and 2000–2005, with red indicating yield declines and blue indicating yield increases.

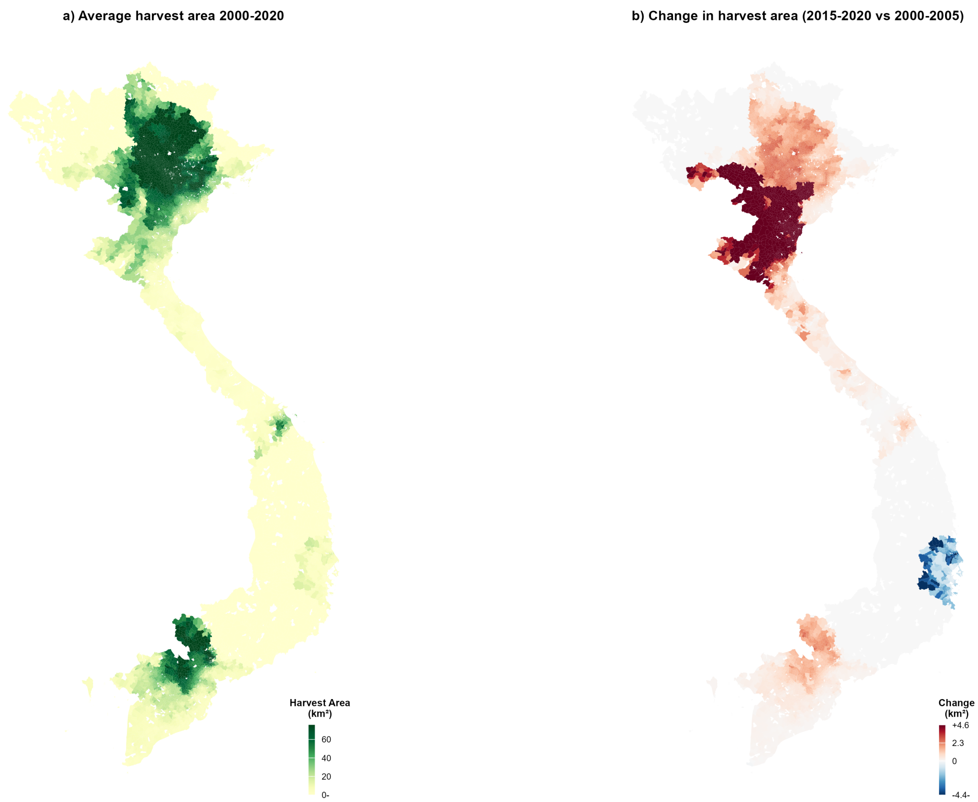

Figure 4: Spatial Patterns of Rice Harvest Area in Vietnam, 2000–2020

Notes: Panel (a) shows the commune-level average rice harvest area (km^2) over the period 2000–2020. Panel (b) shows the change in harvest area between 2015–2020 and 2000–2005, with red indicating decreases and blue indicating increases.

