Heterogeneous Impacts of Climate Change – The Ricardian Approach Using Vietnam Micro-Level Panel Data

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Abstract
This analysis investigates economic impacts of climate changes on Vietnam agriculture. The Ricardian approach is applied to ten-year panel data using the Hsiao two-step method. Estimates of the Ricardian model suggest heterogeneous impacts of climate change. Rising temperature is especially harmful to the Northern Central and the Southern region. Shortage of rainfall in spring only causes losses to the Central Highlands and Northern region. Rising summer precipitation is extremely harmful. Increases in precipitation help to harness the benefit of rising autumn temperature. The simulation indicates net agricultural surpluses in the long-run, with the Central Highlands being an exception.

Keywords: Climate change, Vietnam, Ricardian approach, Hsiao two-step method

1. Introduction

Vietnam is expected to be among the hardest-hit countries by future climate changes (Dasgupta, Laplante, Meisner, Wheeler, & Yan, 2009). Likely consequences of changing climatic conditions are believed to be serious and present threats to hunger eradication, poverty reduction, and sustainable development. The report by the Ministry of Natural Resources and Environment (MONRE, 2009) indicates non-uniform changes in climate patterns. Temperature is predicted to increase faster in autumn and winter over the country. While the Northern region of the country will experience shortage of rainfall in spring, the Southern region will suffer from lower precipitation for winter and spring. These changes are expected to affect the agriculture, especially the Southern agriculture. Climate impact assessment for Vietnam is, therefore, important for government adaptation policy.

Previous analyses of climate impacts on Vietnam agriculture and on sub-national regions indicate nonlinear impacts of rising temperature and precipitation. Simulation of climate change by Trinh (2018) presents net losses due to rising temperature and rainfall in the wet season. Le Thi Diem Phuc, Vu, and Xuan (2015) estimated net losses of VND 180,000 to 1,600,000 per hectare between 2050 and 2100. These analyses are subject to limitations due to the use of inappropriate climate data and lack of adaptation (Le Thi Diem Phuc et al., 2015), aggregation bias (Trinh, 2018), and the endogeneity of irrigation (Trinh, 2018; Le Thi Diem Phuc et al., 2015).

This study makes use of high-quality data from the Vietnam Access to Resources Household Surveys. The Probabilistic Data Record Linkage method is applied to generate a ten-year panel on crop income which is used as the dependent variable in the Ricardian analysis. Climatic and geographic data with high resolution are extracted to match with households' location. The Ricardian model is estimated on the panel using the Hsiao two-step method.

This Ricardian analysis makes a threefold contribution to the existing literature on climate impact assessment. It is one of the few Ricardian analyses using micro-level panel data which is expected to avoid aggregation biases and gain robust estimates. In contrast to most previous Ricardian analyses ignoring the endogeneity of irrigation, we take endogeneity of irrigation into account using the control function method. We demonstrate that Ricardian analyses, which fail to account for endogenous irrigation, overstate the role of irrigation and climate change impacts. We consider heterogeneous climate conditions by proper classification of seasons and regions. This allows better insights into how variations of climate conditions affect regional agricultural production. The simulation of climate impacts indicates short-term negative impacts of projected climate change on Vietnam agriculture, with the Central Highland being the most affected. Variations in temperature and rainfall produce seasonal effects.

2. Literature Review

Agriculture is considered to be most affected by climate change as it is directly exposed to climate elements. Crop yields show a strong correlation with temperature change and with the duration of heat or cold waves (Yohannes, 2016; Hoffmann, 2013). Changes in precipitation patterns enhance water scarcity and associated drought stress for crops and affect irrigation cost. On a global scale, climate change currently decreases the yield (and income as a consequence) of rice, maize, wheat and potatoes (Yohannes, 2016). While climate change is expected to be harmful, estimated impacts of climate change are largely dependent on the impact horizons, the methods applied, and types of data used. This section outlines the key features of climate change impact assessments in terms of economic theory, assessment methods, and data used.

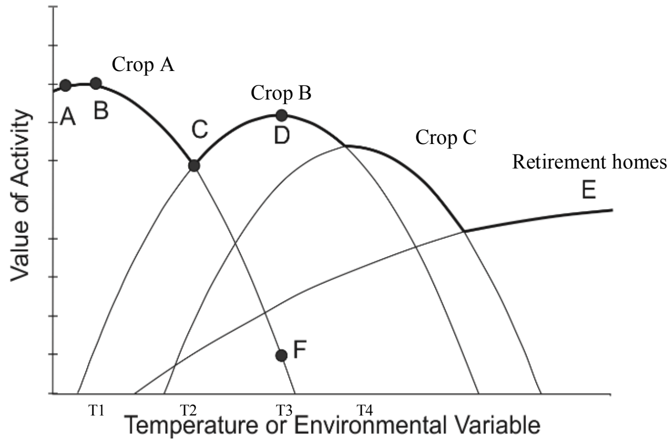
Estimates of climate variations on agriculture production are subject to biases depending on the uncertainty of climate change scenarios, regions of study and assessment models. Studies investigating impacts of climate change on agriculture can be divided into two different modelling approaches: An agriculturally oriented approach and an economically oriented approach. The former approach focuses on modelling the responses of crops to climate variations (also known as crop model) while the latter considers the economic responses to changes in crop yield (Francisco & Maria, 2015). Recent reviews by Ewert et al. (2015) and by Francisco and Maria (2015) provide a comprehensive examination of these approaches to assess the impacts of climate change on agricultural production.

Dynamic, process-based crop models (also known as the production function approach) have been developed since the 1960s to better understand and manage crops. These models give insights into how crops grow in response to weather, soil and management conditions (Lobell, Schlenker, & Costa-Roberts, 2011). Application of crop models can be seen in several studies. Lobell et al. (2011) indicated that global maize and wheat production would decline at a rate of 3.8 and 5.5 percent, respectively, relative to a scenario without climate change. Leif Christian et al. (2006) shown that the changes in productivity of crops and livestock in Africa in the period 1961-2003 were associated with changes in climate conditions. The authors suggested changes in crop selection and storage strategies to respond to climate uncertainty. Wolfram and Michael (2009) highlighted that yields for corn and soybeans in the United States are expected to decrease at least 30-46% by the end of the 21st century under the slowest warming scenario. The differences in geographic locations affect the estimated impacts of climate change on agriculture. Aggarwal and Mall (2002) shown positive effects of climate change on rice production in India, irrespective of the various uncertainty in climate scenarios.

