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ORIGINAL ARTICLE

Measuring the impact of climate change on agriculture in Vietnam: A panel Ricardian analysis

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Abstract

This article investigates the economic impacts of changes in climatic conditions on Vietnamese agriculture. We apply the two-step Hsiao method to a 10-year panel of household data which focuses on the production of 20 crops across seven regions in Vietnam. This study allows for variable market feedbacks across regions that grow different selections of crops. In this way, our article differs from most panel Ricardian analyses which assume uniform market shocks on households. Our analysis also includes climate interactions to allow the effects of temperatures to be dependent on the levels of rainfall. Panel evidence from the Ricardian model suggests heterogeneous climate impacts across seasons and regions. Rising seasonal temperatures are associated with losses to most regions, with spring temperatures being the exception. Increases in summer precipitation are valuable to mitigate the negative effects of rising temperatures. Changes in climate normal should not be the focus of policymakers since the simulation indicates marginal losses to agricultural productivity, both in the short term and the long term. Regions with cool climates are likely to be most affected by the projected climate change.

KEYWORDS

climate change, climate interactions, panel Ricardian model, two-step Hsiao method, Vietnam

JEL CLASSIFICATION

Q15, Q54, O13

1 | INTRODUCTION

Vietnam represents an interesting case for assessing the impact of climate change. The country is characterized by highly heterogeneous climatic conditions, and researchers expect Vietnam to be among the countries hit hardest by climate change (Dasgupta et al., 2009). The long narrow shape of the country and its diverse typological conditions has resulted in seven climate regions where different selections of crops are grown. A report by the Ministry of Natural Resources and Environment (Ministry of Natural Resources and Environment, 2009) indicates changes in climate patterns are not uniform. The report predicts that temperatures across the country will increase faster in autumn and winter. The northern region of the country will experience a shortage of rainfall in spring, and the southern region will suffer from lower precipitation during winter and spring. Researchers believe the likely consequences of changing climatic conditions are serious and threaten hunger eradication, poverty reduction, and sustainable development (Dasgupta et al., 2009; Trinh, 2018). Therefore, assessing the impact of climate change in Vietnam is important for adaptation policy.

Although the literature on climate impact is vast, little is known about how Vietnamese agriculture will be affected. The simulation by Trinh (2018) presents significant losses due to non-marginal changes in long-term climate normal. Unfortunately, the estimated impacts of climate on Vietnamese agriculture are prone to several sources of bias, which could limit the insights. First, although the model allows market shocks to have effects on agriculture, Trinh hypothesized price effects to be homogeneous across regions. Given the high heterogeneity in crop choice across regions, not allowing for heterogeneous price feedbacks across regions leads to biased estimates. Second, the assumption of additive separability of temperature and precipitation effects is misleading (Fezzi & Bateman, 2015), such that the estimated temperature effects also include the confounding effects of rainfall.

This Ricardian analysis for Vietnam uses a 10-year panel of household data on production of 20 crops across seven regions. We extract high-resolution climatic and geographic data to match with the location of households. We test for stability of climate effects to justify the use of time-mean residuals in a two-step Hsiao method developed by Massetti and Mendelsohn (2011). In contrast to previous analysis assuming uniform market shocks, our analysis allows variable market feedbacks on regions with different selections of crops. In line with plant physiology (Monteith, 1977; Morison, 1996), our Ricardian analysis allows the relationship between temperature and precipitation to be mutually dependent.

Our findings show that while assuming uniform effects of exogenous market feedbacks produces marginal biases, the consequences of omitting climate interactions are severe when estimating climate impacts. Vietnamese agriculture is shown to be more sensitive to changes in temperature than changes in precipitation. Rising seasonal temperatures are associated with losses in most regions. Rising precipitation is beneficial in hot summers. Our simulation of climate impacts indicates marginal losses to agricultural productivity, with net losses ranging from .02% to 2.6% between 2030 and 2100. Regions currently with cool climates, such as the Central Highlands and the Northwest, are expected to be affected the most.

2 | LITERATURE REVIEW

Agriculture is arguably the sector most affected by climate change as it is directly exposed to climate elements (Rosenzweig et al., 2014). The projected impacts are severe for developing countries where agriculture directly supports the livelihood of a large proportion of the population and they have limited adaptive capacity. Estimated climate impacts on agricultural productivity are, however, subject to uncertainty, even for the same region under similar scenarios of global warming. For instance, Schlenker and Roberts (2009) projected large decreases in crop yields for U.S. crops while Deschênes and Greenstone (2012) estimated small losses in agricultural profits. Deschênes and Greenstone (2012) attributed this difference in estimated impacts to the difference in the output measured, contending the important role of adaptation in mitigating climate impacts.

There have been two main approaches to assessing climate impacts on agriculture: the agroeconomic approach, and the Ricardian (hedonic) climate models. Agroeconomic analyses control for factors associated with crop yields such that researchers can ideally isolate the effects of climate on crop growth and yield. Ewert et al. (2014) and Antle and Stöckle (2017) presented in-depth reviews of this approach. The main argument regarding this approach is that this method does not allow for actual adaptation taken by farmers to be measured in its outcome. The literature on climate change adaptation shows that farmers around the world have adopted different adaptation strategies. These include short-term climate-smart agriculture practices such as changes in sowing date, input mix, crop rotation, crop diversification, and improving irrigation efficiency (Abdulai, 2018; Bradshaw et al., 2004; Mall et al., 2004; Shahzad & Abdulai, 2021). Long-term adaptations can be achieved by crop substitution (Rezaei et al., 2015; Seo & Mendelsohn, 2008), or bundling agricultural technologies (Fleischer et al., 2011). Therefore, the agroeconomic approach tends to overstate negative impacts (Blanc & Reilly, 2017). Mendelsohn et al. (1994) termed this as the "*dumb farmer scenario*." In addition, the use of projections from this approach is limited due to the fact that the controlled variables used in agroeconomic analyses do not represent the diverse conditions of agricultural production.