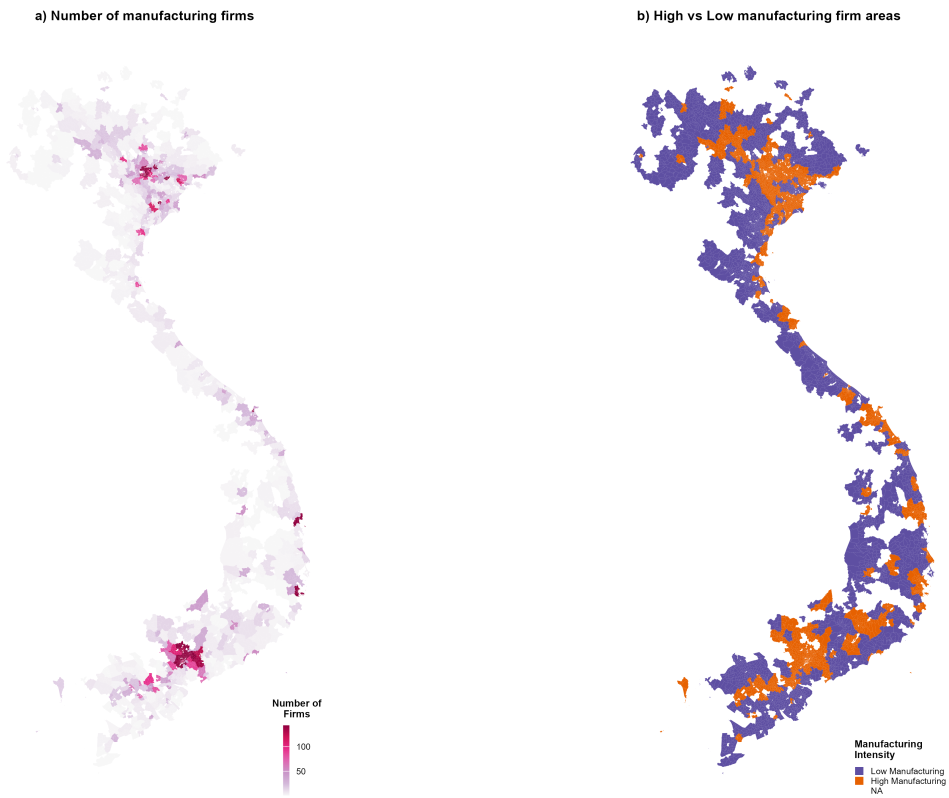

Figure 5: Spatial Patterns of Manufacturing Firm Numbers in Vietnam, 2000–2020

Notes: Panel (a) shows the commune-level number of manufacturing firms over the period 2000–2020. Panel (b) classifies communes into high- and low-manufacturing areas based on firm density.

A Appendix

A.1 Tables

Table A1: Average Commune-Level Land Use Area by Category in Vietnam, 2000–2020 (VLUCD)

Land Use Category	Average Area (km^2) Per Commnue in 2000	Average Area (km^2) Per Commnue in 2020
Residential	0.166	0.803
Rice Paddies	4.209	3.712
Croplands	5.068	5.360
Grassland	0.698	1.106
Barren	0.610	0.580
Shrub	0.823	1.072
Forest	18.465	17.002
Wetlands	0.259	0.209
Aquaculture	0.267	0.858
Water	0.753	0.617
Whole Commune Area	29.725	29.725

Notes: Values represent average land use area (in km^2) per commune. Data are derived from the VLUCD dataset and reflect commune-level averages across Vietnam.

Table A2: Effects of Droughts on Rice Productivity and Land Allocation by High- and Low-firm Districts

	Rice yield (ton/km^2)		Concentrated rice cultivation area (km^2)		Rice paddy land area (km^2)		Other crop land area (km^2)		Aquaculture land area (km^2)	
	Panel FE	Long difference	Panel FE	Long difference	Panel FE	Long difference	Panel FE	Long difference	Panel FE	Long difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A - High-firm districts										
Droughts	2.715***	-4.002***	-0.060***	-0.316***	-0.034***	-0.022	0.023	0.114***	0.009**	0.014
	(0.420)	(0.703)	(0.005)	(0.023)	(0.005)	(0.013)	(0.012)	(0.022)	(0.003)	(0.008)
Dep. Var. mean of High-firm districts	544.152	29.472	41.215	1.511	3.217	-0.385	3.216	0.024	0.149	0.111
Effect Relative to mean (%)	0.499	-13.578	-0.146	-20.943	-1.070	5.648	0.703	470.186	6.161	12.528
Observations	43,614	4,736	99,456	4,736	99,267	4,736	99,267	4,736	99,267	4736
R-squared	0.935	0.027	0.998	0.141	0.959	0.034	0.911	0.085	0.915	0.028
Panel B - Low-firm districts										
Droughts	2.523***	-3.471***	-0.187***	-0.795***	-0.049***	-0.068***	0.060***	0.251***	0.013***	-0.032*
	(0.312)	(0.679)	(0.008)	(0.043)	(0.007)	(0.020)	(0.012)	(0.028)	(0.002)	(0.015)
Dep. Var. mean of Low-firm districts	503.114	18.745	24.091	1.947	4.919	-0.036	6.297	0.220	0.763	0.358
Effect Relative to mean (%)	0.501	-18.519	-0.778	-40.844	-0.989	190.060	0.950	114.117	1.710	-8.908
Observations	37,491	4,854	101,934	4,854	101,892	4,854	101,892	4,854	101,892	4854
R-squared	0.939	0.044	0.997	0.376	0.945	0.026	0.898	0.123	0.957	0.105
Difference in pct. chg. A-B	-0.002	6.943	0.633	21.147	-0.080	-185.086	-0.246	348.925	4.451	22.179
P-value of equality A = B	0.980	0.107	0.000	0.000	0.681	0.001	0.552	0.000	0.022	0.005
Commune FE	Y	N	Y	N	Y	N	Y	N	Y	N
Year FE	Y	N	Y	N	Y	N	Y	N	Y	N
Region-Year FE	Y	N	Y	N	Y	N	Y	N	Y	N
Region FE	N	Y	N	Y	N	Y	N	Y	N	Y
Including controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The regressions control for population count but the coefficient of the control variable is not shown here. Standard errors are clustered at the commune level and reported in parentheses. Stars denote statistical significance as follows: * p < 0.1, ** p < .05, *** p < 0.01.