Albeit, studies using the production function approach share an inherent shortcoming and tend to overstate the damage (Fezzi & Bateman, 2015; Mendelsohn, Nordhaus, & Shaw, 1994). This bias arises due to the omitted variety of adaptations, and substitutions of old and new activities that farmers take in response to changing climate and other environmental conditions. Figure 1 shows the hypothetical output values of four different activities as a function of a single climate variable to illustrate the nature of the bias.

Assuming that the production functions produce accurate estimates of climate impacts on crops, when temperature increase from T1 to T2, income of crop A decreases from B to C. As the production function does not allow for crop substitution, value of crop A will decrease to the point F when temperature increases further, to T3. In reality, farmers may react to changes in climate condition by switching into new crops (such as crop B) that are more lucrative given changes in climate. In addition, evaluation of the impacts of climate variations and adaptation measures on agricultural production often requires crop simulations for periods of at least 15 years (Van Wart, Kersebaum, Peng, Milner, & Cassman, 2013). Another disadvantage of the process-based crop models is that they require a large amount of input data for simulation as well as frequent time data. Economic models only require final yields in response to management practices and climate conditions.

Figure 1. Bias in Climate Impact Assessment in Production Function Analyses



The economically oriented approach can be divided into two approaches: The structural economic approach and the spatial-analogue approach (Francisco & Maria, 2015). The structural economic approach simulates crop and farmer responses based on the economic relationships suggested by theory (Adams, 1999). This approach includes changes in land values within the models so that adaptation responses of economic units are taken into account. Additionally, this approach provides an explicit representation of the causal effects between the agricultural sector and climate change. However, the main weakness of this approach is that it requires cumbersome data collection and model construction.

The structural approach can be classified into six methodologies corresponding to geographical scales. These include general equilibrium models, partial equilibrium models and basic linked system models at a global scale, and general equilibrium models, partial equilibrium models and farm economic models at a regional scale.

Amongst the six categories, farm economic models are important tools for evaluating the climate impacts because they focus on local adaptation options that would improve production and farm income in the face of changing climate. However, farm economic models have two main disadvantages. First, they ignore the global scale of climate change which may affect the local climate pattern. Second, these models do not account for climate-induced price changes.

The spatial-analogue approach is based on econometric techniques used to analyse spatial production patterns. Information collected from farms across a wide range of production conditions is used to simulate how future changes in climate may affect profit. Within this approach, adaptations are embedded in the information collected regarding the farmer's behavior (Adams, 1999), which is the main difference between this approach and the structural economic approach. Mendelsohn and Dinar (2003) applied the spatial-analogue approach to US agriculture. The results show that the value of irrigated cropland is not sensitive to precipitation while it increases with temperature. Massetti and Mendelsohn (2014) shown the sensitivity of Southern Europe farms to global warming with losses ranging from 9% to 13% per Celsius degree by 2100.

Limitations of the spatial-analogue approach are associated with its assumptions. It produces aggregate results that put obstacles for the measurement and proposal of adaptation techniques. Particularly, the farmer's adaptation in terms of crop choice is considered '*black box'*. Thus, one can know neither how the crop substitution takes place nor how this adaptation affects farm profit. The assumption that agricultural prices do not respond to changes in agricultural production resulting from climate change ignores the future impacts of weather-induced price changes on supply and demand. Nevertheless, several studies have applied this approach to evaluate the economic effects of climate change on agricultural production and farmers' welfare.

Within the spatial-analogue approach, the Ricardian approach is a model that uses cross-sections to analyze climate impact. The model was developed from the initial studies on land values reflecting net productivity by David Ricardo (1772-1823). If land markets are efficient, land value is equal to the present value of net revenue from farm-related activities (Mendelsohn et al., 1994) when farmers put their farmland to the most profitable use given a set of conditions and constraints (Dall'erba & Domínguez, 2016). Mendelsohn et al. (1994) developed this method to evaluate the impact of climate change on US agriculture.

The Ricardian approach has been applied in several studies of climate change impacts on agriculture. Dinar (1998) employed the Ricardian approach to analyze the climate sensitivity of Indian marketed agriculture. Maddison (2000) used a Ricardian model for England and Wales. The results show the importance on agriculture of frost days in winter. Maddison, Manley, and Kurukulasuriya (2007) evaluated the impact of climate change on African agriculture using farm-level data from 11 African countries in 2003. The authors indicated that African agriculture is particularly vulnerable to climate change even with full adaptation. However, the extent of losses due to spatial climate variations are different across regions. While most parts of Africa are severely affected by climate change, Ethiopia and South Africa are hardly affected at all.

While assessed impacts vary across regions, estimated impacts from Ricardian models are also sensitive to types of data used. Numerous impact assessments have used aggregate data of county or regional levels including the United States (Massetti & Mendelsohn, 2011; Deschenes & Greenstone, 2007; Schlenker, Hanemann, &

Fisher, 2006; Mendelsohn et al., 1994), Africa (Seo, Mendelsohn, Dinar, Hassan, & Kurukulasuriya, 2009), Brazil (Timmins, 2006), Germany (Lippert, Krimly, & Aurbacher, 2009). Imbs, Ravn, and Rey (2005) highlighted that in nonlinear specifications, the aggregation process typically produces biased estimators and predictions despite using appropriate weights. Fezzi and Bateman (2015) compared the results from Ricardian models for farm-level and aggregated data on Scottish farms. The results from farm-level data show significant nonlinear interactions between temperature and rainfall. These interactions disappear in the model with aggregated data indicating distorted estimates and predictions. The results highlight the importance of using microdata for climate impact assessment.

There is also a rich literature discussing the strengths and weaknesses of the Ricardian technique. In comparison with the traditional production function approach, the Ricardian technique can measure long-run effects of climate change. It is also applicable to capture adaptations and substitutions that farmers have already taken in response to changing climate conditions. As depicted in Figure 1, farmers switch from crop A to crop B when temperature increases from T2 to T3. Therefore, the Ricardian approach does not measure climate impact on a single crop. Rather, it focuses on the economic impact of climate variation under full adaptation by exploiting data on agricultural production from cross-sections.

The most noticeable weakness of the Ricardian model is that it does not capture future technical change to either crops or farming techniques which have effects on farm values (Massetti & Mendelsohn, 2014). Both the Ricardian model and the farm economic models do not account for the effects of climate change on prices. Therefore, farm economic models, as well as the Ricardian approach, should be extended to capture market feedback in the model. Ricardian studies using cross-sectional data also suffer from omitted variable bias (Fezzi & Bateman, 2015; Massetti & Mendelsohn, 2011). Panel models can correct for the omitted variable bias by absorbing possible time-invariant unobserved heterogeneity such as soil characteristics. By using panel data, one can also overcome the fixed price assumption of the standard Ricardian model as long as the panel is long enough for price adjustments to take place in the markets.