The Ricardian model uses statistical tools to estimate relationships between climate and agricultural productivity. The model was first developed by Mendelsohn et al. (1994) based on a basic assumption that in a competitive market, land values reflect net productivity. Within this approach, adaptations are embedded in the information collected regarding farmers' behavior (Adams, 1999), which is the main difference between this approach and the agroeconomic models. Assuming a farmer is looking to maximize income from his farm given the exogenous variables that are beyond his control, the farmer would choose a different crop or different inputs if the exogenous variables change. Looking across an array of climatic conditions, there would be different crops chosen in each climate and different inputs applied (Mendelsohn & Massetti, 2017). Therefore, the profit-maximizing outcomes that the Ricardian model estimates incorporate long-term adaptation taken by farmers.

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The Ricardian model has been applied to quantify economic impacts of climate change in a large number of countries across continents (see Mendelsohn & Massetti, 2017; for more details about these analyses). Most of these studies estimate relationships between climate and agricultural productivity using cross-sectional data. The potentially omitted variable problem is a well-known issue associated with cross-sectional analyses (Blanc & Reilly, 2017; Fezzi & Bateman, 2015). Panel Ricardian models allow the use of location fixed-effects and time fixed-effects to account for potential omitted variables associated with unobserved time-invariant factors and common shocks, respectively. Another advantage of panel Ricardian models is the ability to test for the stability of climate effects over time for climate impact simulation. The standard assumption underpinning climate impact simulation is that climate is the only variable that changes over time. This is a restrictive assumption that assumes no future changes in agricultural technology that affects either agricultural productivity or adaptation capacity. Therefore, the estimated negative impacts should be regarded as the upper bound of climate impacts. However, this enables researchers to detect the likely changes in agricultural income that are attributable to climate change.

Panel Ricardian analyses, including Fezzi and Bateman (2015), Massetti and Mendelsohn (2011), Schlenker and Roberts (2009), Trinh (2018), and Deschenes and Greenstone (2007) detect the likely impacts of climate change against the backdrop of possible changes in global agricultural markets by the inclusion of time fixed-effects. The underlying assumption made by this approach is that the time fixed-effects capture the common shocks exogenous to climate. The estimated climate impacts are still subject to potential biases if time fixed-effects capture any confounding effects of climate through climate-induced price change.

Ignoring interactions between climate temperature and precipitation can result in biased estimates of climate variables, however, few Ricardian analyses address this. Monteith (1977) and Morison (1996), among others, have shown the significance of interactions between temperature and precipitation on crop growth. Surprisingly, most Ricardian analyses do not document such interaction but rather assume the impact of temperature and precipitation to be additively separable. Fezzi and Bateman (2015), Wang et al. (2009), and Schlenker and Roberts (2009) documented significant interactions between climates indicating potential bias in Ricardian analyses which assume the additive separability of climate phenomena.

We use a panel Ricardian model to measure the long-term impacts of climate change on Vietnamese agriculture. The 10-year panel evidence suggests constant climate effects in the period studied justifying the robustness of estimated climate impacts to time-varying confounders. In contrast to previous panel Ricardian analyses assuming uniform effects on households of external changes, we allow these changes to have different effects on households in different regions. This analysis also relaxes the assumption on the additive separability of temperature and precipitation to avoid the confounding effects of rising temperatures. We show in this article that while the likely biases resulted from assuming uniform changes in external conditions are negligible, the consequences of assuming the additive separability of climates are severe when estimating climate impacts for Vietnam.

3 | RESEARCH METHODOLOGY

3.1 | The Ricardian model for valuing economic impact of climate change

The basic hypothesis of the climate impact assessment is that climate shifts the production function for crops. The intuition of the Ricardian model is as follows: if future climatic conditions in location A were analogous to the current climate in location B, then the future behavior of farmers in location A would resemble the current behavior of farmers in location B, *ceteris paribus*. Therefore, information on agricultural production from cross-sections includes the implicit value of climate change. The Ricardian model assumes the farmer is always looking to maximize production income, subject to a set of exogenous conditions of his or her farm. This approach estimates the overall value of each driving factor by specifying the hedonic, reduced form model:

$$Max\ \pi = P_i Q_i (K_i, E_i) - TC_i (Q_i, W, E) \tag{1}$$

where π is net crop income which is the difference between revenue (PQ) and cost (TC) per unit of farmland. P_i is the market price of crop i, Q_i is the production function of crop i, K_i is a vector of production inputs other than land, E_i is a vector of exogenous environmental factors such as climate and geographic conditions. The relationship between climate and production function is expected to be quadratic (Criddle et al., 1997; Körner, 2006) such that the Ricardian model includes square terms of climate variables. Because the dependent variable is net crop income the Ricardian model takes into account adjustment cost pertaining to adaptation in terms of crop switching.

The Ricardian model defined by Equation (1) is a locus of most profitable crops. It is estimated across crops and inputs under different climatic conditions (Wang et al., 2009). Under the assumption of full adaptation given climate, net crop income or land value has attained the long-run equilibrium that contains information on the economic impact of climate change.

For a simpler illustration, we group independent variables into: a vector of time-varying variables X, a vector of time-invariant control variables Z, and a vector of climate variables C which are long-term averages of weather (Romm, 2018) and their square terms. When data are available for different years, one can use the repeated cross-sections to estimate the following Ricardian model in any year for which data are available:

$$V_{it} = X_{it}\beta_t + Z_i\gamma_t + C_i\varphi_t + u_{it} \tag{2}$$

This is equivalent to estimating a pooled Ricardian model with a set of time dummies and their interactions with climate variables. In the above equation, the estimated coefficients are allowed to vary over time. Climate change is a long-term trend. Different estimates of climate impact for different years seem not to be relevant (Massetti & Mendelsohn, 2011). Therefore, the correctly specified Ricardian model using repeated cross-sections is:

$$V_{it} = X_{it}\beta + Z_i\gamma + C_i\varphi + u_{it} \tag{3}$$

Because the Ricardian model measures long-run impacts of climate, a single-stage fixed-effects method is not appropriate since there is no variation in climate variables. Therefore, the Ricardian model for panel data can be estimated in two ways. One is to pool the entire data set to estimate a single stage using the above equation. The second way is to apply the Hsiao two-step method developed by Massetti and Mendelsohn (2011). Researchers prefer the Hsiao method because the fixed-effects estimates of time-varying variables are robust to omitted (time-invariant) variables at the household level (Blanc & Schlenker, 2017). The details of the Hsiao two-step method are as follows:

3.2 | The two-step Hsiao method for the panel Ricardian model

In the first step, net crop income or land value is regressed on time-varying variables using a fixed-effects method:

$$V_{it} = X_{it}\beta + \varepsilon_{it} \tag{4}$$

where ε_{it} is the resulting error term.

