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UMR MOISA

Adaptation au changement climatique au Vietnam avec les mangroves et le riz

Climate change adaptation in Vietnam with mangroves and rice

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Abbreviations

ADB	Asian Development Bank
AIC	Akaike Information Criterion
ASC	Alternative Specific Constant
AWD	Alternate Wetting and Drying
BIC	Bayesian Information Criterion
CL	Conditional Logit
CVM	Contingent Valuation Method
DBDC	Double-Bounded Discrete Choice
DCE	Discrete Choice Experiment
FAO	Food and Agriculture Organization
FE-OLS	Fixed Effect Ordinary Least Square
GAM	Generalized Additive Model
GDP	Gross Domestic Product
GDD	Growing degree days
GHG	Greenhouse Gases
GIZ	Deutsche Gesellschaft für Internationale Zusammenarbeit
GMNL	Generalized Multinomial Logit Model
IPCC	Intergovernmental Panel on Climate Change
KDD	Killing Degree Days
MARD	Ministry of Agriculture and Rural Development
MIXL	Mixed Logit Model
MNL	Multinomial Logit Model
MONRE	Ministry of Natural Resources and Environment of Vietnam
MO-OLS	Mean Observation Ordinary Least Square
RUM	Random Utility Model
RPL	Random Parameter Logit
SBDC	Single-Bounded Discrete Choice
SRI	System of Rice Intensification
VND	Vietnamese Dong
WTA	Willingness To Accept
WTP	Willingness To Pay
XTNP	Xuan Thuy National Park
US	United States

Résumé

La Banque Mondiale place le Vietnam parmi le top 5 des pays au monde les plus exposés aux risques suite aux conséquences du changement climatique induit par les humains. Le pays subit des niveaux élevés de gaz à effet de serre, une intensification des températures, des évènements extrêmes (sécheresses, inondations et typhons), et une augmentation du niveau de la mer qui ne menacent pas seulement les activités économiques telles que la production de riz mais aussi plus directement les moyens de subsistance des habitants du Vietnam.

Chapitre 1 propose une brève introduction à la thèse avec comme focus le contexte du changement climatique au niveau mondial puis au Vietnam.

Les chapitres 2 et 3 portent sur l'évaluation économique des services de l'écosystème mangrove dans le cadre du Parc National Xuan Thuy (PNXT) situé dans le delta du Fleuve Rouge. En effet, la mangrove y subit une dégradation conséquente due à diverses pressions environnementales. La conservation d'aires protégées, et surtout de la biodiversité, est plus que nécessaire pour garantir des moyens de subsistance aux plus pauvres. Ces deux chapitres proposent alors différents scénarios d'investissements quant aux activités de conservation de la mangrove au PNXT ayant pour objectif la bonne santé à long terme de l'écosystème mangrove et examinent des facteurs impliqués dans le processus de prise de décision.

Au chapitre 2, la méthode d'évaluation contingente, et plus précisément, une enquête avec proposant une enchère en deux étapes sont employées afin d'éliciter les consentements à payer (CAP) pour les diverses caractéristiques non marchandes des mangroves. Des résultats montrent que le niveau des revenus est le seul facteur sociodémographique significatif expliquant la variabilité dans les CAP. La perception des bénéfices potentiels liés l'emploi des mangroves parmi les personnes sondées et leur degré d'intérêt pour les activités de conservation de ces mêmes mangroves influencent aussi le CAP. Des estimations non-paramétriques et paramétriques de la somme forfaitaire moyenne (CAP) par ménage

sont alors calculées à partir de l'analyse empirique.

Au chapitre 3, une expérimentation de choix discret est utilisée afin de fournir une évaluation économique de différentes composantes d'un projet de conservation de mangrove. La zone de couverture de la côte par les mangroves et leur capacité de prévention des tempêtes s'avèrent être des attributs largement reconnus alors que les avantages pour la biodiversité apparaissent être d'une importance mineure. Les résultats de l'estimation d'un modèle logit multinomial à paramètres aléatoires (RPL) montrent l'existence d'une hétérogénéité dans les préférences et que celle-ci est lié au degré de dépendance économique des enquêtés aux mangroves, à leur niveau d'éducation, leur métier, et la connaissance des bénéfices potentiels liés aux mangroves. L'analyse quant à l'hétérogénéité non observée dans les préférences et, en particulier, de l'incertitude dans les choix des enquêtés, est approfondie via l'estimation d'un modèle logit multinomial généralisé (GMNL). Les consentements marginaux à payer (CAP) des ménages enquêtés sont déduits des différentes et comparés entre celles-ci.

Le chapitre 4 analyse les impacts du climat sur les rendements du riz au Vietnam. Ce chapitre se propose de contribuer à l'analyse de solutions pour préserver un système alimentaire durable pour les années à venir. Le système alimentaire au Vietnam est entré dans une période critique alors que les solutions via des adaptations mises en œuvre aujourd'hui par des paysans détermineront de quelle manière les rendements des cultures évolueront à l'avenir. Il est alors proposer d'estimer un modèle de panel dynamique pour étudier l'impact du climat sur les rendements du riz au niveau provincial et pour les années 1986-2015. La particularité de ce modèle est d'autoriser la variabilité des réponses au climat non seulement individuelles mais aussi variant dans le temps. Ce type de modélisation est approprié pour analyser les comportements d'adaptation des agriculteurs aux conditions extrêmes en termes de climat. L'impact des températures est résumé par deux indicateurs : les degrés-jours de croissance, indicateur qui est d'autant plus élevé que les températures sont favorables à la croissance de la plante, et les degrés-jours de destruction, indicateur résumant l'occurrence de températures défavorables à la croissance de celle-ci. Il est attendu que le premier indicateur ait un effet positif sur le rendement alors que le deuxième a, quant à lui, un effet négatif. Les résultats empiriques révèlent un lien à la fois quadratique et en forme de U inversé entre le rendement du riz et le niveau de précipitation. Les résultats montrent qu'il existe une hétérogénéité entre provinces quant à la réponse du rendement du riz aux températures élevées. Il apparaît ainsi que les riziculteurs vietnamiens sont capables de s'adapter dans le long terme face aux modifications des diverses conditions météorologiques locales. La diminution de l'effet néfaste des températures élevées sur le rendement au cours de la période de 1986 à 2015 est également cohérente avec cette adaptation à long terme.

En conclusion, le chapitre 5 de la thèse propose des implications en termes de politique économique quant à la conservation des mangroves et l'adaptation au climat au Vietnam, et trace des perspectives de recherche futures sur la promotion de la résilience climatique pour les écosystèmes de mangrove et la production de riz au Vietnam.

Abstract

The World Bank counts Vietnam as one of the top five countries in the world most at risk from the consequences of man-made climate change. The country is highly exposed to elevated levels of greenhouse gases, intensification of temperature, flooding and sea-level rise that not only threaten economic activities such as rice production but also directly affect people's livelihoods.

Chapter 1 gives a brief introduction to this thesis which discusses the context of climate change at the global level and in Vietnam.

Chapter 2 and 3 aim at valuing mangrove ecosystem services in Xuan Thuy National Park (XTNP), Red River Delta that are being degraded aggressively under environmental pressures. Conservation for protected areas, especially biodiversity, is a necessity for the livelihoods of the poor. These two chapters consider different scenarios of investments in conservation activities at XTNP that present a vision of long-term mangrove ecosystem health and examine factors that go into the decision-making framework.

In chapter 2, contingent valuation with double-bounded dichotomous-choice question survey is used to elicit local willingness to pay (WTP) for the total non-use values of mangroves. Findings indicate that income appears as the only significant sociodemographic factor when explaining WTP. Respondents' perceived knowledge of mangrove benefits and interest in conservation activities also influence WTP. Non-parametric and parametric estimates of lump sum mean WTP per household are reported from the empirical analysis.

In chapter 3, a discrete choice experiment is used to provide finer values for different components of a mangrove conservation project. Mangrove coverage area and storm prevention capacity are found to be greatly discerned attributes whereas biodiversity benefits are of minor importance. Results from the random parameter models (RPL) confirms that local preference heterogeneity exists and observed preference heterogeneity could be explained by respondents' economic dependency on mangroves, education, occupation and knowledge of mangrove benefits. Unobserved preference heterogeneity and the degree of

certainty of choices across individuals are further captured by estimating the generalized multinomial logit model (GMNL). Marginal household WTPs are reported given a change in each attribute level across econometric specifications.

In chapter 4, climate impacts on rice yields are addressed in order to create lasting solutions in a sustainable food system for the coming years. The food system in Vietnam has entered a critical time when the adaptation solutions implemented by farmers today will determine how crop yields will flourish in the future. The panel model in this study, called mean observation ordinary least squares (MO-OLS), has intercepts as well as the slope coefficients on the climate variables change over space and time to capture the heterogeneity of rice yield responses under adaptation. Growing degree days (GDD) and killing degree days (KDD) are indexed for temperatures based on the scientific basis for raising crops at a suitable temperature range over the growing season. For the short-run responses, higher beneficial temperature (GDD) advances rice yield but excessive heat (KDD) leads to more yield loss. Empirical results aslo show a quadratic, inverted U-shaped relationship between rice yield and rainfall. The results affirms there exists regional heterogeneity of rice yield responses, meaning Vietnamese rice farmers are highly adaptable to shifts in various local weather conditions in the long-run. The decline in the adverse effect of high temperature on yield over the period from 1986 to 2020 is also consistent with this long-run adaptation.

Chapter 5 concludes the thesis by providing policy implications and future research perspectives on promoting climate resilience for mangrove ecosystems and rice production in Vietnam.

Publications

Paper published in a peer-review journal

- Willingness to pay for mangrove preservation in Xuan Thuy National Park, Vietnam: do household knowledge and interest play a role?, *Journal of Environmental Economics and Policy*, **9**: 4, 402-420, 2020. (with Nguyen, T.V., Simioni, M.)
- Valuing mangrove conservation attributes in Red River Delta, Vietnam: A choice experiment approach, *Marine Resource Economics*, 2021. (with Nguyen, T.V., Simioni, M.)

Presentation in conference

- 6th French Association of Environmental and Resource Economists (FAERE) Conference, 2019, Rennes, France.
- 7th Workshop on non-market valuation 2019, Marseilles, France.

Chapter 1

Introduction

1.1 Motivation for the thesis

The impacts of climate change are found globally, not only today, but even more in the future. Human-caused increases in greenhouse gases remain the dominant lever in the climate system. National economies, agriculture, livelihood, especially in densely populated, low-lying coastal regions, are experiencing the significant impacts of global warming, changing precipitation patterns, rising sea level, and more extreme weather events (IPCC, 2013). Furthermore, climate change is having far-reaching impacts on the global food system. According to the Food and Agriculture Organization of the United Nation (2017), the current amount of food production must double in order to meet the projected human population growth and per capita food requirement by 2050, which is increasingly challenging with the looming climate change.

Despite impressive development gains in the past 35 years, Vietnam is one of the most vulnerable countries affected by climate change (Dasgupta et al., 2007). Climate change poses significant challenges to hunger and poverty eradication goals for the country as food security and livelihoods are at stake (World Bank, 2018). Climate change adaptation remains the priority in the national development plan. Nevertheless, the lack of data and expert opinion about climate change adaptation, in reality, are major bottlenecks for action in Vietnam. This calls for more scientific assessment and evidence to complement the practical efforts to fight climate change.

One major concern is to strengthen the resilience of vulnerable coastal communities against floods and coastal erosion. Mangroves have been given a high value by local communities for erosion control, sustainable tourism and fishery-based livelihoods (Prance and Tomlinson, 1987; Blanco et al., 2012; Polidoro et al., 2010). However, there has been little previous scientific assessment of the values of mangrove forests, especially biodiversity benefits, in the Red River Delta, Vietnam. The first two chapters of my dissertation contribute to the literature on payment for mangrove ecosystem services to ensure sustainable livelihoods of vulnerable communities along the northern coast of Vietnam. An economic valuation is vital to express the value of ecosystem services in monetary units so that decision makers can properly be informed. A contingent valuation method and a discrete choice experiment are adopted to estimate the Vietnamese households' maximum willingness to pay for a community project to protect mangroves against coastal erosion and sea level rise.

As rice is the most important crop in Vietnam, another concern is to have stakeholders in the rice sector see the coming food security challenges and the importance of adopting effective technological measures to address climate change. The last chapter of my thesis aims to exploit the link between climate variations (minimum/ maximum temperature, degree days, rainfall) and agricultural productivity in Vietnam. Province-level rice yield and weather panel data are used to examine how unmitigated climate change would impact rice yields. A flexible empirical model coupling spatial and temporal information of rice yield responses to climatic variables is adopted to account for the adaptation choices of farmers in the long run.

The introductory chapter is structured as follows. Section 1.2 recalls the global climate change context, which is followed by Section 1.3 where I overview the state of climate change in Vietnam and how the government tackles the issue. Section 1.4 summarizes my research studies and shortly previews the dissertation's results.