Vietnam is likely to be among the hardest-hit countries by climate change and uncertainty (Dasgupta et al., 2009). The fast and steady developments in the agricultural sector and poverty reduction may be under threat due to climate variations and extreme events. The heavy dependence on agriculture of small-scale farmers makes Vietnam agriculture more vulnerable to changing climate conditions. There has been, however little expertise on how the smallholding agriculture will be affected by future climate change. To our knowledge, there have been two studies using the Ricardian approach to evaluating the economic impact of climate change in Vietnam. These include Le Thi Diem Phuc et al. (2015), and Trinh (2018).

Le Thi Diem Phuc et al. (2015) used cross-sectional data from households in the Mekong River delta. The results show the nonlinear effects of climate change on net crop income. Rising temperature is shown to be harmful to agriculture while increases in rainfall are beneficial. However, this Ricardian analysis has several pitfalls which bias the estimates. The use of cross-sectional data gives little insights due to omitted variable bias (Francisco & Maria, 2015). In a standard Ricardian model, farmers ake climate as given (Mendelsohn et al., 1994), not as shocks. The use of inappropriate climate data by Le Thi Diem Phuc et al. (2015) may have downward or upward biased the estimated effects depending on the nature of weather change in the observed years. Furthermore, because the authors collected data on cross-sections from a homogeneous region, any interpolation from the analysis is of limited value due to lacking of adaptation.

Trinh (2018) overcame these shortcomings of the previous Ricardian study by using the Hsiao two-step method on micro-level panel data generated from Vietnam nationally representative surveys. He considered long-term impact of climate change by using climate normals with a resolution of 50 square kilometres. The results show heterogeneous impacts on different regions although there exist negative impacts of higher temperature on all regions in the long-run. Increases in precipitation are harmful to only irrigated farms in the Central and in the North. The total impact of climate change is projected to be negative, with losses ranging from USD 30 to USD 87 per square meter.

Despite the appropriate method being applied to panel data, the analysis by Trinh (2018) is subject to limitations. Although the study allowed for nonlinear effects of climate, the assumption on the separability of climate effects is questionable. Particularly, the marginal effects of temperature were captured regardless of potential interactions between temperature and precipitation. We argue that temperature effect can be mitigated or enhanced by different levels of rainfall. In addition, the analysis considered irrigation exogenous to climate change which is problematic in the Ricardian approach. Furthermore, Vietnam agriculture is a diverse picture with different types of crop production and different agro-ecological conditions. The grouping of farms and seasons by Trinh (2018) probably underestimated the heterogeneity of climate impacts.

Based on the review, some gaps need to be filled to provide better insights into climate change impacts on Vietnam agriculture. First, the application of the Ricardian approach using micro-level panel data will extend the literature on climate change impact. Second, this analysis is expected to better control for endogeneous irrigation in order to reveal the true impact of irrigation and of climate variables on the agriculture. Third, this will be the first Ricardian analysis in Vietnam which allows for a more diverse agro-ecological conditions to underpin the heterogeneous impacts of climate change in Vietnam.

3. Research Method and Model Specification

This section outlines the conceptual framework of the Ricardian approach to assessing the economic impact of climate change on land values. The estimation procedure of the Ricardian model using the Hsiao two-step method for panel data is presented.

3.1. The Ricardian Approach to Valuing Economic Impact of Climate Change

The basic hypothesis of the climate impact assessment is that climate shifts the production function for crops. The approach was conceptualized by Mendelsohn et al. (1994) to measure the implicit value of climate change in US agriculture. The intuition of the Ricardian approach is as follow: if future climate 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 approach assumes the farmer is always looking to maximize production income, subject to a set of exogenous conditions of his or her farm. Specifically, the farmer chooses the crops and inputs for each unit of land that maximizes profits:

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

Where л is the net annual income, 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 climate and geographic conditions. The relationship between climate factors and production function is expected to be nonlinear. C_i is the production cost of crop i and is also expected to have nonlinear relationships with climate.

If land (L_i) is a distinct input (Mendelsohn et al., 1994) with heterogeneous cost (P_L), then the profit function of the farmer is specified as:

$$Max\pi = \ P_iQ_i(K_i, E_i\ ) - C_i(Q_i, W, E) - \ P_LQ_i \tag{2}$$

Under the assumption of perfect competition for land, free entry and exit will ensure excess profits are driven to zero:

$$P_iQ_i(K_i, E_i\ ) - C_i(Q_i, W, E) - P_LQ_i = \ 0 \tag{3}$$

Solving the above equation gives:

$$P_L = [P_iQ_i^*(K_i, E_i\ ) - C_i(Q_i^*, W, E)]/L_i \tag{4}$$

The above function indicates that land rents will be equal to net income per unit of land. This Ricardian function is a locus of most profitable crops with respect to each exogenous variables such as temperature or rainfall. Therefore the Ricardian function is not a response function of any single crop (Wang et al., 2009). It is estimated across crops and inputs under different climatic conditions. Changes in these optimal levels will be reflected in changes in annual cost of land (rents). The land value (V_L), is then calculated by the present value of net future income flows from land (P_L):

$$V_L = \ \int P_L\, e^{-rt}dt = \ \int [\![[P_iQ_i^*(K_i, E_i\ ) - C_i(Q_i^*, W, E)]/L_i\ ]\!]\ e^{-rt}dt \tag{5}$$

Where r is the discount rate, t is time.

Under the assumption of full adaptation given climate, land prices have attained the long-run equilibrium that contains information on the economic impact of climate change.

3.2. The Two-Stage Hsiao Method for Panel Data

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 and their square terms. The Ricardian model takes the following form:

$$V = f(X, Z, C) \tag{6}$$

Traditionally, the Ricardian model is estimated across cross-sections in which impact of climate change is embedded in farm values:

$$V_i \ = \ X_i\beta + Z_i\gamma + C_i\varphi + u_i \tag{7}$$

Where i varies across spaces (such as county or individual farmer), β, γ, and φ are the coefficients to be estimated. When data are available for different years, one can use the repeated cross-sections to estimate the following Ricardian model:

$$V_{it} \ = \ X_{it}\beta_t + Z_i\gamma_t + C_i\varphi_t + u_{it} \tag{8}$$

In the above equation, the estimated coefficients are allowed to vary over time. Massetti and Mendelsohn (2011) shown that the pooled regression using repeated cross-sections produces inconsistent estimates. Climate change is a long-term trend. Different estimates of climate impact for different years seem not to be relevant. The Hsiao two-step method allows the estimates of time-invariant variables to be constant over time and provides robust estimates of climate impact on land value. Therefore, the correctly specified Ricardian model using repeated cross-sections is:

$$V_{it} = X_{it}\beta + Z_i\gamma + C_i\varphi + u_{it} \tag{9}$$

The Ricardian model for panel data can be estimated by two ways. One is to pool the entire data set to estimate a single stage using the above equation. The second approach is to apply the Hsiao two-step method. The details of the Hsiao two-step method are as follows:

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

$$V_{it} = X_{it}\beta + \varepsilon_{it} \tag{10}$$

Where ε_{it} is the resulting error term. The fixed effects method applied to the first step rules out time-invariant unobserved heterogeneity which is correlated with both input and agricultural output. The vector β is, therefore, robust estimates of time-varying variables. To control for changes in economic environment which may have effects on agricultural production in the studied period, the estimation of equation (10) includes time-fixed effects by adding a set of time dummies.