In the second step, the time-mean residuals (simple residuals plus fixed effects) obtained from the first step are regressed upon climate and other time-invariant controls:

$$\overline{V_i} - \overline{X_i}\,\hat{\beta} = Z_i\,\gamma + C_i\varphi + \overline{u_i} \tag{5}$$

While the estimated coefficients for time-varying variables in Equation (4) are robust to omitted time-invariant factors, the estimated climate impacts using Equation (5) are still prone to unobserved heterogeneity. Differences across regions in terms of soil properties and climate may lead to systematic differences in crop choice and productivity. Variations in global agricultural markets can be associated with changes in agricultural incomes. Panel Ricardian models can control for those potential omitted variable problems by using two-way fixed-effects (Blanc & Reilly, 2017). The estimation of Equation (5) can include a set of regional dummies to account for unobserved time-invariant heterogeneity across regions. To account for potential omitted time-varying factors, one can include in their regression a set of time dummies to capture common shocks which can affect agricultural income.

3.3 | Methodology considerations

Using two-way fixed-effects can (partly) control for omitted heterogeneity when estimating climate impacts. Panel Ricardian estimates are still subject to biases from time-varying confounders if unobserved time-varying factors are associated with climate. In a long-run panel, there may exist price adjustments to climate change. In this case, the use of time fixed effects is problematic because they are endogenous in the Ricardian model. A simple way to test for the stability of climate effects is to introduce to the model interactions between time dummies and climate (Massetti & Mendelsohn, 2011). The test for stability of climate impacts is simply a test on the joint insignificance of the coefficients associated with time-climate interactions. If the null hypothesis is not rejected, confounding effects of unobserved time-varying factors are not a major concern. The subsequent Ricardian model can be re-estimated without time-climate interactions and the use of time-mean residuals in the second step of the Hsiao method is relevant.

Our Ricardian analysis implicitly models long-term adaptation in terms of crop choice such that farmers in different climatic conditions grow different selections of crops. Agricultural commodities may react differently to market variations. Failing to address heterogeneous price change effects is therefore expected to produce biases to climate and/or other time-invariant controls in Equation (5). A general approach to introduce heterogeneous price feedbacks is to include a set of interactions between regional dummies and time dummies. If the test for the compound hypothesis that all coefficients associated with

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interactions between time and regional dummies are equal is not rejected, then the Ricardian model can be re-estimated without these interactions.

4 | EMPIRICAL MODEL AND DATA

4.1 | Empirical Ricardian model

This analysis uses a 10-year panel of farm-level data which allows us to use two-way fixed-effects to better control for omitted variable problems. Following Van Passel et al. (2017), this analysis uses the log of net crop income as the dependent variable as it has more predictive power compared to the linear model. Some of the independent variables are also in natural logarithm form. Seasonal temperatures and rainfalls are introduced to the model to capture seasonal effects (Van Passel et al., 2017). We relax the assumption of the additive separability of climate effects through the inclusion of interactions between temperature and precipitation, allowing the effects of temperature and precipitation to be mutually dependent.

We first justify the use of the two-step Hsiao method by estimating Equation (2) using the following pooled model:

$$ln\ V_{it} = X_{it}\beta + Z_i\gamma + C_i\varphi + u_{it} \tag{6}$$

Equation (6) includes a set of interactions between time dummies and climate variables. We use the Likelihood Ratio test (LR) to test for stability of climate impacts under the null hypothesis that all coefficients associated with time and climate interactions jointly equal zero. The LR test has an F-statistic of 1.52 and a *P*-value of .07. We fail to reject the null hypothesis that climate impacts are consistent overtime at the 5% level. Our climate estimates are, therefore, expected to be free from time-varying confounders. The LR test also lends itself to the application of the time-mean residuals using the two-step Hsiao method described in the methodology section.

Next, we estimate the first step of the Hsiao method using fixed-effect estimators:

$$lnV_{it} = X_{it}\beta + \varepsilon_{it} \tag{7}$$

Then, the time-mean residuals (simple residuals plus fixed effects) obtained from Equation (7) are regressed upon climate and other time-invariant controls:

$$\overline{lnV_i} - \overline{X_i}\,\hat{\beta} = Z_i\,\gamma + C_i\varphi + \overline{u_i} \tag{8}$$

with interactions between time dummies and climate variables being excluded.

Vietnam's long narrow shape of the country and the complex typology results in seven climate zones. The long-term adaptation taken by farmers in terms of crop choice has resulted in different crop selections across regions (Nguyen, 2017). We capture potential differentiated price effects through the inclusion of interactions between time and regional dummies. Our Ricardian model in the second step of the Hsiao method takes the following form:

$$\begin{aligned}\overline{lnV_i} - \overline{X_i}\,\hat{\beta} &= \alpha + \delta * E + \gamma * R + \tau * D + \mu * R * D \\ &\quad + \gamma_1 * T + \gamma_2 * T^2 + \gamma_3 * P + \gamma_4 * P^2 \\ &\quad + \gamma_5 * T * P + \overline{u_i} \end{aligned} \tag{9}$$

where E represents elevation, R a vector of regional dummies, D a vector of time dummies, $R*D$ a vector of interactions between time and regional dummies used to capture heterogeneous price feedbacks across regions, T a vector of four seasonal temperatures, P a vector of four seasonal precipitations, $T*P$ a vector of interactions between temperatures and precipitations, $\overline{u_i}$ an error term which is assumed not to be correlated with climate.

The marginal impact of seasonal temperatures on agricultural income is calculated using the following equation:

$$\frac{\partial \overline{lnV_i}}{\partial T} = \gamma_1 + 2 * \gamma_2 * T + \gamma_5 * P \tag{10}$$

In addition, the marginal impact of seasonal precipitations on agricultural income is:

$$\frac{\partial \overline{lnV_i}}{\partial P} = \gamma_3 + 2 * \gamma_4 * T + \gamma_5 * T \tag{11}$$

Because the dependent variable is in log form, the estimated marginal effects using Equations (10) and (11) are interpreted as percentage change in agricultural income due to one unit change in the corresponding climate variable. The estimation of Equation (9) uses household farmland as weights for two reasons. First, estimates of climate change from households with large crop production are more precise than from households with small production. Second, using farm size as weights can correct for heteroscedasticity (Deschenes & Greenstone, 2007) which is problematic in econometric modeling.