1.2 Global climate change

1.2.1 Climate change definition

Firstly, it is important to define climate change. Weather is the daily, atmospheric state of a place such as air temperature, precipitation, wind, humidity, etc. at a specific time. Climate refers to the statistical averages of weather conditions over an extended period of time. Climate change is distinctly referred to man-made long term changes in the climate, over decades and centuries, as a result of greenhouse gas emissions: carbon dioxide, methane, nitrous oxide (IPCC, 2007). Climate change is different from climate variability which varies over time for natural reasons such as natural changes due to the earth cycle, El Niño Oscillation, volcanic activities. Climate has changed in the past and will continue to change in the future. However, humans are adding to those changes at a very quick rate, quicker than what has been documented in the history of observed temperature.

1.2.2 Observed changes in the global climate system

Despite comprising less than 1 % of the atmosphere, greenhouse gases (GHGs) have a significant effect on the climate. [1] There are three major human emitted GHGs: carbon dioxide, nitrous oxide and methane, that can absorb some heat energy in the atmosphere, causing the temperature of Earth's surface to rise. [2] Carbon dioxide concentration in the atmosphere is reported on the rise globally, from approximately 315 parts per million in 1958 to more than 400 parts per million today, and shows no sign of slowing down. [3]

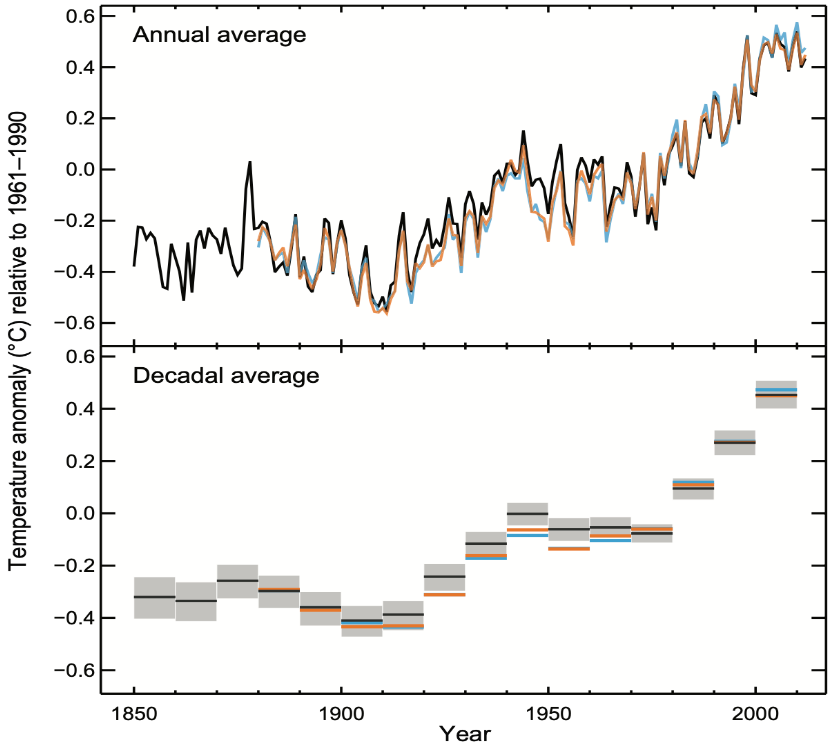
Consequently, global mean land and ocean temperatures have increased over time. As plotted in figure 1.1, the surface temperatures of the earth have warmed more than 1 °C since the mid th19 century. Meanwhile, the IPCC (2013) also reported that the ocean temperatures have risen by less than 1 °C, more slowly than the land because the heat diffuses more slowly down through ocean layers. Furthermore, the increased ocean temperature is found associated with the power dissipation of hurricanes. Figure 1.2 compares sea surface temperatures with a measure of the destructive potential of storms in the North Atlantic, clearly demonstrating a remarkable correlation between these two quantities. [4]

Global warming undoubtedly results in more frequent and intense heat waves. Figure 1.3 uses a graphical representation of the normal distribution to show that even a modest amount of warming can have a profound impact on the frequency of heat extremes. When the temperature of the planet rises by 1 °C, the Bell curve is shifted to the right, resulting in a dramatic change in the extreme right tail of the distribution.

The observed trends in rainfall and drought around the globe over the past century are fairly heterogeneous. There has been a slight increase overall in the average global rainfall as depicted in Figure 1.4 because the warmer atmosphere can hold more moisture. The

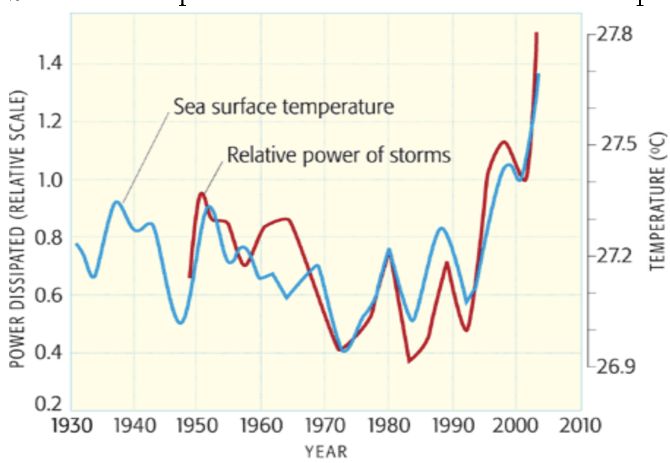
[1] https://climate.nasa.gov/news/2915/the-atmosphere-getting-a-handle-on-carbon-dioxide/
[2] https://www.weather.gov/jetstream/energy
[3] https://scrippsco2.ucsd.edu/graphics_gallery/mauna_loa_record/mauna_loa_record_color.html
[4] https://www.e-education.psu.edu/meteo469/?q=book/export/html/132

Figure 1.1: Observed globally averaged combined land and ocean surface temperature anomaly 1850-20



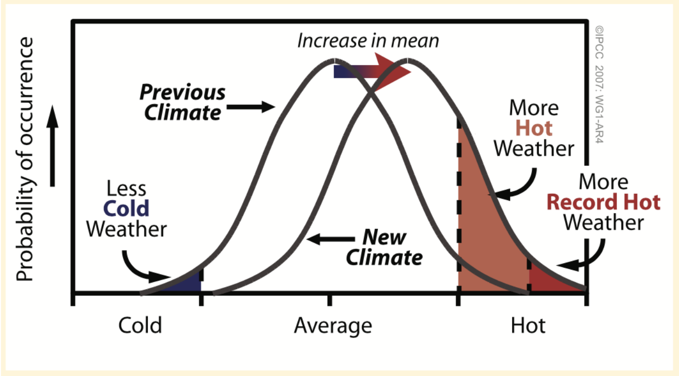
Source: IPCC (2013).

Figure 1.2: Sea Surface Temperatures vs. Powerfulness in Tropical Atlantic Cyclones.



Source: Mann and Kump (2016).

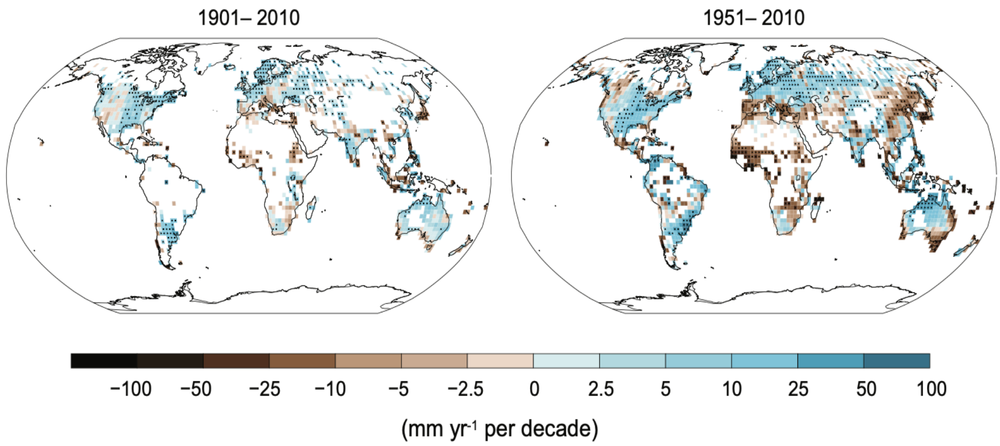
Figure 1.3: Hot extremes become more common



Note: The Bell shape curves shows the effect on extreme temperatures when the mean temperature rises, for a normal temperature distribution. *Source:* IPCC (2007).

patterns of drought reflect not only the precipitation coming down to the surface, but also the loss of moisture back up into the atmosphere through evaporation. The Mediterranean and West Africa are reported to experience higher frequency and intensity of drought since 1950. The IPCC (2007) reported that some regions in the mid latitudes of the earth have experienced worse summer droughts also increases in rainfall as the earth warms up.

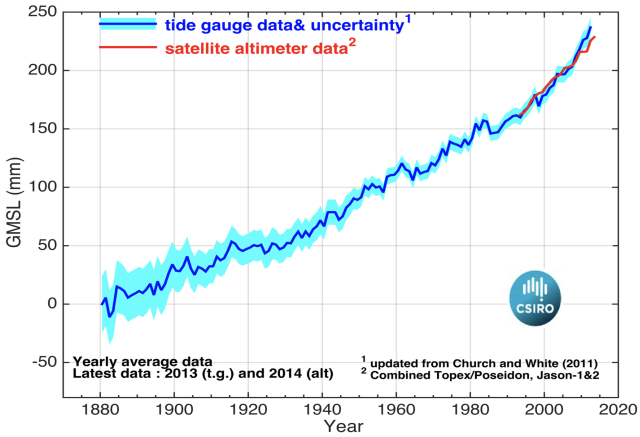
Figure 1.4: Observed change in annual precipitation over land



Source: IPCC (2013).

There is a risk of significant rise in sea level which has dramatic effects on all coastal cities. Multiple sources contribute to sea level rise including the melting of glaciers, the continental ice sheets, the thermal expansion of the sea water. Figure 1.5 presents the global sea level rise since 1880 with tide gauges based on satellite measures of how high the ocean is. The sea level rise is accelerating from roughly 1.3 millimeters per annum for the period 1850 to 1992, to 3.4 millimeters per annum now.

Figure 1.5: Global sea level rise since 1880



Note: Rise of more than 20 cm since 1880, now 3.4 mm per year versus 1.3 per year 1850-1992. *Source:* https://research.csiro.au/slrwavescoast/sea level/sea level-changes/

1.3 Vietnam's climate risk profile

1.3.1 Country overview

Vietnam went through remarkable political changes since Doi Moi reform was introduced in 1986 to create a socialist-oriented market economy. Vietnam had decades of uninterrupted GDP growth with an average annual growth of 5.3 % between 1986 and 2010, the second highest growth rate in Asia after China (Breu et al., 2012). Vietnam has been successful in making a rapid transition from being a low per capita income nation to become a lower middle income nation. The extreme poverty rate (at the poverty threshold of $1.9 a day, PPP adjusted) fell from from 58 % in 1993 to 4.5 % in 2015 (Diez, 2016). Per capita income has been lifted from around $100 USD in the 1980s to about $2,100 USD in 2015 (PPP adjustment amounts to $5,000 USD) .

Vietnam is the world's th13 most populous country in the world. The country experienced high demographic growth, from 62 million in 1986 to 93 million people in 2016 (Diez, 2016). In addition, Vietnam has a very young educated population with a median age of 30 and a literacy rate of about 94 % (Dang and Glewwe, 2017). Vietnam has the highest urbanization rate in South East Asia and the rate continues at a rapid pace. In 1986, just 20 % of the population lived in urban areas, by 2015, the proportion rose to 34 % (Diez, 2016). Urbanization helps the economy become more productive and move forward.

Businesses benefit from knowledge transfers and a more diverse pool of labor.

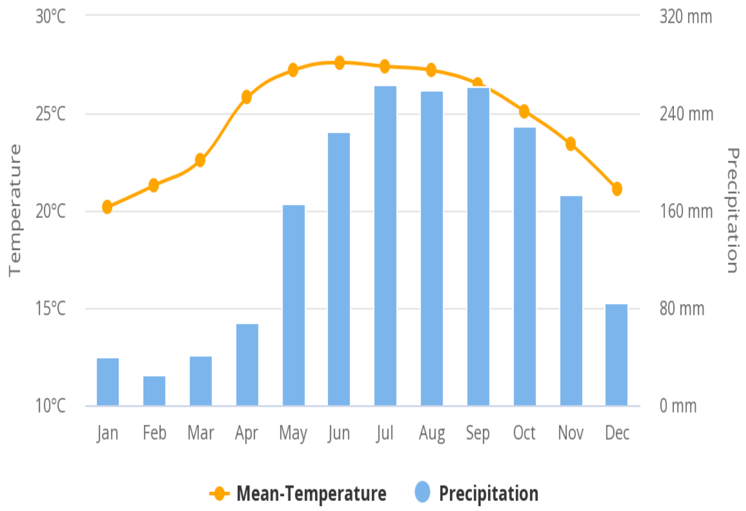
Vietnam's development has been built on an open economy. Trade for Vietnam (the level of exports and imports combined) accounts for roughly 210 % of national output in 2019, more than any other countries with a population of at least 50 million people (OECD, 2021). There has been an impressive green transition from subsistence agriculture to export-oriented agriculture. One crucial achievement for Vietnam is that the country becomes the world's third largest rice exporter after Thailand and India (The Anh et al., 2020).