In the second step, the time-mean residuals obtained from the first step are regressed upon climate and other time-invariant control variables.

$$\overline{V}_i - \overline{X}_i\hat{\beta} = Z_i\gamma + C_i\varphi + \overline{u}_i \tag{11}$$

Following De Salvo, Raffaelli, and Moser (2013), 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. This Ricardian model also introduces the interaction terms between temperature and rainfall. The estimation of Equation (11) uses household's farmland as weight for two reasons. First, the estimate of climate change from households with large crop production is more precise than from households with small production. Second, using farm size as weights can correct for heteroscedasticity which is problematic in econometric modelling (Deschenes & Greenstone, 2007). The endogeneity of irrigation considered using the control function method developed by Wooldridge (2015).

The welfare impact of climate change on each of the seven regions is obtained by calculating the difference between the land value under the new climate scenario (C_1) and the land value under the current climate (C_0) using regional agricultural land as weight.

$$W_i = [V_i(C_1) - V_i(C_0)] * agricultural\ land_i \tag{12}$$

4. Data

This analysis exploits the high-quality data from the Vietnam Access to Resources Household Surveys (VARHS). These datasets contain rich information on income activities and access to resources by rural households in Vietnam. Particularly, the surveys collected details on crop production of 20 crops that have been produced across regions. The minimum sample size of the surveys is more than 2,000 households. The Probabilistic Data Record Linkage method applied to these datasets produces a ten-year unbalanced panel of 2,341 households or 7,793 year-households. Following Wang et al. (2009), Seo et al. (2009), and Kurukulasuriya (2007), this study uses net crop income per square meter as a proxy for land value in Equations (10), (11), and (12). The words land value and net crop income are hereafter used interchangeably. To ensure the comparability, economic variables are converted to constant 2005 VND.

While cross-sectional Ricardian analyses suffer from omitted variable bias, assessments using panel data is also subject to biases due to omitting time-varying variables. Rising population may put pressure on land use efficiency (Mendelsohn et al., 1994). Increases in agricultural wages may have an impact on household agricultural production. This Ricardian study considers these sources of bias by incorporating socio-economic variables. The VARHS surveys on the commune level represent a rich set of data on commune-level characteristics including men and women agricultural wages. This wage data is combined with household data by applying the same Probabilistic Data Record Linkage Method. Data on population density come from Vietnam Government Statistical Office.

This study uses monthly averages of temperature and rainfall for the period 1970-2000. The climate data with a high resolution of one square kilometre are derived from Worldclim version 2.0. Climate and agricultural production may vary across latitudes (Mendelsohn et al., 1994). We extract data on elevation with the same resolution on a commune-level basis using free spatial data from DIVA-GIS website. These climate and topographical data are extracted with the kind assistance of Ha Manh Thang at the Environmental Research Institute of the University of Waikato. Because we use climate data with high resolution, the combination of climate and household data produces barely any errors. We do not include climate data for twelve months in the analysis for the reason that there is multicollinearity between monthly precipitations and between monthly temperatures. Instead, we construct seasonal temperatures and rainfalls based on season classification of the Ministry of Natural Resources and Environment (MONRE, 2009). 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 have impacts on agricultural performance across regions.

Table 1: Variable Definition

Variable	Measurement
Dependent variable	
income_meter (in log form)	Net crop income per square meter = (total output value-total cost)/farmland Thousand VND/square meter (2005 prices)
Household characteristics	
hh_size	Number of household member (person)
head_sex	Gender of household head, binary (1 = male)
head_edu	Formal schooling of household head (year)
head_age	Age of household head (year)
Extension contacts	Number of extension contacts in the last two years (times)
Farmland characteristics	
No_plots	Number of separate farmland plots
Farm_size	Farm size (square meter)
irrigation	% of farmland irrigated
Socio-economic characteristics	
Woman agricultural wage	Thousand VND/female workday in agriculture
Men agricultural wage	Thousand VND/male workday in agriculture
Population density	Thousand person/square kilometre
Topographic characteristics	
Elevation	Meter
Climate variables	
Winter_tem	Winter monthly temperature (Celsius degree)
Spring_tem	Spring monthly temperature (Celsius degree)
Summer_tem	Summer monthly temperature (Celsius degree)
Autumn_tem	Autumn monthly temperature (Celsius degree)
Winter_pre	Winter monthly precipitation (millimetre)
Spring_pre	Spring monthly precipitation (millimetre)
Summer_pre	Summer monthly precipitation (millimetre)
Autumn_pre	Autumn monthly precipitation (millimetre)
Regional dummies	Northeast, Northwest, Northern Central, Southern Central, Central Highland, South (Red River delta as reference)
Time dummies	2008, 2010, 2012, 2014, 2016 (2006 as reference)

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	0.79	0.79	0.91	0.84	0.74	0.86	0.77	0.82
	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	2,399	4,353	11,861	6,419	5,818	16,384	18,636	8,350
	Irrigation	0.92	0.76	0.42	0.73	0.76	0.65	0.89	0.74
Social-economic conditions	Extension contact	1.05	1.61	1.55	1.91	1.58	1.21	1.57	1.43
	Men agricultural wage	108.04	82.35	158.45	81.52	89.31	91.65	95.47	105.45
	Woman agricultural wage	101.16	75.31	156.89	78.34	74.69	83.03	73.23	97.28
	Population_density	1,825.77	382.19	67.27	183.94	150.80	117.45	323.82	595.26
Climate 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

5. Estimation Results

One criticism that plagues the Ricardian approach to climate impact assessment is the omitted variable bias (Francisco & Maria, 2015; Deschenes & Greenstone, 2007). This study overcomes the omitted variable bias in the Ricardian analysis by applying the fixed effects model on household panel data. Because soil characteristics such as soil quality and slopes are constant over time, the fixed effects model applied to the first step of the Hsiao method will purge out the effects of soil characteristics on agricultural performance. If we assume that unobserved heterogeneity across households is also time-invariant, the estimates of the fixed effects model for observed characteristics are robust.