4.2 | Data

This analysis uses the nationally representative survey data from the Vietnam Access to Resources

Household Surveys (VARHS). These datasets contain rich information on income activities from production of 20 crops across seven regions. The Probabilistic Data Record Linkage method applied to these datasets produces a 10-year unbalanced panel of 2340 households or 8356 year-households. Following Wang et al. (2009) and Seo et al. (2009), this study uses net crop income per square meter as a proxy for land value in Equations 2–11. Household self-consumed products are evaluated at market prices. To ensure comparability, economic variables are converted to constant 2010 VND.

The climate data were derived from Worldclim version 2.0 (Fick & Hijmans, 2017) and have a high resolution of one square kilometer. Because we use climate data with high resolution, the matching between climate and household location results in a low probability of mismatch. This study uses seasonal averages of temperature and rainfall for the period 1970–2000 based on the season classification of the Ministry of Natural Resources and Environment (Ministry of Natural Resources and Environment, 2009) to support the identification of heterogeneous climate impacts. Climate and agricultural production may vary across latitudes (Mendelsohn et al., 1994). We extract data on elevation with the same resolution using free spatial data from the DIVA-GIS website.

Rising population may create pressure to use land efficiently (Mendelsohn et al., 1994). Increases in agricultural wages may be associated with higher opportunity costs for family labor and higher hired labor costs. The VARHS surveys on the commune level represent a rich set of data on agricultural wages. The wage data are combined with household data by applying the same Probabilistic Data Record Linkage method. Data on population density come from Vietnam Government Statistical Office. Table 1 presents a brief definition of the variables while Table 2 provides the regional averages of the data used. The data description highlights the heterogeneity of climate and socio-economic conditions which are hypothesized to have impacts on agricultural performance across regions.

5 | ESTIMATION RESULTS

5.1 | Hsiao estimation of step 1—Effects of time-varying factors on agricultural productivity

We used a fixed-effects method to estimate Equation 7. Household production can be correlated over time as the households exhibit unobserved time-constant characteristics. We take potential serial correlation in household's agricultural performance into account by clustering the errors by household. Table 3 presents the estimates for time-varying variables. Most of the coefficients are statistically significant at 5% indicating the relevance of most variables in explaining variations in agricultural income. Increases in population are positively associated with land-use efficiency due to the pressure of lowering per capita farming areas.

Household size and education positively correlate with agricultural performance. There exists an inverse relationship between farm size and productivity which is consistent with the literature (Barrett et al., 2010; Feder, 1985; Helfand & Taylor, 2020). A one percentage point increase in farm size is associated with roughly a .5% decrease in income per square meter. As expected, increases in irrigation coverage are associated with higher agricultural income. Land fragmentation, in contrast, is associated with higher productivity. Our finding is contrary to the findings for South Asian countries by Niroula and Thapa (2005), and for Vietnam by Tran and Vu (2019). These analyses attribute the negative effects of land fragmentation to the disadvantages associated with higher production costs and lower production efficiency. However, land fragmentation is associated with crop diversification which is an adaptation strategy to natural and economic shocks in the Vietnam context (Nguyen et al., 2017).

5.2 | Hsiao estimation of step 2—Impacts of climate and other time-invariant controls

Previous panel Ricardian models (Deschenes & Greenstone, 2007; Fezzi & Bateman, 2015; Massetti & Mendelsohn, 2011; Schlenker & Roberts, 2009; Trinh, 2018) capture changes in global agricultural markets as common shocks to all households. However, variations in global commodity prices are not uniform (Haile et al., 2016). We allow for differentiated market shocks to farmers in regions that grow different selections of crops by including a set of interactions between time and regional dummies. The estimation of step 2 of the Hsiao method also includes a set of interactions between seasonal temperatures and precipitations. Most coefficients of these interactions are significant at the conventional level. We report in Table 4 hypothesis tests to support our arguments before reporting the estimates of step 2 using Equation (9).

The test results indicate heterogeneous price feedbacks across regions as a result of inherent differences in farming structures and non-uniform changes in agricultural commodity prices. The inclusion of interactions between regional and time dummies are, therefore, expected to improve the precision of regional impacts of climate. In addition, the LR test on climate interactions strongly

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TABLE 1 Variable definitions

Variable	Measurement
Dependent variable	
income_meter (in log form)	Net crop income per square meter = (total output value evaluated at market price - total cost)/farmland Thousand VND/square meter (2010 prices)
Household characteristics	
hh_size	Number of household members (persons)
head_sex	Gender of household head, binary (1 = male)
head_edu	Formal schooling of household head (years)
head_age	Age of household head (years)
Extension_contact	Number of extension contacts in the last two years (times)
Farmland characteristics	
no_plots	Number of separate farmland plots
farm_size	Farm size (square meters)
irrigation	% of farmland irrigated
Socio-economic characteristics	
Wage	(log) Thousand VND/ workday in agriculture (communal average)
Population density	(log) Thousand persons/square kilometer
Topographic characteristics	
Elevation	Meters
Climate variables	
Winter_tem	Winter monthly temperature (Celsius degrees)
Spring_tem	Spring monthly temperature (Celsius degrees)
Summer_tem	Summer monthly temperature (Celsius degrees)
Autumn_tem	Autumn monthly temperature (Celsius degrees)
Winter_pre	Winter monthly precipitation (millimeters)
Spring_pre	Spring monthly precipitation (millimeters)
Summer_pre	Summer monthly precipitation (millimeters)
Autumn_pre	Autumn monthly precipitation (millimeters)
Regional dummies	Red River delta, Northeast, Northwest, Northern Central, Southern Central, Central Highlands (Mekong River delta as reference)
Time dummies	2008, 2010, 2012, 2014, 2016 (2006 as reference)

rejects the null hypothesis on the additive separability of climate. The inclusion of climate interactions is expected to produce more accurate estimates of each climate phenomenon. Table 5 contrasts the estimates for climate variables across assumptions on effects of price change and climate interactions.