A.2 Figures

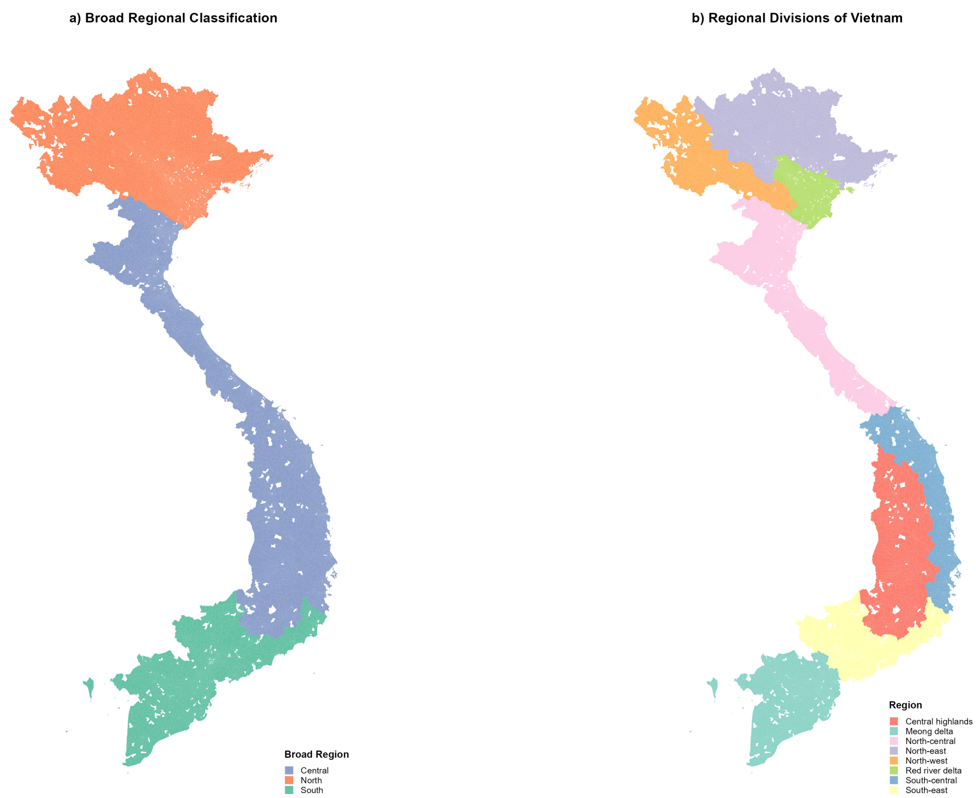

Figure A1: Region Division of Vietnam

Notes: Panel (a) for the broader region of Vietnam and Panel (b) for the more detailed region of Vietnam.

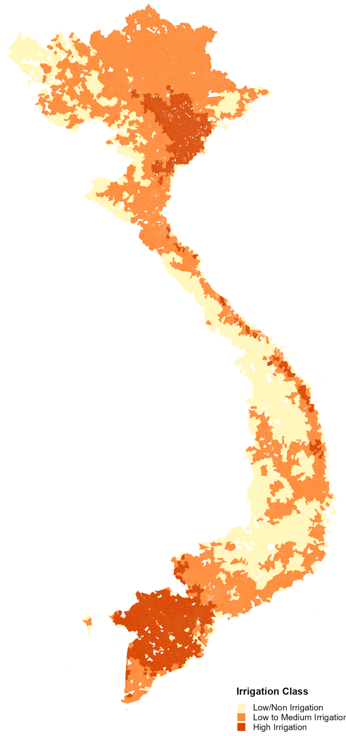

Figure A2: Irrigation Class of Vietnam in 2001

Notes: The classification is based on irrigated area within an 86 km^2 grid cell: no or very little irrigation, low-to-medium irrigation ($\leq$ 2000 hectares), and high irrigation ($>$ 2000 hectares) according to Nagaraj et al. (2021).