Most Ricardian analyses have treated irrigation as an exogenous variable by either ignoring it or regressing separate equations for irrigated and rainfed farms. Dall'erba and Domínguez (2016), Wang et al. (2009), and Schlenker, Michael Hanemann, and Fisher (2005) found smaller climate impact on irrigated farmland than on rainfed farms. By treating irrigation as an exogenous variable, such estimates of climate impact are subject to biases. Irrigation is an adaptation practice to climate change. It is, therefore, reasonable to expect a confounding impact of irrigation. In addition, economists often classify irrigation into a binary choice. Vanschoenwinkel and Passel (2018) show that the climate response of irrigated and rainfed farms also differs according to how irrigation is defined. The authors call for better irrigation measures in Ricardian analyses of climate change.

This analysis attempts to overcome the above two shortcomings of the Ricardian literature regarding the irrigation variable. Because of inherent land fragmentation in Vietnam, each household has several plots with different irrigation conditions. We constructed an irrigation variable which represents the percentage of household's farmland irrigated to better investigate the real impact of irrigation. We defined irrigation as endogenous of climate change and applied the control function method developed by Wooldridge (2015).

Using the control function method, irrigation is first regressed on its instrument, alongside other exogeneous explanatory variables. Estimated errors obtained from this step are then plugged in the Ricardian model, alongside irrigation. If the coefficient of the error term is not statistically significant, irrigation is considered exogeneous. The main task of the control function method is to identify an instrument that is correlated with irrigation but does not affect agricultural income. From the dataset at hand, we found irrigation is positively correlated with household's rice sold proportion as rice production requires good irrigation condition. However, as rice accounts for a small portion of marketed agricultural surplus, rice market participation is not correlated with income per meter. Therefore, rice sold proportion of households was used as the instrument for irrigation. Because the F-statistics from the control functions are larger than 10, the rule of thumb confirms the relevance of our control functions for this study.

Table 3 reports the Hsiao estimates of the time-varying control variables while Table 4 represents the estimates of climate variables and other time-invariant controls under different endogenous irrigation hypotheses. The first columns in the two tables are the estimates for control and climate variables under the assumption of endogeneous irrigation using the control function method proposed by Wooldridge (2015). The second columns in the two tables are the estimated parameters of corresponding variables when irrigation is treated as an exogenous variable while the third columns assume irrigation as omitted exogeneous variable.

Table 3: The Hsiao Method Estimation of Step 1

Income_meter (log form)	Hypothesis of Irrigation		
	Endogeneous	Exgogeneous	Omitted Exogeneous
irri_error_sum	0.031	-	-
irrigation	0.186**	0.207**	-
hh_size	0.039**	0.038**	0.039**
head_sex	-0.015	-0.016	-0.02
head_edu	0.002	0.002	0.005
head_age	0.001	0.001	0.001
no_plots	0.038**	0.038**	0.039**
log_farm_size	-0.536**	-0.533**	-0.555**
extension_contact	0.018**	0.018**	0.019**
log_men_agricultural_wage	-0.121	-0.121	-0.097
log_woman_agricultural_wage	0.033	0.033	0.01
log_population	0.004	0.005	0.054
I_2008	0.704**	0.704**	0.55**
I_2010	0.125*	0.127*	0.089
I_2012	-0.047	-0.046	-0.076
I_2014	0.151**	0.153**	0.11
I_2016	0.221**	0.221**	0.193**
_cons	4.768**	4.731**	4.785**
R2	0.17	0.17	0.15
N	7,532	7,532	7,793

*legend: * p<0.05; ** p<0.01*

Comparing the last two columns gives a sense of omitted variable bias. When irrigation is considered an omitted exogenous variable, estimates of most time-varying controls and climate variables are larger in magnitude than when we take irrigation as an exogenous explanatory variable. This indicates potential biases in Ricardian analyses which ignore irrigation. The estimates of irrigation variable reveal something interesting. In the second column of Table 3, the estimate of irrigation is 0.207 and statistically significant at 1% level. Therefore, if we consider irrigation exogeneous in the face of climate change, we can conclude that irrigation is truly a good response which increases agricultural value. The control function method estimate reported in Column 1 of Table 3 shows a smaller estimate for irrigation. The interpretation of the Hsiao two-step Ricardian model is, therefore, based on the estimation of the control function method reported in the first columns of the two tables.

While most household characteristics are not statistically significant, household size shows a positive impact on net crop income. Household size is a good measure of family labour for agricultural production. Therefore, the sign and statistical significance of this variable is as expected. Farmland characteristics are strongly correlated with agricultural income. The interesting finding is that while the number of farmland plots (or land fragmentation) is correlated with higher income, farm size has a negative impact on net income per land unit. The estimate of farm size (in logarithm form) is -0.536 and statistically different from zero indicating a 0.536 percentage decrease in net income due to a one-percentage increase in arable land. The rationale behind this is the land fragmentation economics in Vietnam. Small-scale farmers tend to be more productive than large-holding farmers (Barrett, Bellemare, & Hou, 2010; Van Hung, Macaulay, & Marsh, 2007).

Changes in the local socio-economic environment are found to influence agricultural income. Estimates of extension contacts in Table 3 are positive and statistically different from zero at 1% level indicating a 0.018% net return to extension services. Albeit insignificant, growing population is associated with higher crop income. Changes in the macro-economic environment in the period 2006 - 2016 are found to be the most important factors accounting for increases in farm value. Estimates of time dummies for 2008, 2010, 2014 and 2016 are statistically significant. The removals of export barriers to rice in 2009, and increases in agricultural supports (OECD, 2015) contributed to nearly a 0.125% return to agricultural income in 2010, and more than 0.221% return in 2016.

Column 1 of Table 4 shows the estimates of climate variables and other time-invariant controls in step 2 of the Hsiao method under endogeneous irrigation assumption. Latitude is negatively correlated with land value. A one-meter increase in elevation results in a 0.001% decrease in net crop income. Estimates of regional dummies for the Northeast, Northern Central, Southern Central are statistically negative. Particularly, the estimate for Southern Central is -2.317 indicating a 2.3% lower income per square meter of Southern Central farmers in comparison with their counterparts in the Red River delta. The Northwest and the Central Highlands are shown to be better off as the estimates for regional dummies are positive. The estimate for the South region dummy is negative (-0.374) but not statistically different from zero. Therefore, one can conclude the Red River delta in the North and the Mekong River delta in the South have the same agricultural performance in terms of agricultural income per farmland unit.