The estimated coefficients of most climate variables and their square terms are statistically significant in the three models indicating nonlinear responses of agriculture to climate. Once climate has been controlled for, farms located in higher elevations tend to be less productive as the estimated coefficient for elevation is negative (−.002). The sign and statistical significance of variables do not change substantially across the first two models under the alternative assumptions on market shocks. However, the assumption of homogenous market shocks in Model (2) produces relatively larger estimates for most climate variables indicating potential overstatements of climate impacts due to confounding effects between external changes and regional farming systems.

We find the effects of rising temperature are dependent on the levels of rainfall in the four seasons. Figure 1 illustrates interactions between climate elements. Rising temperature in the winter is harmful to agriculture. The negative impact of rising winter temperature is even more severe with higher levels of rainfall (Figure 1a). Spring temperatures below 24°C are harmful. Further increases in spring temperature are more beneficial as long as there is a low level of rainfall for plant pollination (Figure 1b). Rising summer temperature is expected to cause losses. The likely negative impacts of a hotter summer are mitigated by a high level of rainfall of 350 mm/month

TABLE 2 Sample means by region

Group	Variable	Red River	Northeast	Northwest	Northern Central	Southern Central	Central Highland	South	Total
Agricultural income	Income_meter	3.67	3.78	1.75	2.30	1.69	5.35	2.81	3.12
Household characteristics	hh_size	4.31	4.09	5.42	4.27	4.23	4.88	4.34	4.53
	head_sex	.79	.79	.91	.84	.74	.86	.77	.82
	head_edu	6.95	7.34	4.25	7.44	6.03	6.42	5.29	6.25
	head_age	51.74	53.15	47.25	53.43	55.53	47.91	55.64	51.65
Farmland characteristics	no_plots	5.35	6.58	5.30	5.38	4.40	3.41	3.00	5.00
	farm_size	2399	4353	11,861	6419	5818	16,384	18,636	8350
	Irrigation	92.00	76.00	42.00	73.00	76.00	65.00	89.00	74.00
Social-economic conditions	Extension contact	1.05	1.61	1.55	1.91	1.58	1.21	1.57	1.43
	wage	119.91	90.95	214.52	94.59	93.73	109.59	98.45	123.91
	Population_density	1825.77	382.19	67.27	183.94	150.80	117.45	323.82	595.26
Climatic conditions	Winter_tem	17.50	16.98	16.04	18.65	21.74	21.28	25.88	18.99
	Spring_tem	23.71	23.31	22.64	24.25	26.44	24.77	28.54	24.40
	Summer_tem	28.86	28.07	25.68	28.95	28.97	24.15	27.96	27.53
	Autumn_tem	24.53	24.14	22.07	24.61	25.60	22.82	27.24	24.20
	Winter_pre	20.35	26.65	22.07	32.16	112.71	20.07	18.09	33.18
	Spring_pre	103.72	105.78	117.30	67.91	45.16	110.25	84.83	95.55
	Summer_pre	287.29	276.80	351.89	167.68	111.62	210.29	206.32	249.33
	Autumn_pre	154.96	149.29	94.19	205.07	398.44	205.54	211.38	187.27
Topographics	Elevation	7.89	61.40	601.52	49.28	78.93	569.37	2.29	202.32

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TABLE 3 The Hsiao estimates of step 1

	Coef.	Std. Err.
hh_size	.054***	.010
head_sex	−.012	.070
head_edu	.010**	.004
head_age	−.002	.002
no_plots	.016***	.006
log_farm_size	−.497***	.035
irrigation	.198***	.040
extension_contact	.021***	.005
wage	.000***	.000
log_population	.141*	.074
Observations	7539	
Number of panel_id	2340	

***$p < .01$,
**$p < .05$,
*$p < .1$. Standard errors are clustered at household level.

TABLE 4 Hypothesis testing

Null hypothesis	Variable on which its coefficient(s) is (are) tested	Value to be tested	*F*-test value	*P*-value	Decision
Homogenous market shocks across regions	Interactions between time and regional dummies	Jointly equal	3.45	.000	Reject
No climate interactions	Interactions between seasonal temperatures and precipitations	Jointly equal zero	9.52	.000	Reject

(Figure 1c). Agricultural income exhibits an inverse U-shape relationship with autumn temperature. High precipitation of 350 mm/month is expected to maintain the positive marginal impact of rising autumn temperature (Figure 1d). These findings of beneficial impacts of precipitation in seasons with high temperatures are in line with the farm-level findings by Fezzi and Bateman (2015) for Great Britain. Ignoring climate interactions severely biases our climate impacts. Comparing Models (1) and (3) gives a sense of omitted climate interaction. The estimates for seasonal temperatures and precipitations are much smaller in magnitude in Model (3) indicating that the estimated climate impacts hide their nature due to the inseparability of temperature and precipitation.

The inclusion of square terms, and interactions between climate variables makes each coefficient in Table 5 no longer represent the true marginal effect of each variable. We derive the average marginal effects of seasonal climates using Equations (10) and (11) for Model (1) reported in Table 5. Vietnam is characterized by diverse climatic conditions and topology. We are interested in how the marginal effects vary across regions in order to understand how non-marginal changes in climatic conditions will likely affect agriculture. Table 6 summarizes the estimated marginal effects of a one-unit change in seasonal temperatures and precipitations across seven regions. We do not sum across seasons because it does not make sense to assume uniform changes in climate patterns in the whole year.

Table 6 also indicates that Vietnamese agriculture is less sensitive to precipitation than to temperature. Increases in winter precipitation are associated with losses to the whole Northern region and the Southern Central with net losses ranging from .039% to .1%. More precipitation in spring, in contrast, is associated with losses to the Central Highlands and the Mekong River delta. Because these two regions are the most important producers of coffee, fruit and other perennial crops, rising spring rainfall is harmful to plant pollination. Although increases in summer precipitation are beneficial, the estimated impact is significant for the Central Highlands. In the autumn when precipitation is high (as shown in Table 2), further increases in rainfall are likely to cause losses to the Northern region where annual crops are grown. The estimated impacts are positive and statistically significant for the Southern Central and the Central Highlands where irrigation coverage is relatively limited.