The country is developing fast but is still under-equipped to adapt to climate change. Economic growth leads to a rise in the living standard, but also an increase in inequalities. In Vietnam, there are still more than 1.8 million people living under 1.9 dollar a day in 2018 (World Bank, 2018). The majority of the labor is in the informal sector and agriculture. The economy has a large share of agriculture, forestry and fishery sector which accounts for over 14.7 % of GDP and 38 % of the labor population (General Statistics Office of Vietnam, 2018). 57.2 % of informal workers are in the non- agricultural sectors in 2016. Natural disaster impact is not equal among different social classes. Informal workers and the poor that lack financial ability to cope with climate change are the most vulnerable groups in society.

1.3.2 Climate baseline

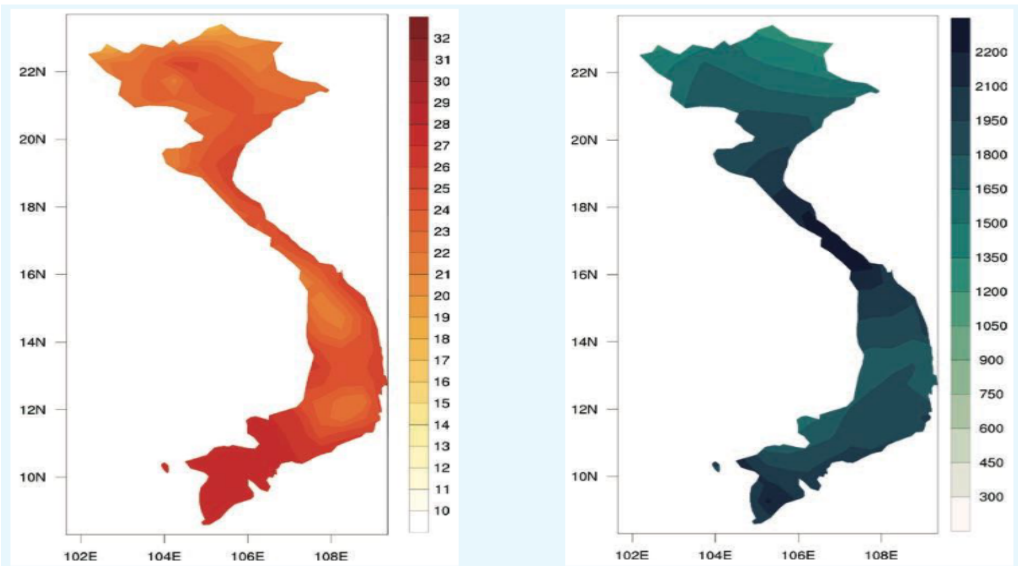
Vietnam has a diverse geography that is very susceptible to natural disasters. This is a huge coastal country that extends over 3,400 km of coastline and is organised around two Deltas: Red River in the North and Mekong River in the South. These two major Deltas are extremely fertile and densely populated low-lands. Moreover, Vietnam is situated on the tropical belt and bordered by the Pacific Ocean to the east, next to the most active typhoon ocean basin in the earth (World Bank, 2010a). Hence, the country can be humid and hot throughout the year, with localized flooding becoming more prominent. The El Niño Southern Oscillation also affects Vietnam's climate including rainfall, temperature patterns, sea level and drought incidences (The World Bank and Asian Development Bank, 2020). The southern region has distinct rainy and dry seasons, with warmer temperature than the northern terrain. The annual average temperatures for southern Vietnam range from 26°C–29°C. In the northern regions, there are four seasons (spring, summer, fall, and winter) in which the annual temperature ranges from 22°C–27.5°C in summer and goes down to 15°C–20°C in winter (see spatial variation of weather in Figure 1.7). Average monthly rainfall can be between 25 (February) and 260 mm (from July to August) as depicted in figure 1.6.

Figure 1.6: Monthly mean temperature and precipitation 1991-2020 in Vietnam



Source: https://climateknowledgeportal.worldbank.org/country/vietnam/climate-data-historical

Figure 1.7: Annual mean temperature (°C) and rainfall (mm) in Vietnam from 1901 to 2019



Source: https://climateknowledgeportal.worldbank.org/country/vietnam/climate-data-historical

1.3.3 Human development impacts

The environment is submitted to intense anthropogenic stresses. A large part of mangrove forests has been destroyed due to urbanisation, intensive shrimp farming and over-exploitation of ecosystems such as bird trapping, fishing, cutting mangroves for wood (McNally et al., 2011; Beresnev and Broadhead, 2016). Economic development and urbanisation also increase related risks for human health and the environment in Vietnam due to more molecules of micro-plastics, agricultural inputs, metals from industrial waste circulating in the air, soil and water [5].

More urgent problem is land subsidence as a result of agriculture and construction works. The over-extraction of groundwater for cropping creates pressure on the soil layers, thereby accelerating land subsidence in the two Deltas. Many areas in the Mekong Delta are experiencing subsidence at a rate of about 1 to 4 centimeters per year. On top of that, there are many hydro power reservoirs upstream, causing the deprivation of the sediment and rampant erosion of riverbanks. The consequences of this stress are also visible in urban zones. Main cities (Ho Chi Minh City, Hanoi) experience the risk of spontaneous flooding from the ground and are sinking at about 4 cm per year (Minderhoud et al., 2018; Erban et al., 2014).

Sediments trapped in dams or extracted from the riverbed for construction purposes also result in soil salinization (International Centre For Environmental Management, 2014). Once the soil is sanitized, it takes years of washing by fresh water to remove the salt from the soil, posing challenges for farmers to grow rice. It is estimated that phenomena such as salinity intrusion have caused a loss of over $43 million USD per year for agricultural production (Vu et al., 2018).

1.3.4 Observed trends of the climate system in Vietnam

According to the World Bank, Vietnam is consider as one of the five country's most vulnerable to climate change (Dasgupta et al., 2007). The most vulnerable areas are the Mekong Delta, the Red River Delta and the Central Coast. Vietnam's climate action

[5] https://th.boell.org/en/2019/11/06/plastic-wastes-pose-threats-vietnams-environment

report for 2015 acknowledged that over the past 50 years, the average temperature in Vietnam has risen from 0.5 °C to 0.7 °C and the sea level has risen by about 20 centimeters. The maximum temperature change ranged from -3.0 ° C to 3.0 ° C, and the minimum temperature change varied from -5.0 ° C to 5.0 ° C, consistent with the global temperature trend seen over the past 50 years (Harvey, 2009; MONRE, 2012).

Higher temperature undoubtedly alters evaporation and precipitation patterns. Both droughts and floods are intensified in Vietnam. In particular, there was a decline in rainfall in northern regions, yet an increase in southern regions for the last 50 years. Rainfall in the northern climate zones experienced minimal change from November to April but dropped from 5 % to 10 % from May to October. Meanwhile, in the southern climate zones, there was a sizable decline in rainfall in the dry season but an increase from 5 % to 20 % in the rainy season.

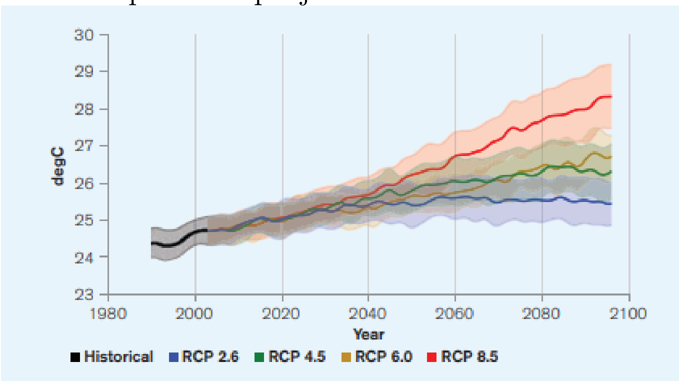
Vietnam is highly exposed to flooding which threatens economic activities and people's livelihoods. Every year, Vietnam encountered a total of 12 tropical storms hit. The Central Coastal areas of Vietnam and the Northern regions are more vulnerable to tropical cyclones. Meanwhile, drought has increased in frequency and severity overall despite significant variation across territories. In particular, given the increased number of hot days, severe droughts happened more frequently in the Central and Southern regions (MONRE, 2012).

1.3.5 Projections

The IPCC used climate scenarios called representative concentration pathways (RCP) to make future predictions of plausible human emitted GHG concentrations. These scenarios (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5) measure the warming effect of increased GHG concentrations as total radiative forcing by 2100. These pathways indicate a range of policies from strong mitigation, RCP 2.6 aimed at maintaining global warming below 2 °C relative to the pre-industrial period, to business as usual RCP 8.5, which could result in to 4 to 5 °C of global warming by 2100. The global information (the ocean, the atmosphere, the ice and the land surface, demographic and energy usage) from the IPCC's integrated assessment models can be zoomed to finer details of small regions of Vietnam to provide more regional climate change projections.

According to the climate change scenarios in Vietnam by 2100, the annual mean temperature in Vietnam is expected to increase by 3.4 °C by 2100 under the business as usual RCP 8.5, three times greater warming under that of RCP 2.6, the lowest emissions pathway as shown in figure 1.8. Projected temperature increases will be greater in southern Vietnam than other parts of the country (Katzfey et al., 2014).

Figure 1.8: Temperature projection in Vietnam from 1980-2010

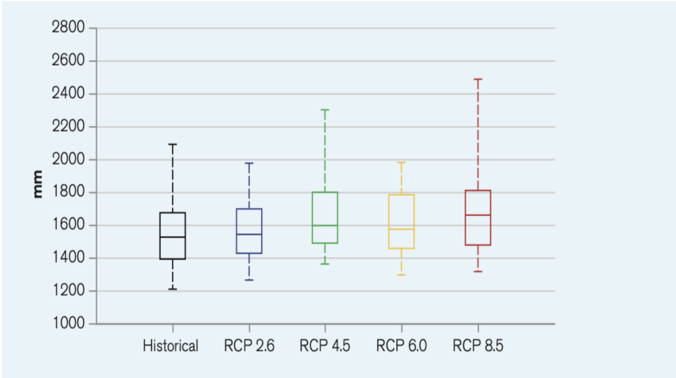


Notes: Historic and projected average annual temperature in Vietnam under RCP 2.6 (blue) and RCP 8.5 (red). The shaded areas showing the 10-90 the percentile. *Source:* https://openknowledge.worldbank.org/country/vietnam

Annual precipitation is projected to increase across all mainland regions of Vietnam (MONRE, 2012). A change in rainfall pattern is expected to increase precipitation during the country's rainy season and decrease it during the dry season. Precipitation is not expected to be uniform across regions. Increased precipitation is expected in the form of fewer but heavier rainfalls in southern and central Vietnam, which might lead to flooding and soil erosion whereas slight reductions are expected to occur elsewhere. Precipitation is projected to increase by 10-20 % by 2045-2065 under both the RCP 4.5 and RCP 8.5 emission scenarios as depicted by figure 1.9.

The average sea level could rise by 26 cm by 2050 and 77 cm by 2100 under the highest emission pathway RCP 8.5 (Tran et al., 2016). Saltwater intrusion in the Mekong Delta is forecast to enter local rivers 30-40 km deeper than the annual average. IPCC scenarios show a high probability that 75 % of the Mekong River Delta be permanently flooded by 2050. (Kulp and Strauss, 2019; Minderhoud et al., 2019).

Figure 1.9: Box plot showing the projected average annual rainfall for Vietnam from 2080-2099



Source: https://openknowledge.worldbank.org/country/vietnam

1.3.6 Climate change impacts on livelihoods and rice production

Natural disasters have cost the equivalent of about 0.8- 1.5 % of Vietnam's GDP annually (World Bank, 2010b). Without major action, this would inundate nearly 10 % of the total national land surface (MONRE, 2012). The epicenter of this vulnerability is Vietnam's densely populated and low-lying Mekong and Red River Delta. Unsustainable use of land and water resources, increasing salinity and erosion along the coastline, ever higher floods as the sea level rises put the economic future of the Delta regions in jeopardy. Cruz et al. (2007) estimates that if the sea level rises by 1 meter, about 5,000 square kilometers of the Red River Delta. About 15,000 to 20,000 square kilometers of the Mekong Delta will be inundated, which could threaten the livelihoods of 4 million people in the Red River Delta and between 3.5 and 5 million people in the Mekong Delta. Many of these Delta households are near poor and dependent on rice farming for their livelihoods, meaning that even small shocks can push them back over the poverty line. In addition, predominantly poor people in coastal areas live in unsafe housing, in part due to rapid urbanization, a lack of suitable employment, and persistent poverty- all of which increase their vulnerability to extreme climate events.

Climate change is a major challenge for rice production. From 2015 to 2016, El Nino event led to extensive droughts especially in the central islands with severe consequences on food securities and livelihoods. Year 2016 was the year with the most serious drought and salinity levels ever in the Deltas, destroying 160 000 hectares of paddy fields [6]. Rising temperatures, more pests and diseases, and more severe drought are predicted to reduce rice production in the 2016-2045 period by 4.3%, compared to production levels in the absence of climate change (Nguyen et al., 2017).