Our variables of interest in the Ricardian analysis are the climate variables and their interaction terms. At the sample mean of 19°C, rising winter temperature is shown to have a negative impact on net income although the estimates for winter temperature and its squared terms are not statistically significant. Particularly, increases in temperature in regions with warmer winter are harmful to the development of rice in early stage and are associated with higher irrigation cost due to evaporation. Moreover, this is the most important season when most fruit trees in the South are blossoming. Increases in temperature reduce the fruiting rate. This finding is contrary to the analysis by Trinh (2018) which shows the positive impact of rising temperature in the dry season.

Net agricultural income is nonlinearly correlated with higher temperatures in the wet season. Estimates of spring (March to May), and summer (June to August) temperatures, and their squared terms, are statistically different from zero. The optimal spring temperature is 17.8°C while the sample mean is 24.4°C. Rising temperature in spring is harmful to crop development and increases cost for irrigation. Likewise, the optimal summer temperature is 28.4°C. Because the regional means of summer temperatures are around this optimal level, further increases in summer temperatures are expected to bring agricultural losses. However, increases in autumn temperature (September to November) are beneficial for agricultural production.

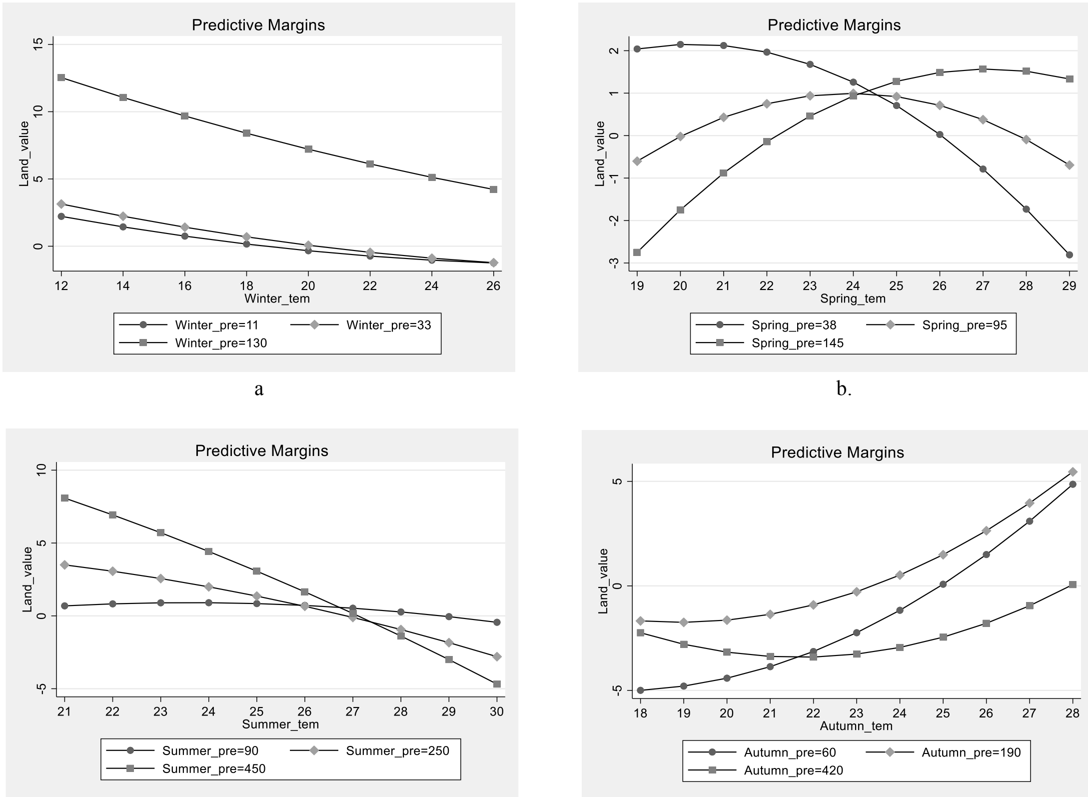
Table 4: The Hsiao Method Estimation of Step 2

Income_meter (log form)	Hypothesis of irrigation		
	Endogeneous	Exgogeneous	Omitted Exogeneous
Winter_tem	-0.670	-0.676	-1.012*
square_Winter_tem	0.012	0.012	0.019*
Spring_tem	2.351**	2.328**	2.952**
square_ Spring_tem	-0.066**	-0.065**	-0.078**
Summer_tem	1.877**	1.836**	1.932**
square_ Summer_tem	-0.033**	-0.032**	-0.034**
Autumn_tem	-2.885**	-2.810**	-2.809**
square_ Autumn_tem	0.087**	0.085**	0.088**
Winter_pre	0.056**	0.056**	0.052**
square_ Winter_pre	5E-04**	5E-04**	4E-04**
Spring_pre	-0.209**	-0.208**	-0.214**
square_ Spring_pre	3E-05	3E-05	3E-05
Summer_pre	0.088**	0.088**	0.094**
square_ Summer_pre	1E-05**	1E-05**	2E-05**
Autumn_pre	0.083**	0.083**	0.089**
square_ Autumn_pre	-8E-05**	-8E-05**	-8E-05**
c.Winter_tem#c.Winter_pre	-0.003**	-0.003**	-0.003**
c.Spring_tem#c.Spring_pre	0.008**	0.008**	0.009**
c.Summer_tem#c.Summer_pre	-0.004**	-0.004**	-0.004**
c.Autumn_tem#c.Autumn_pre	-0.002**	-0.002**	-0.002**
Elevation	-0.001**	-0.001**	-0.001**
Northeast	-0.773**	-0.768**	-0.773**
Northwest	0.301**	0.305**	0.425**
Northern_central	-1.531**	-1.518**	-1.516**
Southern_central	-2.317**	-2.301**	-2.124**
Central_highlands	0.726*	0.725*	0.915**
South	-0.374	-0.372	-0.327
_cons	-18.338*	-18.355*	-24.708**
R2	0.58	0.580	0.61
N	7,532	7,532	7,793

*legend: * p<0.05; ** p<0.01*

Variations in precipitation across seasons are also associated with agricultural value. This relationship fits a U-shape for winter, spring, and summer while autumn precipitation puts an inverse U-shape. In contrast to relative redundancy of rainfall in the rainy season, the dry season (October to May) in Vietnam is experiencing shortage of rainfall (Nguyen, Renwick, & McGregor, 2013) including the Red River delta, the South, the Northwest. Expected decreasing rainfall in this season is, therefore, harmful to agricultural production across regions.