TABLE 5 Hsiao estimates of step 2

Variables	(1) Heterogeneous market shocks across regions, climate interactions	(2) Homogeneous market shocks across regions, climate interactions	(3) Heterogeneous market shocks across regions, no climate interactions
Winter_tem	−10.163***	−10.242***	−4.216***
Winter_tem square	.225***	.229***	.097***
Spring_tem	9.901***	9.615***	5.083**
Spring_tem square	−.168***	−.161***	−.096**
Summer_tem	−10.134***	−10.932***	−6.854***
Summer_tem square	.194***	.209***	.127***
Autumn_tem	23.510***	25.201***	8.918***
Autumn_tem square	−.471***	−.513***	−.192***
Winter_pre	−.261***	−.228***	−.032*
Winter_pre square	−.001***	−.001***	.000
Spring_pre	.235***	.270***	−.043*
Spring_pre square	−.000	−.000	.000
Summer_pre	.133***	.121***	.026***
Summer_pre square	−.000	−.000	−.000**
Autumn_pre	.057	.023	−.041***
Autumn_pre square	.000***	.000***	.000***
Winter_tem * Winter_pre	.014***	.012***	
Spring_tem * Spring_pre	−.008***	−.010***	
Summer_tem * Summer_pre	−.004***	−.004***	
Autumn_tem * Autumn_pre	−.005***	−.003*	
Elevation	−.002*	−.002	−.000
Constant	−186.041***	−189.743***	−27.634**
Time dummies	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes
Time * regional dummies	Yes	No	Yes
observations	8356	8356	8356
R-squared	.100	.089	.095

***$p < .01$,
**$p < .05$,
*$p < .1$.

Rising winter temperature is likely to cause losses. As depicted in Figure 1a, a 1°C increase in winter temperature is associated with losses ranging from .25% to 2.6% for most regions. Figure 1b indicates the optimal spring temperature is 28°C. Because the current spring temperature in most regions, except the Mekong River delta, is below this optimal level, a 1°C increase in spring temperature is likely to be beneficial for most regions, with net surpluses ranging from .5% to 1.3%. The Northwest and the Central Highlands with cool summer climates are expected to suffer from hotter summers. The optimal autumn temperature is 24°C, as shown in Figure 1d. Because the current autumn temperature is above this level, a warmer autumn is likely to be associated with losses to the Southern Central and the Mekong River delta, with the Mekong River being the most severely affected.

6 | CLIMATE IMPACT SIMULATION

In the long term, Vietnam is expected to experience nonmarginal changes in climate patterns. Changes in temperature and rainfall are not expected to be uniform across seasons and across regions (Ministry of Natural Resources and Environment, 2009). Temperature is projected to increase by .4°C–3.2°C between 2030 and 2100. Autumn and winter temperatures are projected to increase faster than those in spring and summer. The Northern region will experience faster increases in seasonal temperatures. Regional and

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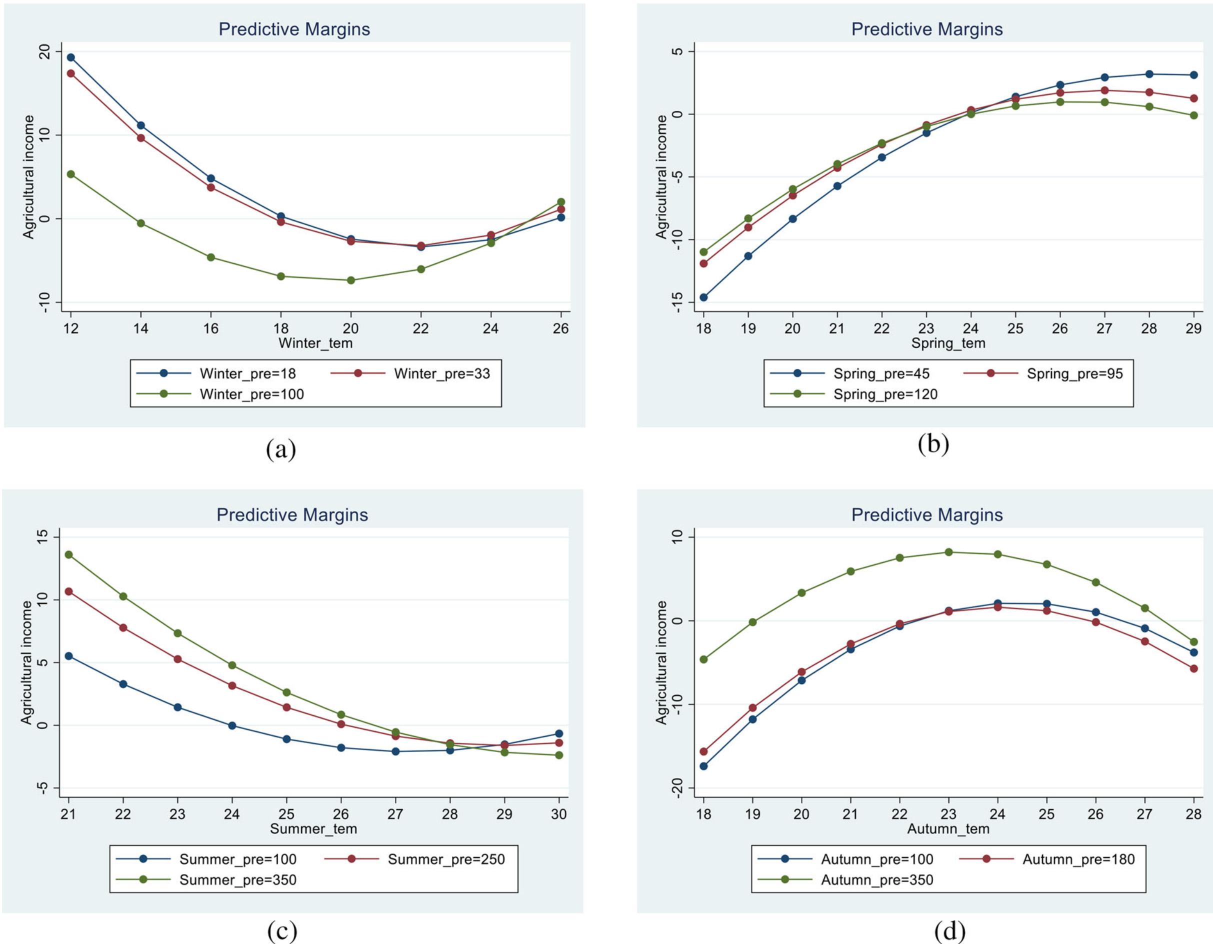

FIGURE 1 Interactions between temperatures and precipitations [Color figure can be viewed at wileyonlinelibrary.com]

national averages of precipitation are projected to increase but with different patterns for seasons. Therefore, it is important to measure how these non-marginal changes in climatic conditions will affect Vietnamese agriculture so as to propose adaptation policy.