1.3.7 Institutional framework for climate change adaptation in Vietnam

Consequently, the risk associated to climate change has recently become a major political issue in Vietnam. The Vietnamese government understands the severe impacts of climate change as well as the need to implement solutions to address this challenge. Vietnam is one of the signatories to the Paris climate change agreement in 2016 and has figured out many policies focused on addressing investment policy and capacity-building problems. In the Paris agreement, Vietnam has agreed to curtail 8-25% of GHGs produced in agriculture sector[7] and increase the forest coverage from 39.7% in 2011 to 45% in 2030 (MARD, 2012). Vietnamese authorities are mainly seeking risk reduction through the planning of adaptation rather than mitigation. 90% of agricultural expenditure has been allocated to adaptation whereas mitigation efforts received very little support (Nguyen et al., 2017). A large part of the adaptation effort translates into reducing exposure and vulnerability, reflected in a number of strategies programs and action plans in table 1.1 (Nam, 2012).

[6] https://e.vnexpress.net/news/news/mekong-delta-faces-historic-salinity-threat-4062769.html

[7] Vietnam's Intended nationally determined contribution, accessible at the following link: https://www4.unfccc.int/sites/ndcstaging/PublishedDocuments/Viet%20Nam%20First/VIETNAM%27S%20INDC.pdf

Table 1.1: Government strategies and plans on climate change

Strategy/Plan	Priorities	Implementing Legislation
Socio-Economic Development Plan (SEDP) for 2011–2015	Emphasize actions to cope with climate change; increase forest coverage; improve water supply coverage, treatment of industry waste, treatment of solid waste, and prosecute pollution violators.	
	Emphasize response to sea level rise and vulnerability of low-lying coastal regions	
Strategic Orientation for Sustainable Development in Vietnam (2004) (National Agenda 21)	Develop an institutional system supporting sustainable development (e.g., National Sustainable Development Council).	
	Develop local Agenda 21: 6 pilot provinces (Son La, Thai Nguyen, Ninh Binh, Quang Nam, Lam Dong, Ben Tre), 4 pilot sectors (agriculture, fishery, construction, industry)	.
National Strategy for Environmental Protection (NSEP) until 2010 and Visions to 2020 and 5-year action plans	Promote environmental protection, pollution prevention, area-specific environmental management, and biodiversity conservation	Revised Land Law (2003).
		Amended Law on Environment Protection (2005)
		Law on Water Resources.
National Strategy on Climate Change for 2050 and Visions to 2100; National Target Program to Respond to Climate Change (2008)	Focus on construction of coastal breakwaters and irrigation works to combat seawater intrusion.	Benefits of a Climate Change Act being considered by the National Assembly
	Require all sectors and local governments to implement.	Law on Electricity 2004 climate change action plans in areas of responsibility, plus report on progress
		Amended Law on Environment Protection (2005)

National Biodiversity Action Plan to 2010 and Orientations towards 2020	Conserve terrestrial biodiversity; biodiversity in wetlands and marine areas.	Law on Forest Protection and Development 2004 (implemented through the MARD)
	Conserve agricultural biodiversity.	Law on Biodiversity 2009
	Use biological resources sustainably.	Law on Water Resources
	Strengthen state management capacity on biodiversity.	
Second National Strategy and Action Plan for Disaster Mitigation and Management 2001–2020	Stress importance of coexistence with floods in situations that demand it.	Disaster Risk Reduction and Management Law under consideration by the National Assembly.
	Establish disaster forecast centers in the north, center, and south of the country.	
	Construct flood corridors and flood retention areas in southern Vietnam.	
	Design principally to address short-term climate extremes	
Action Plan on Climate Change Response of Agriculture and Rural Development (2011)	Ensure stable agricultural production and food security; the maintenance of dyke and infrastructure systems.	Law on Forest Protection and Development 2004.
	Focus on the Cuu Long and Red River deltas and the central and mountainous areas.	
	Reduce emissions from deforestation.	
Strategic Environmental Assessment, Environmental Impact Assessment, Environmental Protection Commitments	Improve capacity for the review of Strategic Environmental Assessment, Environmental Impact Assessment, and Environmental Protection Commitments for master plans (socioeconomic development plans).	2011 Environment Decree (29/2011/NĐ-CP)
The National Strategy on Disaster Risk Management to 2020 and the Ordinance on Flood and Storm Control	Mandate the creation of provincial and other subnational disaster risk management strategies and plans and establish subordinate provincial and district committees for flood and storm control.	Draft Law on Disaster Prevention for approval in 2012.

1.3.8 Climate change adaptation in the agriculture sector

The agricultural sector in Vietnam has actively implemented many climate change adaptation solutions, with technical assistance and financial support from the international community. This section reviews some notable examples of innovative climate smart farming models.

The mangroves are currently being regenerated and managed in five coastal provinces: Thanh Hoa, Nam Dinh, Quang Nam, Quang Ngai and Ca Mau- thanks to the project " Improving the resilience of vulnerable coastal communities to climate change related impacts in Vietnam", supported by the Green Climate Fund, the Government of Vietnam, and the United Nation Development Program. Since the project started in 2018, more than 3,500 ha of mangroves have been newly planted, restored and seasonably managed. More local people are also recognising the key roles of these green shields and continuously working to protect the mangroves in their communities. The project's livelihood activities have helped to increase outcome for the local people, who are directly involved in regenerating and protecting the forests. [8]

Over the last few years, Directories of Fisheries, Vietnam Fisheries Society, and other organisations such as Oxfarm, GIZ, and FAO have promoted certified shrimp farming in mangrove forests. Shrimp farming with certification in mangrove forests contributes to better management of mangrove forests because one standard of certified shrimp farming is that farmers need to ensure that at least 40% of the farming areas are mangroves (Mcewin and Mcnally, 2014). In terms of ecosystems, certified shrimp farming means not only mangrove forests are protected through the mechanism but also ecosystems dependent on mangrove forests are also protected such as fish and crabs. Clearly, environmental impacts from shrimp farming are reduced. The second aspect is for enterprises because the market for certified organic shrimp has been very stable. Mangrove-shrimp and organic shrimp products are widely popular in European and American markets. Currently, there exists various specification systems for organic shrimp, for instance Naturland, EU organic and other certifications. For the farmers, they can receive greater income by adopting certified

[8]https://www.adaptation-undp.org/projects/improving-resilience-vulnerable-coastal-communities-climate-change-viet-nam

shrimp farming because seafood companies have increased the price of organic shrimp by 20-30% compared to conventional shrimps. In addition, throughout the process of forming new models of shrimp farming in mangrove forests, state management agencies as well as other companies working with certified shrimp farming will provide capacity building training and technical support for farmers throughout the application process.

System of Rice Intensification (SRI) was first introduced in three provinces (Hanoi, Hoa Binh, Quang Nam) in 2003. SRI includes adopting young seedlings (2.5 leaves or 8–15 days old), transplanting one plant per hill ; reducing the use of fertilizer, water and pesticides, etc. 21 of 33 provinces in the Northern region with a total area of 185,065 ha and 1,070,384 farmers have implemented the SRI practices, thanks to the support of The Ministry of Agriculture and Rural Development (MARD) (Van Mai and Lovell, 2017).

The floating rice is very well tolerable to the drought when there is little water. In the flooding season, the rice stalk will grow up by the water level. The floating rice is also well capable of alum tolerance. Besides, the rice grain is delicious, rich of nutrients and healthy. " Integrated Coastal Management Program", which is funded by the Governments of Germany and Australia, and implemented by the MARD has supported An Giang province to develop the Floating Rice Conservation Plan (GIZ, 2018). Accordingly, the area of floating rice will increase up to 500 ha in 2020.

Another example of adaptation can be found in Bac Lieu where 41 rice models have been applying the alternate wetting and drying (AWD) in the framework of integrated coastal management. [9] AWD is a water saving technology that lowland rice farmers can apply to reduce water use in irrigated fields. In AWD, the rice field is allowed to dry for a number of days before being flooded again. Hence, the field is alternately flooded and left dry. The number of days that the field can be left dry depends on the soil type and other field conditions. In the past, irrigation primarily relied on natural rainfall, but now farmers are using AWD techniques to measure water levels that help to increase productivity and decrease the cost of inputs for rice cultivation significantly (GIZ, 2018).

[9] https://snrd-asia.org/integrated-coastal-management-programme-icmp/

1.4 Summary of chapters

1.4.1 Chapter 2

Due to the increased public awareness towards the conservation of mangrove forests, the need for a quantitative measure of the state of mangrove ecosystem in the context of climate change in Vietnam has become more relevant. The study aims to estimate the total economic value for the mangrove forest ecosystems at Xuan Thuy National Park, the Red River Delta. This is a coastal wetland of international importance as habitat for many endangered bird species.

The survey was conducted with 350 households in the five communes constituting the buffer zone, i.e. Giao Thien, Giao An, Giao Xuan, Giao Hai and Giao Lac. The survey was started off with organizing stakeholder participation to understand the existing issues with the coastal landscape and build out a mangrove management planning. The hypothetical scenario with a vision up to 2030 with details of the implementation plan was presented to respondents. The hypothetical scenario needs to be understandable, meaningful and plausible to respondents so that they believe that environmental improvement will happen. Pilot testing and discussing with experts in the public were conducted prior to the main survey to see what worked for the scenario. The payment vehicle was contingent donation to trust fund for biodiversity conservation.

The study contributes to the literature on economic valuation of mangrove ecosystems by using contingent valuation method (CVM) in combination with double-bounded discrete choice (DBDC) questions. CVM is a kind of state preference method that is used to elicit WTP for the overall environmental change based on survey responses to hypothetical scenario (Carson and Hanemann, 2005; Aizaki et al., 2015). CVM studies in Vietnam mainly utilized single-bounded discrete choice question to estimate willingness to pay for the water quality improvement in the Mekong Delta (Phuong and Gopalakrishnan, 2003), flood prevention program (Navrud et al., 2012), conservation of the northern yellow-cheeked gibbon in the Bach Ma National Park (An et al., 2018), mangrove restoration of Thi Nai lagoon, Binh Dinh province (Tuan et al., 2014), mangrove conservation in the Cat Ba

Biosphere Reserve Pham et al. (2018). The DBDC technique in chapter 2 adds additional bid amounts in the survey questions to increase estimation efficiency of community's WTP for the improved environment quality (Hanemann et al., 1991).

The nonparametric estimate of mean WTP for overall changes in mangrove eco-system services is 511,090 VND (22 USD) per household. The mean WTP, calculated assuming the log-logistic distribution, is 619,908 VND (26.63 USD). The total non-use value was estimated at about 6.487 billion VND (or 277,100 USD) per year. These findings suggest that respondents's concern for the environment, income, perception of mangrove benefits could lead to increased acceptance of mangrove restoration when climate change emerges. This information can be used for cost-effectiveness analyses of the different measures proposed. The results of this study emphasise the critical need for local government to raise public awareness of mangrove's importance via media, training programs, etc.

1.4.2 Chapter 3

The applied topic of the paper is a contribution to the relatively sparse literature on valuing the component attributes of mangrove ecosystem services in developing nations. A convenience sample of 145 respondents was profiled to estimate four different WTP models for the maintenance of mangrove ecosystem services at Xuan Thuy National Park. We came up with research questions based on conversations with decision-makers and stakeholders who figured out how to tackle these challenging development, conservation and management issues. Respondents were presented with a series of choice tasks where these levels are presented different amount. The choice experiment presents respondents with three different attributes (mangrove coverage area, storm prevention capacity and biodiversity benefits) of a community project to protect mangroves against climate change.

Discrete choice experiments (DCE) are used in a number of international studies of wetland valuation including Birol et al. (2006) on Cheimaditida wetland restoration in Greece; Rezende et al. (2015) on the case of mangrove conservation in the northern region of Rio de Janeiro state, Brazil; Tan et al. (2018) on the coastal wetland restoration in Ximen Island Special Marine Protected Area, China. In Vietnam, Do and Bennett

(2009) estimated biodiversity values at Tram Chim National Park, a wetland reserve in Mekong River Delta. These studies mainly applied conditonal logit and random parameter logit models to capture preference variation for different types of improved outcomes related to wetland restoration. Chapter 3 exploits four econometric models for robustness checks: conditional multinomial logit (CL), basic random parameter model (RPL), random parameter model with interactions, and generalized multinomial model (GMNL). The random parameter models capture the high level of heterogeneity in household preferences. In particular, the GMNL is an innovation in this analysis to capture various degree of uncertainty across individual decision-makers.

The four different models yield statistically significant parameters for expanded area of the forest, avoided storm damage losses, and payment fees. Results from the fit of the models suggest that there is no consistent association between WTP and biodiversity attributes of mangrove conservation project. However, the standard deviation on the biodiversity coefficient infers that there is a large heterogeneity in individual responses, i.e. some respondents would be willing to pay for higher biodiversity level while others would see the additional biodiversity as a costly option. WTPs for different attributes also vary by respondents' characteristics such as mangrove dependency, education, occupation and knowledge of mangrove benefits. Marginal household WTPs were computed given a change in each attribute level.

The purpose of the analysis was to capture the non-market values of wetland management attributes as well-priced public goods, taking into account the fact that people are different in their choice preferences. The findings help the local understand the existing issues within the coastal landscape and see what is really driving transformation in the mangroves. The findings can be useful for decision-makers to design the details of the implementation plan such as the issue of mangrove care management, success rates, costing, how budget would be allocated for improving different attributes of the ecosystems. Our study stresses the scope for awareness raising through training and education activities because not all local people understand the value of wildlife and biodiversity conservation.