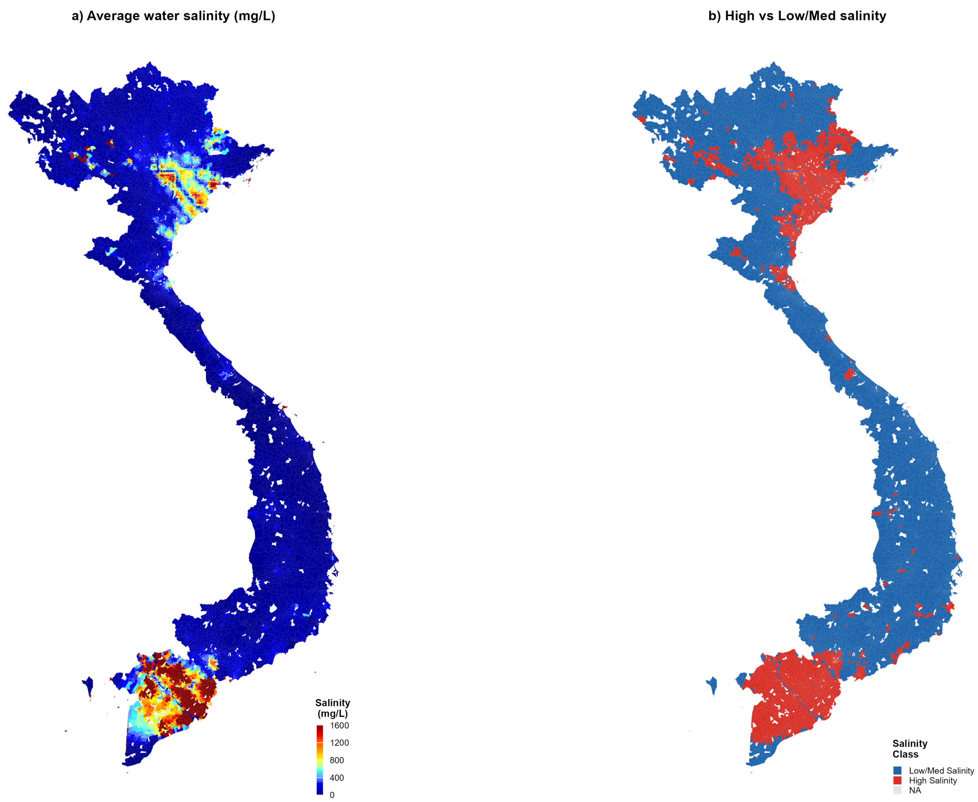

Figure A3: Spatial Patterns of Water Salinity in Vietnam, 2000

Notes: Panel (a) shows the commune-level average surface water salinity concentration (mg/L) in 2000. Panel (b) classifies communes into high-salinity versus low/medium-salinity areas.

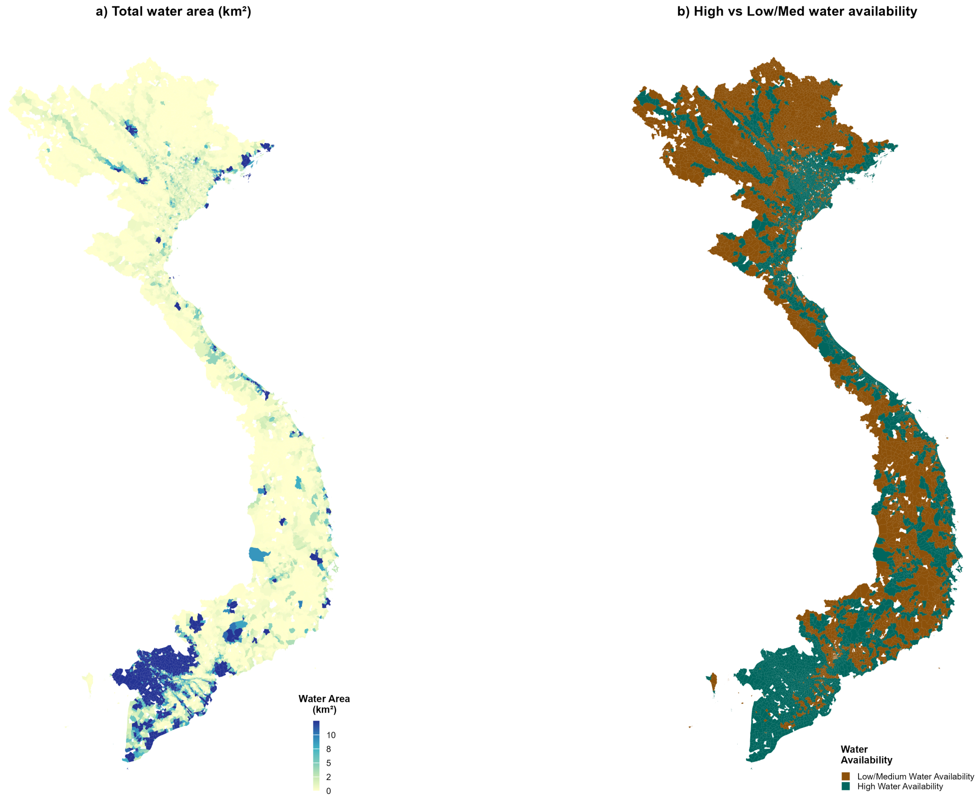

Figure A4: Spatial Patterns of Water Availability in Vietnam, 2000

Notes: Panel (a) shows the commune-level total surface water area (km^2) in 2000. Panel (b) classifies communes into high versus low/medium water availability categories.