Figure 2: Interactions between Temperature and Precipitation



a b. c d.

We find the effects of rising temperature are also dependent on the levels of rainfall in the four seasons. Estimates of interaction terms between temperature and precipitation in the spring, summer, autumn, and winter, are all statistically significant. Figure 2 illustrates interactions between climate elements. As discussed earlier, rising temperature in the winter is harmful to the agriculture. However, the negative impact of a warmer winter can be mitigated by a high rainfall of 130 millimetres (Figure 2.a). In early spring when the temperature is below 24.5°C, increases in temperature are beneficial as long as there is a low level of rainfall for plant pollination. When the spring proceeds, rising temperature is harmful if there is a shortage of rainfall (Figure 2.b). In early summer when temperature is below 27°C, a high rainfall of 450 millimetres helps to maintain the positive marginal effect of rising temperature (Figure 2.c), relative to lower precipitation levels. Rising temperature is shown to be beneficial in the autumn. Figure 2.d shows that the optimum level of precipitation to harness the positive impact of rising temperature in the autumn is 190 millimetres, which is above the current trend.

6. Climate Change Impact Simulation

In order to obtain a sense of climate change, we simulated the impacts of future climate changes on Vietnam agriculture using the Ricardian model results. We started with projected climate change for Vietnam developed by the Ministry of Natural Resources and Environment (MONRE, 2009) under medium emission scenario. Changes in temperature and rainfall are not in uniform across seasons and across regions. Temperature is projected to increase by 0.4°C to 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 national averages of precipitation are projected to increase but with different patterns for seasons. Therefore, the impact simulation of these climate changes across space and time is especially of interest to policy-makers so as to propose adaptation responses.

As all coefficients in the Ricardian model are evaluated at sample means, we calculated the differences between projected climate and sample means for each region and for each season. These differences were then multiplied by corresponding coefficients from step 2 of the Hsiao estimation results. The impact of climate change on each region was calculated using regional agricultural land as weight (Equation 12). Estimated impact of changing temperature or rainfall for a given region was obtained by summing across seasons. The national impacts of seasonal climate change were summed across regions. The total impact of changing seasonal climate is the sum of temperature and rainfall impact. Tables 6 – 7 provide detailed impacts of changing temperature and precipitation on seasonal and regional agricultural income. Seasonal variations in climate result in both losses and surpluses ranging from -12.5% to +16%. The positive influences of rising precipitation overwhelm the negative effects of changing temperature in the long-run. As a result, the combined effect of climate change is positive in most of the regions, with the Central Highland being the exception.

Table 5 provides the seasonal and regional distribution of estimated impacts. It is interesting to note that projected climate changes bring net benefits to Vietnam agriculture in most of the regions in the period 2050-2100. In the short-term, the Northwest, the Central Highland and the South (including the Mekong River delta and the Southeast) will experience agricultural losses in 2030 resulted by both rising temperature and changing precipitation. Expected losses range from 6.26 to 298 million USD. In the long-term when more precipitation is expected, severe losses resulted by rising temperature are mitigated by higher rainfall. The Central Highland is the only region where severe losses are anticipated.

Table 5: Income Impact of Climate Change on Vietnam Agriculture (Million USD)

Region	Arable Land (1000 ha)	Winter	Spring	Summer	Autumn	Whole year
				2030		
Red River delta	799	-10.55	-16.93	56.07	-4.31	24.28
Northeast	938.3	-3.98	-21.62	49.39	-16.33	7.46
Northwest	1,178.4	-6.75	-58.25	186.61	-127.87	-6.26
Northern Central	985.6	-2.36	78.33	-100.96	42.39	17.40
Southern Central	1,219.9	165.17	116.17	-182.90	159.11	257.56
Central Highlands	2,420.6	-59.39	-96.03	-146.11	3.36	-298.17
South	3,987.3	-131.29	-161.04	-228.42	449.62	-71.13
Whole country		-49.16	-159.37	-366.32	505.97	-68.87
				2050		
Red River delta	799	-11.68	-21.95	67.03	5.93	39.34
Northeast	938.3	-5.34	-25.91	59.80	-3.04	25.51
Northwest	1,178.4	-9.50	-61.21	203.19	-117.53	14.94
Northern Central	985.6	-3.79	69.49	-94.20	58.68	30.17
Southern Central	1,219.9	155.87	113.39	-181.74	171.74	259.26
Central Highlands	2,420.6	-62.77	-73.92	-142.75	26.47	-252.98
South	3,987.3	-134.77	-153.10	-224.85	538.80	26.08
Whole country		-71.99	-153.21	-313.52	681.04	142.33
				2100		
Red River delta	799	-14.88	-32.14	89.01	30.14	72.12
Northeast	938.3	-9.71	-39.18	81.30	28.60	61.00
Northwest	1,178.4	-15.11	-74.52	238.30	-87.29	61.39
Northern Central	985.6	-6.95	54.92	-81.54	98.36	64.78
Southern Central	1,219.9	138.18	98.98	-180.15	205.84	262.84
Central Highlands	2,420.6	-71.15	-46.26	-136.68	83.64	-170.46
South	3,987.3	-141.39	-178.07	-221.10	714.85	174.29
Whole country		-121.02	-216.28	-210.85	1074.13	525.97

Looking at the distribution of income effects across seasons and across regions gives insight on how the combined changes of temperature and rainfall affect Vietnam agriculture. Expected rising temperatures in most seasons are associated with losses in the Northwest, Southern Central, South, and the Central Highlands (Table 6).

Table 6: Estimated Agricultural Income Impact of Rising Temperature (Million USD)