1.4.3 Chapter 4

The chapter explores the impacts of climate change on rice yields and discusses potential implications of climate change adaptation on rice production in Vietnam. The data includes high resolution climate data (precipitation and temperature) beside rice production data for 60 different sub national regions from 1987 to 2015.

Agronomy literature suggests that degree days are a more important predictor of phenological development of the crop during the growing season than the calendar days (Gilmore and Rogers, 1958; Baskerville and Emin, 1969; Snyder, 1985). Growing degree days (GDDs) are computed to indicate the optimal cumulative beneficial temperatures (between 7°C and 29 °C) for the growth of rice whereas killing degree days (KDDs) (above 29 °C) are a metrics for heat stress that delays flowering, fertility and reduces rice yields (Krishnan et al., 2011).

Earlier studies used panel data to identify the causal impact of the short run weather variations on a regional outcome and assumed that the marginal impacts described by the slope coefficients are the same everywhere and every time. Chung et al. (2015) qualifies the rice yield sensitivity to seasonal climate variability in the Central Highland of Vietnam by exploiting the annual time-series of yield, temperature and precipitation from 1986 to 2012. Trinh (2017) utlizes the Ricardian approach to study the household level impact of climate change on land value in Vietnam, using panel data from 2004-2012. Nonetheless, these studies fail to capture the long run adaptation of farmers in the face of climate change that drives the heterogeneity of marginal effects of climate severity on crop yields across regions and years (Kolstad and Moore, 2020). A few studies such as Schlenker and Roberts (2009) developed a model that have time-varying parameters to conclude that adaptation advancements in the United States from 1950 to 2005 made crops more resilient to precipitation fluctuations over time, but not to intense heat. Butler and Huybers (2013)'s approach captures region-specific property of slope parameters on weather statistics to study how adaptation vary significantly across the United States between 1981 and 2008. In our study, beside the traditional "fixed effect OLS" (FE-OLS) models, the “mean observation OLS” (MO-OLS) model recently proposed by Keane and Neal (2020a) is applied to allow both temporal and spatial heterogeneity of marginal yield sensitivity. Following Butler and Huybers (2013), a logarithm specification is added to characterize the diminishing, adverse yield response to KDD due to the net benefit of adaptation.

The FE-OLS models confirm earlier studies that GDD would accelerate crop productivity whereas KDD would do harm to crop. Enhanced rainfall can improve yields, however, the intensified variation of rainfall patterns will adversely affect crop yields. There is a considerable amount of heterogeneity in regions' abilities to adapt. Despite experiencing negative impacts of extreme heat on crops, in warmer parts of the country that are major rice growing areas such as Red River Delta, Mekong River Delta, adaptation efforts on average more substantial and do not see much of a drop off in yields on those extreme hot days. The marginal effect of heat on yield was declining over the time period of study, but recent adaptation has not been observed clearly. Our study also includes a suite of non parametric controls by utilizing Generalized Additive Model (GAM) to overcome the shortcomings of the parametric models for prediction of sensitivity (Wood, 2017a).

The paper delivers the understandings of threats to rice production and the importance of adaptation to unfavorable weather conditions in certain regions to ensure yield resilience in the years to come. An adaptation management along with government's educational outreach programs for farmers are essential to enhance awareness of sustainable practices. Government and other organizations should offer more grants to help farmers replacing conventional techniques with sustainable practices.

Chapter 2

Contingent valuation of willingness to pay for mangrove preservation in Vietnam[1]

[1]This chapter has been published as: Vo, H.T , Nguyen, T.V. and Simioni, M. (2020). Willingness to pay for mangrove preservation in Xuan Thuy National Park, Vietnam: do household knowledge and interest play a role? *Journal of Environmental Economics and Policy*, 9:4, 402-420, DOI: 10.1080/21606544.2020.1716854. A summary of the questionnaire survey of this chapter can be found in the appendix.

2.1 Introduction

While mangrove forests represent a small proportion of the world forests, researchers have placed them among the most important ecosystems on earth (Barbier and Sathirathai, 2004; Barbier, 2011). Mangroves typically grow in tidal coasts and act as a natural buffer zone against flooding, erosion (Prance and Tomlinson, 1987; Blanco et al., 2012). Mangroves also serve as nurseries in a vital food source for marine life while providing critical habitat for endangered species (Polidoro et al., 2010). The leaf litter of mangroves accumulates in the root where it forms a carbon reserve fifty times larger than that captured by a tropical forest (Cummings and Shah, 2018). However, the world's mangroves are found disappearing at an alarming rate, three to four times faster than land-based forests during the past 30 years due to flawed developmental activities (McNally et al., 2011). Since the mid 1900s, between 20% and 35% mangrove forests have been lost worldwide (Polidoro et al., 2010).

Around 34-42% of the world mangrove forests are located in Southeast Asia, the world's largest area of mangroves (Giesen et al., 2007). Vietnam is a tropical country with a coastline of 3,260 kilometers (Quang Tuan et al., 2017). 78% of mangroves are located in the Mekong Delta, the southern end of Vietnam and 28% of mangroves remain in the Red River Delta, in northern Vietnam (Tuan, 2016). The mangrove forests of Vietnam were reported to decline dramatically from around 400,000 hectares in 1943 to 157,500 hectares in 2005 (McNally et al., 2011). The main cause of mangrove degradation in Vietnam included the use of herbicides during the Vietnam wars from 1945 to 1975 and shrimp aquaculture, which boomed since the mid 80s (Beresnev and Broadhead, 2016; Ha et al., 2012; Lan, 2013).

The removal of mangrove ecosystems has had far-reaching economic, social and environmental impacts. Vietnam faces annual monsoon and heavy inland flooding (Francisco, 2008). As sea level rises due to climate change, the impact of the annual floods has increased over recent decades. Many regions have also suffered severe soil erosion. In Kien Giang Province, as well as the Mekong Delta, active and severe erosion was observed, with a coastal retreat of around 25 metres per year at the examined site (McNally et al., 2011). Therefore, Vietnamese authorities with international assistance have implemented several major development projects to promote investment in coastal ecosystems for sustainable development and build resilience in coastal communities. These projects involved rehabilitating mangrove areas through the development of nurseries and planting activities. Special nature reserves were designed to protect the mangroves and wildlife. Furthermore, understanding the environmental and economic value of mangroves is crucial to preserving them. Environmental valuation is a tool used to estimate a marketable price for the quality of services natural ecosystems provided in the absence of a market (Champ et al., 2017). The main purpose of environmental valuation is to find best alternatives that can put the resources needed to maintain a good environment for human benefit.

Our study focuses on recognizing the values of ecosystem services in mangrove forests in Xuan Thuy National Park (XTNP) at the Ba Lat estuary, Nam Dinh province. This typical wetland is selected as the study site because of its international importance as habitat for several endangered bird species. This wetland also brings great economic worth to local community, posing trade-offs between short-term economic gains and long-term ecological, non-use benefits. Hence, a scientific assessment of the economic value of mangrove forests is critical to systematic resource management. The Contingent valuation Method (CVM) (Carson and Hanemann, 2005) is used to determine the economic value of mangrove forests and examine factors influencing willingness-to-pay (WTP) for the conservation of the mangroves and biodiversity in XTNP in the context of climate change. CVM has been used in a number of studies in Vietnam dealing with the water quality degradation in the Mekong Delta due to pesticide (Phuong and Gopalakrishnan, 2003), flood prevention program (Navrud et al., 2012), viral load testing among HIV-positive patients (Nguyen et al., 2017), conservation of the northern yellow-cheeked gibbon in the Bach Ma National Park (An et al., 2018), etc. Only a few studies were interested in the economic valuation of mangrove ecosystem in this country. For instance, Tuan et al. (2014) used CVM with single bounded discrete choice (SBDC) question to show that the mean WTP per household was estimated at 146,700 VND per year for mangrove restoration of Thi Nai lagoon, Binh

Dinh province. Factors significantly affecting household WTP were housing condition and attitude of locals toward future climate scenarios. However, WTP was not significantly affected by most socioeconomic or subjective characteristics of the respondents. The lack of perception indicators of respondents regarding mangroves ecosystem could result in biased estimation of their WTP because mangroves play an essential role for local livelihoods. The study conducted by Pham et al. (2018) was the first one that explored the perceptions of respondents towards mangroves as significant predictors of their WTP for mangrove conservation in the Cat Ba Biosphere Reserve. Apart from socio-demographic indicators such as gender, education level, occupation, other explanatory variables influencing the WTP include respondents' volunteer experience in mangrove conservation activities and attitudes toward climate change impacts. The estimation using the single bounded CVM yielded a mean WTP of 192,780 VND per household.

Our study aims to contribute first to the literature on economic valuation of mangrove ecosystems in Vietnam by using double-bounded discrete choice (DBDC) question. Responses to a SBDC question only reveal if each respondent's WTP value is less than ("no" response) or greater than ("yes" response) the bid amount they received. In a DBDC question, respondents randomly receive an initial bid. If they answer "yes" to the initial bid amount, they receive a higher bid; if they answer "no," they receive a lower bid amount. The DBDC question is a repeated dichotomous choice where a response is required for every bid amount, which is essentially a payment card where respondents indicate their WTP each bid amount, not just the maximum they would pay. This alternative specification of dichotomous-choice questions was proposed to increase estimation efficiency by Hanemann et al. (1991). Compared to SBDC question, adding additional bid amounts in DBDC question reduces the range into which the unobserved values reside. To our knowledge, our study is the first one that relies on DBDC CVM to examine how socio-economic, demographic and subjective characteristics of respondents influence their WTP for mangrove restoration in Vietnam.

The second contribution is to introduce questions about how respondents evaluate the causes of mangrove degradation and perceive the potential benefits occurring from its restoration. This second contribution is in line with the recent paper of Pham et al. (2018) which showed the importance of introducing perceptions of respondents towards mangroves when assessing significant predictors of WTP for mangrove restoration. Therefore, by proposing a more accurate assessment of WTP using DBDC questionnaire and introducing household knowledge and interest as potential determinants of WTP, our study aims to provide a more comprehensive understanding of WTP for mangrove restoration not only in XTNP, but also in Vietnam.

The chapter is organized as follows. Section 2.2 introduces the background of the mangrove ecosystem of XTNP. Section 2.3 presents the methodology used in the paper. Section 3.3 summarizes the main features of data. Results are presented and discussed in section 3.4. Section 3.5 draws some conclusion.

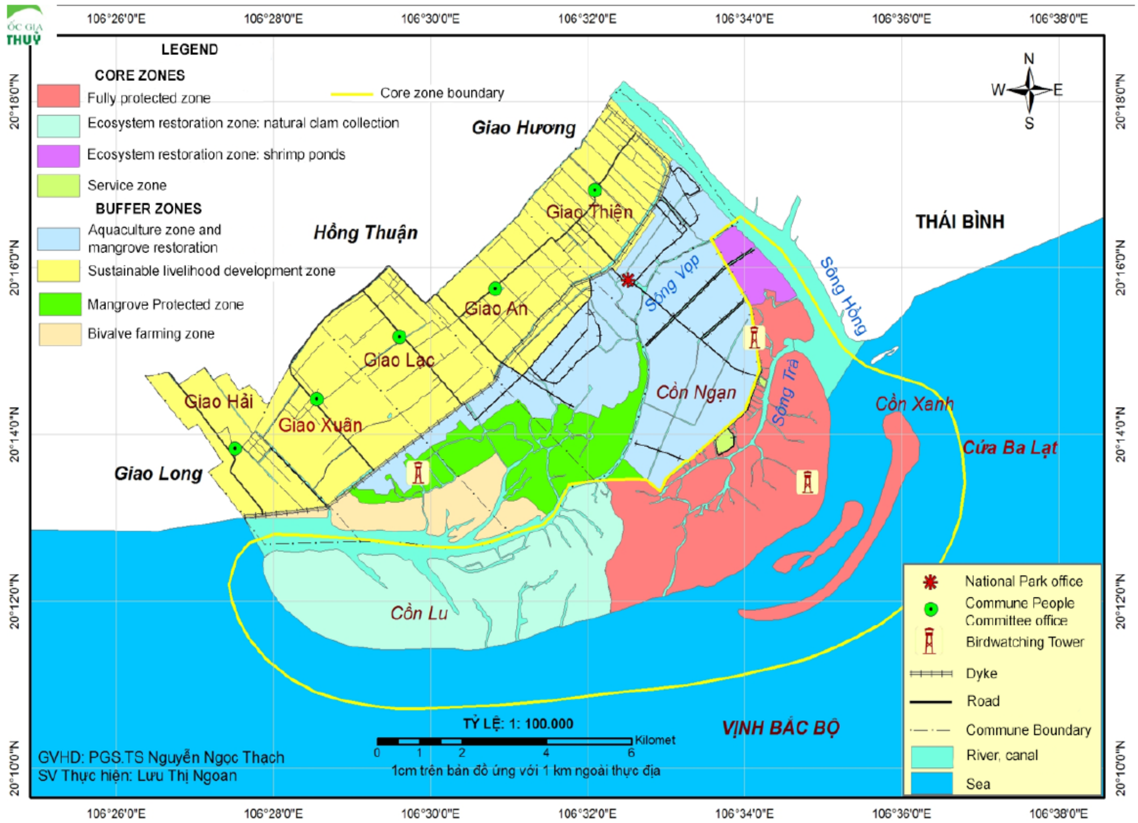
2.2 The mangrove ecosystem of Xuan Thuy National Park

XTNP, the first Ramsar site in South-East Asia approved by the Bureau of the Convention on Wetlands of International Importance, is located in Nam Dinh province, in Red River Delta, Northern Vietnam (Thanh and Yabar, 2015).[2] The park occupies 7,100 hectares of core zone which is strictly protected and 8,000 hectares of buffer zone where human activities are regulated to reduce adverse impacts on the core area (Pham Hong and Mai Sy, 2015). This study was conducted in 5 communes in the buffer zone: Giao Hai, Giao Xuan, Giao Lac, Giao An and Giao Thien (see Figure 3.1).