Vietnam has issued and implemented several mitigation-related policies and programs covering the main sources of greenhouse emission including energy, agriculture, land use, land-use change and forestry, waste management, and industrial processes. The updated version of Vietnam Nationally Determined Contributions (NDCs) submitted in 2020 stated the goal to reduce total emission by 27% by 2030 compared to the business-as-usual scenario. Agriculture is one of the main sources of emission accounting for 35.8% of total national emission (Ministry of Natural Resources and Environment, 2014). However, the current NDCs indicate little contribution by Vietnamese agriculture while the agricultural pathways focus mainly on crop choice, land-use change, and waste management (UNFCCC, 2020). Therefore, we assume no significant changes in future technology will change the productivity of the studied crops. Rather, this simulation is an effort to measure how Vietnamese agriculture is likely to be affected by the projected climate change.

The conventional approach to simulating climate change effects is using the estimated marginal effects and the predicted climate changes (Mendelsohn et al., 1994; Schlenker et al., 2005; Seo et al., 2005; Trinh, 2018; Wang et al., 2009; among others). Because the marginal effects depend on the values of independent variables (Wooldridge, 2012, p. 591), say climate, then these marginal effects do not represent precisely the relationships between agricultural income and climatic conditions when future climate values are not within the observed range of values. In addition, nonlinearity in the production function and climate interactions that are not apparent in the historical range of climate data may change the relationship between the dependent variable and climates (Blanc & Reilly, 2017).

We pay special attention to the prediction of the dependent variable in logarithm form. A consistent estimator for predicting values from a regression on the log form of a dependent variable takes three steps (Wooldridge, 2012, p. 213):

TABLE 6 Marginal effects of seasonal climates

Region	% change in net income per m² per °C			
	Winter_tem	Spring_tem	Summer_tem	Autumn_tem
Red River delta	−2.005***	1.059***	−.194	−.341
Northeast	−2.206***	1.219***	−.496	.129
Northwest	−2.632***	1.305***	−1.769***	2.320***
Northern Central	−1.379***	1.058***	.160	−.494
Southern Central	.899**	.702**	.254	−1.919***
Central Highlands	−.251	.567**	−1.631***	.904
Mekong River delta	1.822***	−.458	−.105	−3.286***
	% change in net income per m² per mm/month			
	Winter_pre	**Spring_pre**	**Summer_pre**	**Autumn_pre**
Red River delta	−.045***	−.008	−.004	−.003
Northeast	−.058***	−.005	.000	−.002
Northwest	−.067***	−.006	.007	−.013
Northern Central	−.039**	−.003	.001	.009
Southern Central	−.100***	−.004	.004	.072***
Central Highlands	.010	−.023***	.018***	.022***
Mekong River delta	.074**	−.041***	.003	.004

***$p < .01$,
**$p < .05$,
*$p < .1$.

TABLE 7 Predicted changes in crop income under medium climate change scenario

Region	Current value (VND/m²)	Predicted value (VND/m²)	2030 % change	2030 Std. Dev.	2050 % change	2050 Std. Dev.	2100 % change	2100 Std. Dev.
Red River delta	3,831	3,510	−.029	.608	−.078	1.509	−.146	3.395
Northeast	3,007	3,776	−.105	.185	−.273	.472	−.555	.946
Northwest	1,955	1,853	−.498	.834	−1.316	2.195	−2.672	4.441
Northern Central	2,449	2,343	−.036	.405	−.102	1.093	−.227	2.176
Southern Central	2,610	2,475	−.021	.616	−.052	1.638	−.108	3.394
Central Highlands	5,088	4,769	−.088	.126	−.225	.303	−.452	.587
South	2,970	2,485	−.100	.527	−.274	1.245	−.632	2.067
Whole country	3,169	3,081	−.120	.581	−.319	1.497	−.673	3.093

(Nation-wide impacts of climate change are averaged across regions using agricultural land as weights)

First, we run the regression of log values of crop income which are time-mean residuals obtained from Equation (7) on explanatory variables to obtain the predicted log values of the dependent variable and residuals using Equation (9).

Second, the mean of the exponentiated residuals is calculated and used as the adjustment factor to scale up the exponentiated predicted log values.

Third, the original values of crop income are regressed on the exponentiated scaled-up predicted log values with no constant.

We replicate these steps for the prediction of crop income for: (1) the baseline climate under the assumption that there will be no future changes in climatic conditions to obtain predicted values $\hat{y}_0$ for each household; and (2) for the years 2030, 2050, 2100 under the climate change scenarios while other control variables remain unchanged, $\hat{y}_1$. The predicted impacts of climate changes on agricultural productivity are derived by subtracting the predicted values $\hat{y}_1$ from the predicted values $\hat{y}_0$. Table 7 presents the estimated results while Figure 2 visualizes the predicted changes in net crop income for regions in the period 2030–2100.