Region	Arable Land (1000 ha)	Winter	Spring	Summer	Autumn	Whole year
				2030		
Red River delta	799	1.82	-2.26	-0.01	15.50	15.06
Northeast	938.3	3.50	3.41	0.37	12.22	19.49
Northwest	1,178.4	9.01	12.17	-2.46	-30.11	-11.39
Northern Central	985.6	-1.41	-10.08	-0.31	25.22	13.42
Southern Central	1,219.9	-10.57	-40.32	-0.02	43.79	-7.11
Central Highlands	2,420.6	-18.15	-29.06	-16.95	-43.65	-107.81
South	3,987.3	-54.93	-332.20	1.51	353.64	-31.98
Whole country		-70.73	-398.34	-17.86	376.62	-110.31
				2050		
Red River delta	799	0.49	-11.27	-0.26	24.58	13.53
Northeast	938.3	1.86	-3.87	0.29	24.65	22.94
Northwest	1178.4	5.86	3.82	-1.73	-20.32	-12.37
Northern Central	985.6	-3.13	-23.61	-1.18	39.15	11.23
Southern Central	1219.9	-11.50	-47.60	-0.33	53.78	-5.64
Central Highlands	2420.6	-19.70	-39.88	-14.29	-30.92	-104.79
South	3987.3	-55.52	-359.11	0.59	425.04	11.00
Whole country		-81.63	-481.51	-16.91	515.97	-64.09
				2100		
Red River delta	799	-3.08	-29.46	-1.44	46.36	12.38
Northeast	938.3	-3.07	-23.42	-0.32	54.58	27.78
Northwest	1178.4	-0.57	-20.69	-0.17	8.70	-12.72
Northern Central	985.6	-6.88	-47.76	-4.27	72.48	13.58
Southern Central	1219.9	-13.53	-71.29	-1.39	83.36	-2.85
Central Highlands	2420.6	-24.30	-79.03	-8.92	5.78	-106.47
South	3987.3	-56.52	-453.86	-3.53	565.56	51.64
Whole country		-107.94	-725.50	-20.04	836.82	-16.66

Projected lower rainfalls in the spring put negative impacts on agricultural income in the Red River delta, the Northeast, Northwest, and the Central Highlands (Table 7). In contrast, higher precipitation in the summer is predicted to be severely harmful to the Northern Central and the Southern region with annual losses ranging from 77 to 229 million USD in the period 2030-2100. The combined effects on Vietnam agriculture of future changes in temperature and precipitation are negative for the winter, spring, and summer with net losses ranging from 49 to 366 million USD in the period 2030-2100 (Table 5). However, rising temperature and precipitation in the autumn results in potential advantage to agricultural production which offsets the negative impacts in other seasons in the long-run.

Table 7: Estimated Agricultural Income Impact of Changing Rainfall (Million USD)

Region	Arable Land (1000 ha)	Winter	Spring	Summer	Autumn	Whole year
				2030		
Red River delta	799	-12.37	-14.67	56.08	-19.81	9.23
Northeast	938.3	-7.48	-25.03	49.02	-28.55	-12.03
Northwest	1178.4	-15.76	-70.42	189.07	-97.77	5.12
Northern Central	985.6	-0.95	88.41	-100.65	17.17	3.97
Southern Central	1219.9	175.73	156.49	-182.88	115.32	264.66
Central Highlands	2420.6	-41.24	-66.97	-129.16	47.01	-190.36
South	3987.3	-76.36	171.16	-229.94	95.98	-39.16
Whole country		21.57	238.97	-348.45	129.35	41.44
				2050		
Red River delta	799	-12.17	-10.68	67.30	-18.64	25.81
Northeast	938.3	-7.20	-22.04	59.50	-27.69	2.57
Northwest	1178.4	-15.36	-65.03	204.92	-97.21	27.31
Northern Central	985.6	-0.66	93.09	-93.02	19.53	18.94
Southern Central	1219.9	167.37	160.99	-181.41	117.95	264.90
Central Highlands	2420.6	-43.07	-34.04	-128.46	57.38	-148.19
South	3987.3	-79.25	206.01	-225.44	113.75	15.08
Whole country		9.65	328.30	-296.60	165.07	206.42
				2100		
Red River delta	799	-11.80	-2.69	90.45	-16.22	59.74
Northeast	938.3	-6.64	-15.77	81.62	-25.99	33.22
Northwest	1178.4	-14.54	-53.83	238.47	-95.98	74.11
Northern Central	985.6	-0.08	102.67	-77.27	25.88	51.20
Southern Central	1219.9	151.71	170.27	-178.75	122.48	265.70
Central Highlands	2420.6	-46.85	32.77	-127.76	77.86	-63.99
South	3987.3	-84.87	275.79	-217.56	149.29	122.64
Whole country		-13.08	509.21	-190.81	237.31	542.63

This is apparently not the first analysis which finds long-term positive impacts of climate change on agriculture. Reinsborough (2003) shown a slightly positive impact of non-uniform climate change on Canadian agriculture although the range of income impact is quite large. Chen et al. (2013) highlighted the potential advantage of rising temperature on China agriculture with net surplus ranging from USD 140 to USD 355 per hectare in 2080. Lippert et al. (2009) estimated an increase in land rent of about 5%-6% in response to climatic change in Germany agriculture in the period 2011-2040. Chatzopoulos and Lippert (2015) shown increases in land rent for all farm types in Germany under moderate climate changes.

7. Concluding Remarks

Vietnam is expected to be among the hardest-hit countries by future climate changes. Yet little is known about how this agrarian economy will be affected by future climate change. This analysis utilized panel data generated from the Vietnam Access to Resources Household Surveys and estimated climate normals with high resolution. Climate data were grouped into four seasons which allowed us to better investigate the distribution of climate impact across time. In contrast to most panel data Ricardian analyses which have treated irrigation as an exogeneous variable, we considered irrigation endogeneous using the control function method.

By using the Hsiao two-step method on the Ricardian model, we confirmed the positive impact of irrigation on agricultural performance. Rising population is positively correlated with higher agricultural income. Farmers with more land fragmentation seem to be more efficient in agricultural production. The results highlight the nonlinear, seasonal role of changing temperature and precipitation. Rising temperature in winter, spring, and summer is especially harmful to the Northern Central, Central Highlands, and the Southern region. The projected shortages of rainfall in winter and spring are associated with severe losses in the Northwest, the South, and the Central Highlands. Higher precipitation in the summer brings net benefits to the North only and is associated with losses for the Southern region. The country is projected to gain agricultural surpluses in the long-run. The Central Highlands is likely to be the most affected by future changes in climate with annual losses ranging from 4.7% - 8.3% between 2030 and 2100. Adaptation responses should focus on improved drainage and irrigation to cope with the negative impact of excessive precipitation and seasonal shortage of water in the dry season.

This Ricardian analysis attempted to quantify the impacts of future climate change on the Vietnam agriculture. The simulation of climate change impact was based on the hypothesis that the Vietnam farming system is still the same at present in the future. Estimated impacts of climate change, therefore, do not capture future technical change to either crops or farming techniques. Irrigation is a positive adaptation response to climate change which covers more than 70% of sample farming land. This Ricardian analysis did not take into account how the expected climate change would affect water availability for irrigation. Although the analysis used panel data of ten years, the likely absence of weather-induced price effects is likely to overstate the negative impacts of changing climate on agricultural income. Analogous to any other Ricardian analyses, this study could not take carbon fertilization into account which may lead to overstatements of the negative impacts of changing climate due to carbon emission.

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