Today, XTNP is internationally-recognized as a migratory bird habitat, many of them are named in the Red List of Endangered species such as the Black-faced Spoonbill, Spotted Greenshank and Spoon-billed Sandpiper. Besides, the coastal wetland is protected by over 3000 hectares of mangroves and has over 500 aquatic species, 120 species of plant, and 10 mammal species (Leslie et al., 2018). This Ramsar site provides invaluable green economy

[2] The Convention on Wetlands, called the Ramsar Convention, is an intergovernmental treaty that provides the framework for national action and international cooperation for the conservation and wise use of wetlands and their resources.

Figure 2.1: Map of Xuan Thuy National Park and survey sites in 2008
Source: Management Board of Xuan Thuy National Park (2014)



services including food, eco-tourism, protection from floods and storms for 48,000 local inhabitants in the buffer zone (Thanh and Yabar, 2015).

Despite a high biodiversity, XTNP is under serious threat from the degradation of its mangrove forests. According to a report by Vietnam Netherlands Water Partnership On Water for Food and Ecosystem (2008), the period 1986- 1998 indicated a dramatic reduction in the area of the mangroves by nearly 70%, mainly due to intensive shrimp farming. The park officers face challenges to prevent illegal human activities such as bird trapping, fishing, cutting mangroves for wood in the core zone because the wetland still plays a major part in local livelihoods and income. Moreover, the low-lying island has a highest elevation of about 0.5 and 0.9 m above sea level making thousands of locals extremely vulnerable to any storm that hits the coast, particularly in monsoon season (Nhuan et al., 2009). In addition, erosion is happening very rapidly here in which land is being lost up to 14.5m per year. Therefore, the implementation of economic instrument is necessary to value mangrove biodiversity of XTNP for effective management of this wetland.

2.3 Methodology

This section introduces the main features of the methodology used in this paper. The focus is first to put on questionnaire design and survey methodology. Then, we describe the estimation techniques used to assess the mean WTP and study its determinants.

2.3.1 Questionnaire design and survey methodology

Questionnaire design From a theoretical point of view, total economic value of an ecosystem service has two major components: use values and non-use values (Albani and Romano, 1998). There are consumptive uses from natural resources that humans can directly benefit from such as fish or water. There are also non-consumptive uses from these natural resources, for instance, recreation, the matter of knowing these resources are existing for ecosystem functioning, or available for future generations, etc. These non-consumptive uses cannot be transacted in marketplaces. Environmental economists find ways to measure the values that humans derive from these ecosystem services for project implementation purposes and policy development. The CVM is a widely used survey-based approach to place monetary values on environment goods and services not bought or sold in the marketplace (Carson, 2000). The goal of the CVM is to improve the the reliability of the estimate results of non-use values. The CVM builds a hypothetical market using a survey questionnaire to form a scenario that allows respondents to state their WTP in return for improved environmental quality (Aizaki et al., 2015).

To guarantee the applicability of the questionnaire in our study, focus group discussions were held with village heads of the five studied communes, and with XTNP's management board. The scenarios for the mangrove rehabilitation project was also informed by baseline studies and expert's opinions about how we can improve the current situation.

This survey has three main sections. The first section of the questionnaire was designed to understand respondents' perception about mangrove ecosystem services, their perception of global climate change, and biodiversity protection. A major part of this section was to explain the biodiversity of XTNP and the threats to biodiversity. In doing so, respondents were provided with adequate information to decide their valuation on the basis of direct benefits and other non-use benefits that can be gained from the mangroves. Our enumerators therefore proposed the following scenario to survey residents. According to the Tran et al. (2016), a climate change scenario is forecast that by 2030, XTNP would experience a sea level rise of 20 cm and the mangroves would be severely affected. Our enumerators clearly stated the vulnerability of XTNP that were informed by research studies. Pictures of coastal erosion and biodiversity degradation were shown as an visual aid to help respondents understand how vulnerable XTNP would be to sea level rise in the coming decades. The scenario supposed a local project would be carried out from now to 2030 and require all locals to donate money for protecting mangroves and biodiversity in XTNP. Respondents were then asked the amount of cash they would be willing to contribute in a lump sum payment for the project.

In the second section, respondents were asked the elicitation questions, that were the WTP questions. Based on the existing literature review, there are two formats to elicit individual preferences: (1) *open-ended* format : respondents are asked directly what their WTP is, no bid value being suggested ; (2) *close-ended* format: a bid value is proposed to respondents and they can choose whether or not to accept it. In order to determine optimal bid design, a pre-test survey with an open-ended format had been conducted with 20 households in the buffer zone prior to the main survey. In the pre-test survey, household members were invited by the management board of XTNP to take interview with our enumerators at the park office. This pre-test survey ensured that the lowest bid rate and the highest bid value used in the close-ended format of the formal survey were applicable and made economic sense. The results showed that the lowest bid value is 50,000 VND and the highest bid value is 2,000,000 VND.

Our study relied on DBDC contingent valuation methodology. Each respondent was required to answer "yes" or "no" to two sequential bid rates. A respondent accepted the initial bid rate would be proposed a corresponding higher bid rate. If the initial bid rate was refused, a lower bid rate would be proposed subsequently. Therefore, there are four possible responses: (Yes, Yes), (Yes, No), (No,Yes), (No, No) (Hadker et al., 1997; Tseng and Chen, 2008).

The questionnaire was designed so that the information respondents presented on willingness or unwillingness to pay was true and accurate as far as their knowledge was concerned. If people replied that they were willing to pay, then our enumerators recorded that. If this was no, there were follow-up questions to ask why respondents were unwilling to pay. This procedure made sure respondents understood the scenario presented to them and avoided the hypothetical bias that would affect the validity of the results. Reasons for refusing any payment for mangrove conservation included : a) the government should be responsible for conservation, b) the project cannot succeed in preserving biodiversity, c) the funds contributed by respondents might not be used for the right purpose, d) respondents have not made up their mind yet. It is worth noting that respondents with these answers would be removed from the valuation analysis (the protest bid).

Finally, information on demographic and social economic conditions of the survey site was collected for statistical purposes and used as explanatory variables in the regression analysis, in a third section. Enumerators asked respondents questions about their employment status, age, marital status, educational level, etc.

Survey method The survey was conducted in the five communes constituting the buffer zone, i.e. Giao Thien, Giao An, Giao Xuan, Giao Hai and Giao Lac in March and April 2017. In doing so, our study aims to provide an initiative for local engagement in biodiversity conservation. According to Giao Thuy District's Statistical Yearbook in 2015, there are total 12,972 households in the five surveyed communes. To determine a statistically visible sample size for the CVM in this study, the following formula was used to select the total number of surveyed households, or n:

$$n = \frac{N}{1 + N * \varepsilon^2} \tag{2.1}$$

where N is a total number of households in the area, and ε is desired margin of error (Tuan et al., 2014). In this study, the error was fixed at 5%, and, consequently, the survey sample size at 350 households.

Multi-stage sampling was used to select villages and households. At the first stage, two villages were selected by random sampling from the list of villages in each commune. At the second stage, 350 households were surveyed by convenience sampling, i.e. surveying any household in each village without any prior notice given their proximity to enumerators. In the main survey, enumerators were sent to conduct face-to face interviews instead of phone or email survey.

2.3.2 Econometric modelling

Nonparametric estimation Non-parametric and parametric estimation methods were used to measure mean WTP for surveyed households. As WTP is not observable, non-parametric method allows the researcher to consider WTP as a random variable with a particular cumulative distribution function that defines the probability of the WTP being less than a certain threshold. This distribution can be estimated using Kaplan-Meier survival estimator as shown by Turnbull (1976). Then, the mean WTP for mangrove conservation can be seen as the probability of total number of households accepting bid values. The general formula is:

$$\text{Mean WTP} = \Sigma(t_j * f_j)$$

where t_j shows the different bid values and f_j is the change in density (Carson and Hanemann, 2005). In this method, the estimation results completely depend on the statistical characteristics of the observations.

The Kaplan-Meier-Turnbull estimator can be used to compare survival curves across values of a given covariate when this latter is discrete. Testing a difference between the estimated survival functions is then possible using statistical test. However, this test does not provide strong evidence that the considered covariate influences survival because other factors may be correlated with both this covariate and with survival. Thus, the effects of the covariates cannot be modelled explicitly using this estimator.

Parametric estimation There are four potential outcomes per respondent in a DBDC questionnaire, as mentioned before: (Yes, Yes), (Yes, No), (No, Yes) and (Non, No). For each outcome, there is an interval at which WTP belongs. So,

$$\begin{cases} \text{(Yes, Yes)} & \text{indicates that} & WTP \geq b^U \\ \text{(Yes, No)} & \text{indicates that} & b \leq WTP < b^U \\ \text{(No, Yes)} & \text{indicates that} & b^L \leq WTP < b \\ \text{(No, No)} & \text{indicates that} & WTP < b^L \end{cases} \tag{2.2}$$

where b, b^L, and b^U are known values. In contrast to the SBDC model, which results in only one minimum or maximum value for each respondent's WTP, the DBDC methodology allows the construction of a bounded interval, or minimum or maximum bound, of each respondent's WTP, and is shown to improve the asymptotic efficiency of parameter estimates (Hanemann et al., 1991; Nayga et al., 2006).

From the knowledge of the b, b^L, and b^U values and the answer, it is then possible to build the following probabilities:

$$\begin{cases} P^{YY} & \equiv \text{Prob}[(Yes, Yes)] & = \text{Prob}[WTP \geq b^U] & = 1 - G(b^U) \\ P^{YN} & \equiv \text{Prob}[(Yes, No)] & = \text{Prob}[b \leq WTP < b^U] & = G(b^U) - G(b) \\ P^{NY} & \equiv \text{Prob}[(No, Yes)] & = \text{Prob}[b^L \leq WTP < b] & = G(b) - G(b^L) \\ P^{NN} & \equiv \text{Prob}[(No, No)] & = \text{Prob}[WTP \leq b^L] & = G(b^L) \end{cases} \tag{2.3}$$

where $G(.)$ is the cumulative distribution function of a known statistical distribution such as logistic, normal, or Weibull.

The format of Eq. (2.4) is used to display the WTP function:

$$\log WTP = X\beta + \varepsilon \tag{2.4}$$

where X is a vector of explanatory variables, including initial bid (in logarithm), β, a vector of parameters to be estimated, and ε, the error term.

For a sample of n independent observations, the log-likelihood can be expressed as follows

$$\ln L = \sum_{i=1}^{n} \left[d_i^{YY} P_i^{YY} + d_i^{YN} P_i^{YN} + d_i^{NY} P_i^{NY} + d_i^{NN} P_i^{NN} \right] \tag{2.5}$$

where d_i^{AA} indicates whether respondent i answered (A, A) with $A = Y, N$ (dichotomous variable). Estimates of parameters β can be recovered by maximizing the log-likelihood given in Eq. (2.5).

2.4 Data

2.4.1 Individual characteristics

Table 3.3 shows the socio-demographic characteristics of the respondents. In this study size, the number of female participants (52.3% of the 350 respondents) is slightly greater than the number of males, reflecting gender balance in the survey. The respondents aged over 45 account for almost 60% of the total sample, dominating the age distribution of respondents in the sample. This indicates that while younger generations are leaving villages for work, the middle-aged and elderly (over 45) tend to work in the villages. Married individuals make up 92.8 percent of the sample. Most respondents in the survey (94.5%) reported that they were born in Giao Thuy District. The survey indicates a sample with a low education level, given that 92% of the respondents could complete high school. In this study, there are four main categories of jobs: farmers working in the aquaculture or agriculture sector, business owners, and hired employees at public or private sectors. These main labor force groups account for 89.5% of the total sample. The remaining sample consists of students, retirees, housewife, and unemployed. Over one-third of the respondents (38%) has a monthly household income of lower than 3 million VND (about 129 USD), followed by 28.8% receiving between 3 and 6 million VND (about 129-258 USD), and 22.7% in the range between 6 and 10 million VND (about 258–430 US$). And only 10.5 % of respondents has a monthly income of over 10 million VND (about 430 USD). Furthermore, the majority of respondents (81.3%) said that their household's income partially or totally depent on the mangrove ecosystem. Average household size in the sample is about 3.71

and can represent normal family size in Nam Dinh Province. The largest household has 10 people and the smallest household has 1 person. Finally, less than one-third (28.5%) had their field of career or study very related to environment and biology and more than one-half (53%) showed strong interest in environmental conservation activities.