Previous Ricardian analyses present a mixed picture of climate change impacts across continents. European

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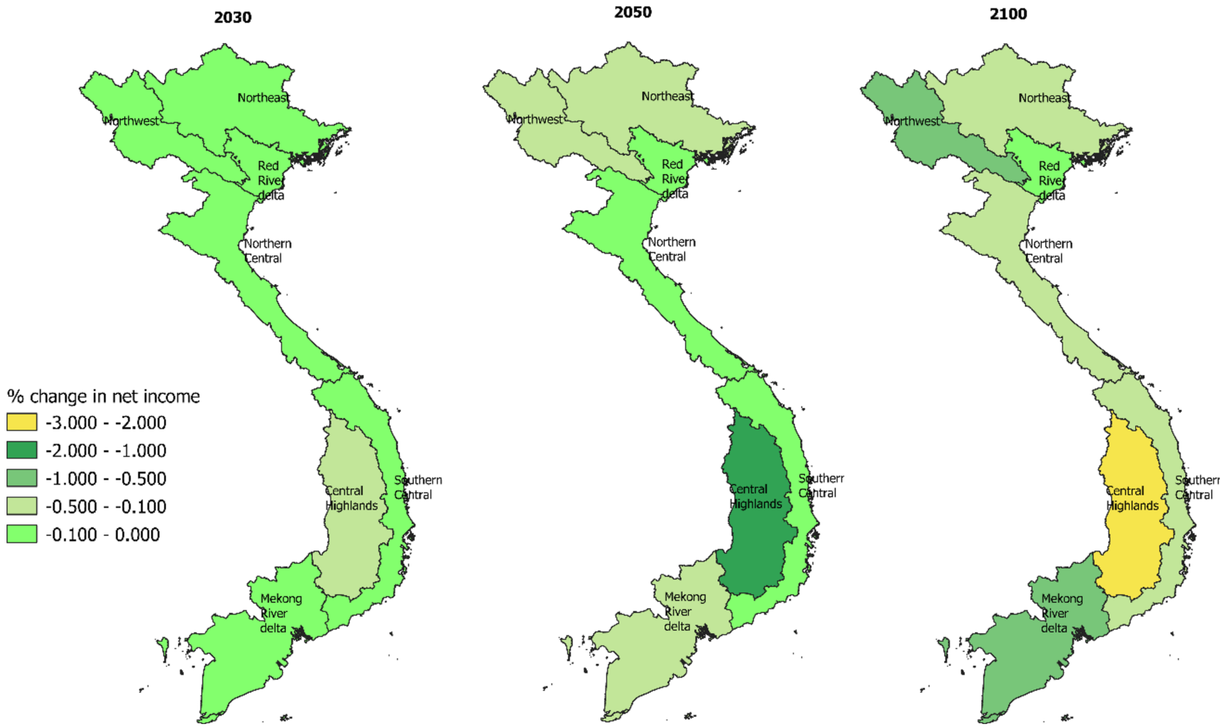

FIGURE 2 Percentage change in net income predicted by medium emission scenario [Color figure can be viewed at wileyonlinelibrary.com]

agriculture is more sensitive to climate change than American agriculture (Van Passel et al., 2017). While Southern European countries are expected to be vulnerable to the projected climate change, Northern Europe is expected to benefit (Van Passel et al., 2017). Maddison et al. (2007) showed that African countries are likely to suffer from future climate change but the estimated impacts vary by country. Ethiopia and South Africa are hardly affected with mild losses ranging from 1.3% to 3% by 2050. Our simulation for Vietnam indicates that Vietnam is likely not to be affected by future changes in climate normal, with average losses ranging from .1% to .6% between 2030 and 2100. Given the assumption of no future technology change in agriculture, the impacts might end up being even smaller if future technology is introduced into agriculture. This finding is contrary to the simulation by Trinh (2018) which presents huge losses to Vietnamese agriculture. In addition to potential errors pertaining to the simulation method, the overstated climate impacts by Trinh (2018) are attributable to the failure to capture climate interactions and heterogeneous seasonal and regional climates.

Figure 2 visualizes the distribution of changes in net agricultural income by region between 2030 and 2100. Among the regions, the Central Highlands with current cool climate is expected to be the most affected by future climate changes. In the short term, the projected climate change in 2030 is likely to cause losses of .5%–1% to income in the region. In the long term when the projected increases in temperature and declines in precipitation are likely to result in 2%–3% losses in income. The Mekong River delta and the Northwest are expected to experience marginal losses of .5%–1%. However, the Red River delta where irrigation covers more than 90% of the cropping area is hardly affected by future changes in climate normal.

7 | CONCLUSION

This panel Ricardian analysis measures the sensitivity of Vietnamese agriculture to climate change using the Hsiao-two step method on a panel of 10 years. We tested for potential confounding effects of unobserved time-varying factors in the model. The results indicate that our climate estimates are free from unobserved time-varying confounders. Most previous panel Ricardian analyses assumed global price changes to be common shocks to all households. However, our article shows that market shocks have variable effects on regions growing different selections of crops. While ignoring heterogeneous price feedbacks across regions produces biases to climate estimates, the likely consequences of omitting climate interaction are even more severe.

Empirical evidence from this panel Ricardian analysis suggests that farms located at higher altitudes are less productive. Rising population puts pressure on the efficiency of land use. The results confirm the inverse relationship between landholdings and agricultural productivity, which is in line with findings from Barrett et al. (2010) and Tran and Vu (2019). The Ricardian results highlight the nonlinear, seasonal role of changing temperature and precipitation. Increases in winter, summer, and autumn temperatures are harmful to agriculture, while the opposite is true for spring temperature. More rainfall in winter and spring is likely to reduce agricultural income, while increases in precipitation in the summer and autumn are predicted to benefit agriculture. The simulation indicates marginal regional losses ranging from .02% to 2.6% between 2030 and 2100. Regions currently with cool climates such as the Central Highlands and the Northwest are likely to experience above-average losses. The Red River delta is shown to be minimally affected in the long run. Consequently, the projected changes in long-term temperature and precipitation should not be a major concern.

Our analysis is an advance on prior research. However, there are opportunities for further research to progress understanding. We based the simulation of climate change impact on the hypothesis that Vietnam farming systems remain unchanged in the future. Therefore, our estimated impacts of climate change do not capture future technical changes to either crops or farming techniques. Further, although we had data on agricultural wages at the commune level, we did not use market wage to evaluate labor cost due to the concern over differentiated labor costs between households who hire in and those who hire out labor. Hence, the estimated net income was not solely a return to land. Finally, consistent with most Ricardian analyses, this study implicitly assumes farmers will adapt by crop switching in the changing climate. Future research could investigate these issues and how responsive the Vietnam agricultural system is to changing climate. Investigating the changing allocation of land would facilitate a better understanding of climate impacts and their implications for policy.

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