Table 2.1: Socio-demographic characteristics of the respondents

	Category	**Frequency**	**Percentage**
Gender	Female	183	52.3
	Male	167	47.7
Age	18-25	29	8.382
	26-35	54	15.6
	36-45	57	16.5
	46-55	76	22
	>= 56	130	37.6
Marital Status	Married	324	92.8
	Single	25	7.2
Born in Giao Thuy district	Yes	328	94.5
	No	19	5.4
Education	Below high-school	320	91.9
	High-school or above	28	8.1
Career	Farmer/Fisherman	224	64.5
	Business owner/Self-employed	27	7.7
	Public sector employee	16	4.6
	Private sector employee	44	12.6
	Students	7	2
	Retired/Housewife	27	7.8
	Unemployed	2	0.6
Household Size	1	21	6.1
	2	63	18.3
	3	65	18.8
	4	90	26.1
	5	73	21.1
	6	26	7.6
	7	4	1.2
	9	2	0.6
	10	1	0.3
Monthly Income of household (million VND)	Low income (Up to 3)	132	38
	Lower middle (Between 3 and 6)	100	28.8
	Upper middle (Between 6 and 10)	79	22.7
	High income (Over 10)	34	10.5
Environmental work	Not at all	181	52.1
	Slightly related	67	19.3
	Very related	99	28.5
Passion for environmental protection	No	30	8.6
	Like a little	133	38.3
	Like a lot	184	53
Mangrove dependency	Yes	65	18.7
	No	282	81.3

2.4.2 Local awareness about mangrove restoration in Xuan Thuy National Park

Table 3.4 shows respondents' perceived benefits for local communities from mangrove ecosystems. Over 60% of respondents believed that the mangroves in XT help mitigating flooding, storms and soil erosion. The results also indicate that a major number of the respondents have realized the vital roles of mangrove ecosystems in their livelihood, including a necessary supply of aquatic products, raw material for production and consumption. Table 3.5 displays the local perception of mangrove degradation. Human activities such as aquaculture, fishery, etc. (40%) were perceived to be the major threat to mangrove forests. Table 3.6 shows reasons for protection in Ba Lat estuary. First, respondents were given clear demonstration of how the mangroves in Ba Lat estuary has changed from time to time and were provided with various scenarios of the mangroves in the context of climate change . Respondents were asked to rate the importance of reasons to protect the mangroves, on a scale from 1 to 5, with "1 = Not at all important", "2 = Not so important", "3= Neutral" , 4= important", and "5= very important". Respondents were also left with the choice of not being able to evaluate. These results suggest the two most important reasons are preventing the coastlines against floods, erosion, salinization and providing benefits for future uses. Conserving biodiversity is the third most important reason for mangrove rehabilitation.

Table 2.2: Perceived benefits from mangrove forests

Benefits from mangrove forest	**Percentage**
Aquatic products, raw material for production and consumption	42.6
Recreation, tourism	7.1
Prevention of storms, floods, tides, and coastal erosion	61.1
Underground water protection, preventing salinization	7.4
Climate regulation, carbon dioxide absorption	17.7
Preserving silt, sea encroachment	11.7
Habitat for fish and animals	22.6
Biodiversity	10
Cultural values	0.9
Other	10
Do not know	16

Table 2.3: Perceived causes of mangrove degradation

Reasons	**Percentage**
Human activities: aquaculture, fishery, etc.	40.9
Pollution	13.40
Climate change	18.60
Other	5.70
Do not know	2.00

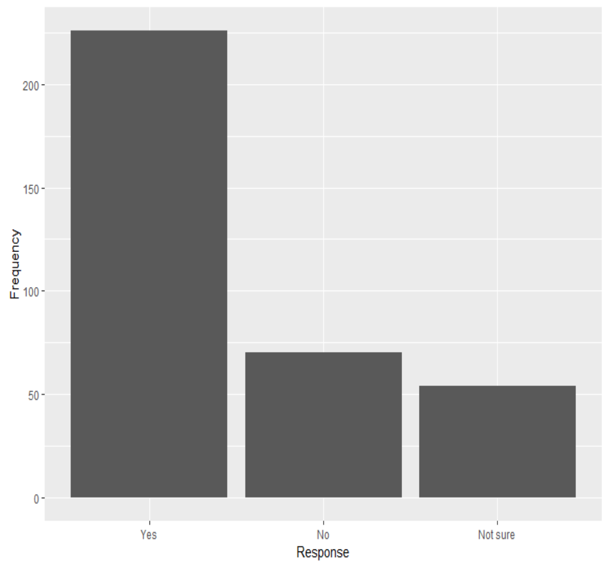
Table 2.4: Perceived motives for mangrove conservation

Reasons	**Not at all important**	**Not so important**	**Neutral**	**Important**	**Very important**	**Can not evaluate**
Providing wood, fish and raw materials	8.3	11.1	20.6	46.9	10	3.1
Providing recreation	4	12.3	20.3	52	10	1.4
Preventing floods, erosion, salinization	0	0	2.6	15.4	81.4	0.6
Conserving biodiversity	3.1	10.3	14.6	58.6	11.4	2
Benefits for future uses	2.3	6.6	9.7	52.4	28.4	0.6

2.4.3 Bid responses

The interviewers randomly selected 350 respondents. Answers from 226 respondents were used in estimating WTP after excluding protested zero-bids: 70 respondents who were not willing to pay to protect mangroves, and 54 who answered they were not sure. Table

Figure 2.2: Willingness to pay responses



2.5 gives the main reasons for respondents' being willing or unwilling to pay. The most important reason for WTP for mangrove restoration is that mangrove restoration is a good program for their own benefit (70.4%). About 57.5% of the respondents believed that their contributions now would bring benefit for future generation. On the other hand, the main reason for not being willing to pay for the restoration of mangroves was household income constraints, accounting for 37.9% of the negative responses; followed by the statement that the project is likely to fail (11.3%). 9.3 % of the respondents did not agree to pay because they thought that only those who had direct benefit from the program should finance. About 29.8% of respondents provided other answers not listed in the questionnaire such as the need for more information, depending on other people's contributions, etc.

Table 2.5: Reasons for being willing to pay and for not being willing to pay.

Reasons	**Percent**
Respondent's reasons for being willing to pay	
The program is good for my own sake	70.4
The program is good for the next generation	57.5
The program is necessary for preserving culture, beliefs	5.8
The program is good for the whole society	34.1
Others	9.7
Respondent's reasons for not being willing to pay	
My family has no money to contribute	37.9
The biodiversity in this area does not mean much to my family	4.8
I am afraid my family contribution shall not be used properly	6.5
I do not believe in the success of the project	11.3
Biodiversity conservation is the sole responsibility of the local authority	0.8
It is the beneficiary who should finance	9.7
Others	29.8

Table 2.6 shows how bid rates were presented to respondents. For each respondent, the interviewer made a random selection of A, B, C or D options. If the respondent did not accept the first bid rate in column 2, the interview was followed up with a proposal of smaller bid rate (initial bid divided by two) as shown in column 3. If the first bid rate was accepted, the second bid rate was doubled, as shown in column 4.

Table 2.6: Bid options proposed to respondents.

Options	**Initial bid** or b	**Lower bid** or b^L	**Upper bid** or b^U
A	100,000	50,000	200,000
B	300,000	150,000	600,000
C	500,000	250,000	1,000,000
D	1,000,000	500,000	2,000,000

Table 2.7 displays the distribution of the answers of respondents in (Yes, Yes), (Yes, No), (No, Yes), and (No, No) for each bid option, and for all options without distinction between them. No clear pattern appears when reading this table except that, when the initial bid rate increases, the percentage of respondents accepting both the first and second

bid rates decline from 44.3% to 11.1% , and, conversely, the percentage of respondents refusing both the first and second bid rates increase from 18% to 44.4%.

Table 2.7: Distribution of responses by bid option

Bid options	**Yes-Yes**	**Yes- No**	**No- Yes**	**No- No**
A: (100.000; 50.000 ; 200.000)	44.3% (27)	29.5% (18)	8.2% (5)	18.0% (11)
B: (300.000; 150.000 ; 600.000)	26.9% (14)	36.5% (19)	13.5% (7)	23.1% (12)
C: (500.000; 250.000 ; 1.000.000)	19.0% (12)	30.2% (19)	15.9% (10)	34.9% (22)
D: (1.000.000; 500.000 ; 2.000.000)	11.1% (7)	28.6% (18)	15.9% (10)	44.4% (28)
All options combined	25.1% (60)	31.0% (74)	13.4% (32)	30.5% (73)

Note: Frequency counts are in parentheses.

2.5 Results

2.5.1 Non-parametric estimation

The Kaplan-Meier Turnbull nonparametric approach was used to estimate the proportion of respondents willing to pay falling into the intervals defined by the different monetary thresholds (Turnbull, 1976). The change in density occurring in each interval was used to determine the lower bound estimate for the mean of WTP by multiplying the density estimated to be in each interval and the lower endpoint of the interval. Table 2.8 shows then that about 13.1 % of the respondents fall into the interval 0 to 50,000 VND, and about 7.4 % were willing to pay over 2,000,000 VND, and that the median falls into the interval 300,000-500,000 VND. The nonparametric estimate of mean WTP is 511,090 VND (22 USD) per household. As emphasized by Carson and Hanemann (2005), this value provides a lower-bound to mean WTP for mangrove preservation in XTNP.

Table 2.8: Turnbull estimation results

Lower bound (t_j)	**Upper bound**	**Probability of being greater than upper bound**	**Change in density** (f_j)	**Mean WTP**
0	50,000	0.869	0.131	0
50,000	100,000	0.81	0.059	2950
100,000	150000	0.745	0.065	6500
150000	200,000	0.596	0.149	22350
200,000	250000	0.596	0	0
250000	300,000	0.596	0	0
300,000	500,000	0.476	0.12	36000
500,000	600,000	0.263	0.213	106500
600,000	1,000,000	0.263	0	0
1,000,000	2,000,000	0.074	0.189	189000
2,000,000	∞	0	0.074	148000

2.5.2 Parametric estimation

The empirical interval regression model based on Eq. (2.4) is as follows:

$$\begin{aligned} \ln \text{WTP} = \; & f(\text{Initial Bid, Gender, Age, Household size, Education,} \\ & \text{Income, Knowledge, Passion}) + \varepsilon \end{aligned} \tag{2.6}$$

where ln WTP is the WTP for mangrove preservation (in logarithm). The definitions for all explanatory variables used in Eq. (2.6) are presented in Table 3.3. Results of estimation by maximum likelihood of the corresponding model with different assumptions about the cumulative distribution function $G(.)$ are reported in Table 3.8.

We first tested if the introduction of the individual characteristics in addition to initial bid, was statistically meaningful. We performed a likelihood ratio test comparing the estimated model with a model where the values of the parameters associated to individual characteristics were all fixed to zero. The p-value for log-logistic (0.014), log-normal (0.009), and Weibull (0.003) clearly indicate the rejection of the null hypothesis that all the latter parameters are equal to zero.

Although the estimated coefficient of an independent variable does not directly measure the marginal effect of that variable on WTP, the sign of the estimated coefficient does

Table 2.9: Description of variables.

	Variable	Description	Value
1	Probability	The probability of a respondent being willing to pay for mangrove forest restoration	1 =Yes WTP 0 = No WTP
2	Bid	Bid levels (thousand VND) [a]	Option A (100; 200; 50) Option B (300; 600; 150) Option C (500; 1,000; 250) Option D (1,000; 2,000; 500)
3	Age	Age of respondent	Numeric variables
4	Gender	Gender of respondent	1 = Male 0 = Female
5	Education	If respondent was educated to high-school level or above	1 = High-school or above 0 = Otherwise
6	Hhsize	Number of members of each households	Numeric variables
7	Knowledge	Respondent has knowledge about benefits of mangroves	1 = Yes 0 = No
8	Passion	Respondent is interested in activities for environmental conservation	1 = Yes 0 = No
9	Income	Total household income per month (million VND)	1 = Up to 3 2 = Between 3 and 6 3 = Between 6 and 10 4 = Between 10 and 15 5 = Over 15

[a] 1 USD is equivalent to 22,300 VND.

indicate the direction of the effect, as emphasized by Knapp et al. (2018). The estimation results were found to be highly consistent in three model specifications. Table 3.8 indicates that the signs and significance of the parameters in the three specifications are relatively similar. As expected, we found a significant negative impact of the initial bid on WTP. This result corroborates the observation made when reading Table 2.7. Characteristics of respondents such as gender, age, household size and education did not appear to have an impact on WTP. Only respondents belonging to upper middle and higher income classes seemed ready to pay for mangrove restoration.

The results reveal two additional important facts. First, the passion of respondents for environmental protection activities was found to have a positive impact on respondent WTP for mangrove restoration, implying that the interest in improving climate scenarios led to a respondent being willing to pay more. This finding is consistent with Pham et al. (2018) that volunteer experience in conservation activities has a positive influence in explaining WTP for mangrove rehabilitation project. Second, the respondent's knowledge about the benefits of mangroves allowed respondents to better appreciate mangroves, modifying Pham et al. (2018) the perceptional determinants of WTP for mangrove restoration.

The results of the interval regression estimation provide estimates of the mean and median values of WTP as by-products. Table 3.9 reports the estimated values of truncated mean, adjusted truncated mean, and median WTP for the three specifications.[3] Confidence intervals can then be computed using nonparametric bootstrap technique.[4] For instance, maximizing the likelihood function under the assumption of a log-logistic distribution results in estimates of 619,908 VND (26.63 USD) for the truncated mean WTP, 639,967 VND (27.49 USD) for the adjusted truncated mean, and 358,559 VND (15.41 USD) or the median WTP. Here, the estimation results were also found to be highly consistent for

[3] Details about the computation of these estimates are given in Aizaki et al. (2015). Truncated (at maximum bid) mean estimates are computed to avoid (i) having infinite value when the estimated value of initial bid parameter is lower than one, or (ii) getting some portion of the respondents who have an estimated WTP greater than their income. The adjusted truncated mean makes use of the normalization proposed by Boyle et al. (1988). This normalization allows to set the value of the cumulative distribution function of WTP as soon as WTP is greater than the maximum bid, to one.

[4] The bootstrap method resamples the data at our hands and repeatedly estimates the model with the bootstrapped data to formulate an empirical distribution of the associated WTP. See Hole (2007) for more details. The number of bootstrap replications can be chosen following Davidson and MacKinnon (2000).

the three specifications. Estimated confidence intervals for each of the three measures: truncated mean, adjusted truncated mean, and median, overlap. The total non-use value from the restoration of the mangrove ecosystem in Ba Ria estuary can then be calculated by multiplying mean WTP per household (619,908 VND) by the total number of households (10,465) living in the in Ba Ria estuary in 2015. Table 3.9 displays the computed results for mean WTP, their confidence intervals and total non-use value of mangroves across the three models. In the log-logistic specification, the total non-use value was estimated at approximately 6.487 billion VND which is equivalent to about 277,100 USD per year.

Table 2.10: Maximum likelihood results

Variable	**Log logit**	**Log normal**	**Weibull**
Constant	14.913(1.489)***	8.919(0.835)***	10.867(1.005)***
Log(bid)	-1.237(0.101)***	-0.74(0.056)***	-0.868(0.069)***
Gender	-0.103(0.279)	-0.114(0.163)	-0.048(0.169)
Age	-0.005(0.01)	-0.003(0.006)	-0.003(0.006)
Household size	-0.053(0.096)	-0.032(0.057)	-0.02(0.056)
Education	0.279(0.433)	0.134(0.256)	0.145(0.288)
Income: Lower middle	0.205(0.348)	0.139(0.204)	0.191(0.218)
Income: Upper middle	0.528(0.375)	0.365(0.221)*	0.333(0.228)
Income: High	0.794(0.476)*	0.481(0.276)*	0.568(0.305)*
Knowledge	0.677(0.383)*	0.385(0.227)*	0.44(0.229)*
Passion	0.812(0.277)***	0.508(0.163)***	0.555(0.17)***
Observations	227	227	227
Log likelihood	-306.067	-305.199	-300.864
LR test statistics (p-value)	0.014	0.009	0.003

Note: Standard errors are in parentheses, and *: p<0.1; **: p<0.05; ***: p<0.01.

Compared with other mangrove valuation studies in Vietnam, our non-parametric and parametric estimates of mean WTP per household (511,090 VND and 619,908 VND, respectively) are much higher than those of Tuan et al. (2014) (131,670 VND and 146,700 VND, respectively) and Pham et al. (2018) (only parametric mean WTP was reported at 192,780 VND). The discrepancy could be mainly attributed to the lump sum payment for

Table 2.11: Mean WTP

	Log logit	**Log normal**	**Weibull**
Truncated Mean WTP	619,908.457[a]	607,333.742	592,294.639
	[506,422; 701,113][b]	[515,877; 689,005]	[497,088; 675,590]
	6,487,342,003[c]	6,355,747,610	6,198,363,397
Adjusted truncated Mean WTP	693,966.997	672,705.172	628,172.846
	[547,087; 803,778]	[553,183; 794,871]	[517,606; 741,085]
	7,262,364,624	7,039,859,625	6,573,828,833
Median WTP	358,559.672	346,233.245	391,307.789
	[274,635; 444,357]	[274,715; 429,994]	[308,592; 476,886]
	3,752,326,967	3,623,330,909	4,095,036,012

[a] Computed mean WTP in VND.
[b] 95% confidence intervals are computed with 299 bootstrap replications.
[c] Computed total non-use value of mangroves in VND

each household in our hypothetical scenario whereas the annual payment per household was requested in other studies. The DBDC format in our CVM survey is also noteworthy, producing a better data set and more precise results of WTP estimates. Furthermore, the environmental context of XTNP with more endangered bird species, higher biodiversity values and greater threats of climate change possibly resulted in an increase in yes responses, raising the demand for mangroves forest rehabilitation.

2.6 Conclusion

This research is motivated by the idea that mangrove ecosystem restoration can generate a variety of benefits to human such as carbon sequestration, erosion control, water purification, flood prevention, wildlife habitat, etc. However, many of these benefits are not valued by markets. In addition, mangroves are one of the most threatened ecosystems in Vietnam, and yet there exists few quantitative information on the value of mangroves in Vietnam. This paper used CVM with DBDC questionnaire, to assess the economic value of mangroves at XTNP in the context of climate change. Specifically, it explored the determinants of WTP for improved management of mangroves. Mean WTP was first estimated using either nonparametric or parametric methods. The parametric model gave an estimate of 619,908 VND per household, while the non-parametric model produced a lower bound for mean WTP of 511,090 VND per household. These results suggest that the total non-use value of mangrove in XTNP is estimated at 6.5 billion VND, with a lower bound of 5.3 billion VND. Second, factors affecting people's WTP were found to be income, perception of mangrove benefits and concern for the environment. People with high income, having good understanding of the mangrove benefits or showing strong interest in environmental conservation activities would likely to pay more. The findings provide decision-makers with the true cost of converting mangroves to short-term profitable alternatives, while taking into account indirect economic, ecological and social benefits of mangroves. The study also sets out important policy guidelines including strengthening the role of the mangroves via mass media, especially newspapers and television to raise public awareness of mangrove value. In addition, locals should be given environmental training programs that encourage them to adopt sustainable behaviors and engage their interests in conservation activities.

Chapter 3

Valuing mangrove conservation attributes in Red River Delta, Vietnam: A choice experiment approach[1]

[1] A more simplified version of this chapter has been recently submitted and accepted at Marine Resource Economics journal. The simplified version only includes the Conditional Logit and the basic Random Parameter Logit model whereas this chapter exploits four econometric models: conditional multinomial logit, basic random parametermodel , random parameter model with interactions, and generalized multinomial model for robustness checks. Chapter 2 and 3 are meant to be readable independently of one another and hence, include some minor repetition.

3.1 Introduction

Mangroves are remarkable forests that play an essential role in protecting the community from storm, reducing impact of flooding and coastal erosion in the intertidal zone (Prance and Tomlinson, 1987; Blanco et al., 2012; Menendez et al., 2020). These forests have extensive root systems that not only form a great carbon reserve but also serve as an important nursery ground for marine organisms (Cummings and Shah, 2018; Polidoro et al., 2010). In addition, mangroves also support local livelihoods by providing timber, foodstuff, raw material for traditional medicine (Millennium Ecosystem Assessment, 2005; Veettil et al., 2019). However, there has been a drastic reduction of coastal wetlands in the world due to natural factors and human actions that claimed coastal wetlands for agricultural and industrial development. Since the mid 1900s, 20% to 35% mangrove forests have been lost worldwide, three to four times faster than land-based forests (McNally et al., 2011; Polidoro et al., 2010).

It has been stated that around 34 to 42% of the world mangrove vegetation is located in Southeast Asia (Giesen et al., 2007). Vietnam has a long coastline of 3,260 kilometers, providing a supporting ground for mangroves with high ecological and economic importance (Quang Tuan et al., 2017; Hung et al., 2020). Mangrove forests are found more extensive in the south and north than those in central Vietnam. A recent evaluation of global flood reduction benefits from mangroves in the world shows that Vietnam ranks first in terms of protected population (7.02 millions out of a total Vietnamese population of 97.09 millions of inhabitants), second in terms of averted land flooding (3,120 out of 331,210 km^2), and sixth in terms of property benefits that stem from protecting assets in exposed coastal areas (6.45 billions US dollar, or 3.14% of GDP) (Menendez et al., 2020).

Nevertheless, it was reported that 61% of mangrove forests have been lost in recent decades in Vietnam (Veettil et al., 2019; McNally et al., 2011). Prior to the Vietnam war in 1943, mangrove forests in Vietnam were reported to cover an area of 400,000 ha. The use of herbicides during the Vietnam wars from 1945 to 1975 destroyed more than 100,000 ha of mangrove forest (Veettil et al., 2019). The rise of shrimp farming since the mid 80s caused further destruction of mangrove forests. In 2005, only 157,500 ha of mangrove forests were found (McNally et al., 2011).

The removal of mangrove forests has undoubtedly led to many undesirable consequences such as decreasing the amount of clean water and organism as well as making local residents living near the coastline more susceptible to hurricanes. Mangrove degradation also speeds up soil erosion which leads to a coastal retreat of around 20 to 40 metres per year observed in coastal regions such as Kien Giang Province, the Mekong Delta (McNally et al., 2011).

Non-market values of mangrove ecosystem services such as the ability to lessen the damage from storms, the prevention of coastal erosion, the protection of bird habitats play an important role in maintaining mangroves for the future. These values could provide a baseline not only for climate change mitigation actions to decrease national carbon footprint but also national climate change adaptation plans to reduce flooding risks and enhance the local economy's resilience. However, measuring these values is not straightforward because the market settings for environmental goods are often absent.

Revealed preference and stated preference methods are two major non-market valuation techniques to measure the environmental goods and services. Some wetland ecosystem services such as recreation and tourism could be valued using revealed preference methods. However, our objective is to estimate the willingness to pay (WTP) for non-use values which can be accomplished at best by stated preference methods such as contingent valuation method (CV) and discrete choice experiment (DCE). Contingent valuation (CV) is a method of estimating the willingness to pay (WTP) for overall changes in the ecosystem service. For instance, Hung et al. (2020) recently used the contingent valuation method with double-bounded dichotomous-choice to elicit WTP for mangrove ecosystem restoration in Xuan Thuy National Park, Vietnam. The study found that income, perceived knowledge of mangrove benefits and interest in conservation activities influence WTP.

Discrete choice experiment (DCE) with more voices at the forefront of literature reveals WTP for changes in the component attributes of mangrove ecosystem services (Holmes et al., 2017). The existing wetland valuation studies that use discrete choice experiments include those by Birol et al. (2006) on the case of Cheimaditida wetland restoration in

Greece; Rezende et al. (2015) on the restoration of mangrove forest in the northern region of Rio de Janeiro state, Brazil; Tan et al. (2018) on the coastal wetland restoration in Ximen Island Special Marine Protected Area, China. In Vietnam, only one choice experiment was conducted by Do and Bennett (2009) to estimate biodiversity values at Tram Chim National Park, a typical wetland ecosystem in Mekong River Delta. The study applied conditonal logit and random parameter logit models to capture taste preference heterogeneity for different types of improved outcomes (mangrove coverage, the number of Sarus Cranes, the number of bird species, the number of households affected) associated with wetland restoration. Individual characteristics such as age, education, household income, knowledge of the study site, perceived benefits of mangrove values for future generations were found to affect the WTP for wetland conservation program.

This paper aimed to trace out local preferences by examining how people responded to different types of outcomes associated with mangrove conservation programs at Xuan Thuy National Park (XTNP) at the Ba Lat estuary, Nam Dinh province, in north of Vietnam. The park was chosen as a study site because of its coastal protection capabilities and diverse wetland ecological system that are particularly important in the socio-economic development of the Red River Delta region. XTNP is also an incredible natural spectacle with thousands of wild birds migrating from the north to the park each year.

The study will contribute to the growing literature on mangrove valuation by applying the generalized multinomial logit (GMNL) to explore respondents' preference heterogeneity, in particular, scale heterogeneity to reflect how the degree of certainty of choices varies across individuals. Furthermore, there is scant information on the values of wetlands in the Red River Delta. Hence, this study is necessary to reflect the relative values of resources in alternative wetland management in the region. We employed direct non-market valuation approach for valuing environmental goods by creating hypothetical markets where respondents were asked to state their preferences for improved environmental quality (Champ et al., 2017). Households valued access to mangrove ecosystem services with many benefits expressed in economic terms as household WTP in exchange for better mangrove ecosystem services. The findings will advise policy-makers to take important conservation measures to ensure wetland expansion, maintain coastal protection and preserve habitat for bird species.

The chapter is structured as follows. Section 3.2 presents the background of the study site, survey methodology, sampling strategy and the econometric framework used in the paper. Section 3.3 summarizes the main features of data. Main findings are discussed in section 3.4. Finally, main conclusions are drawn in section 3.5.

3.2 Methodology

3.2.1 Study site

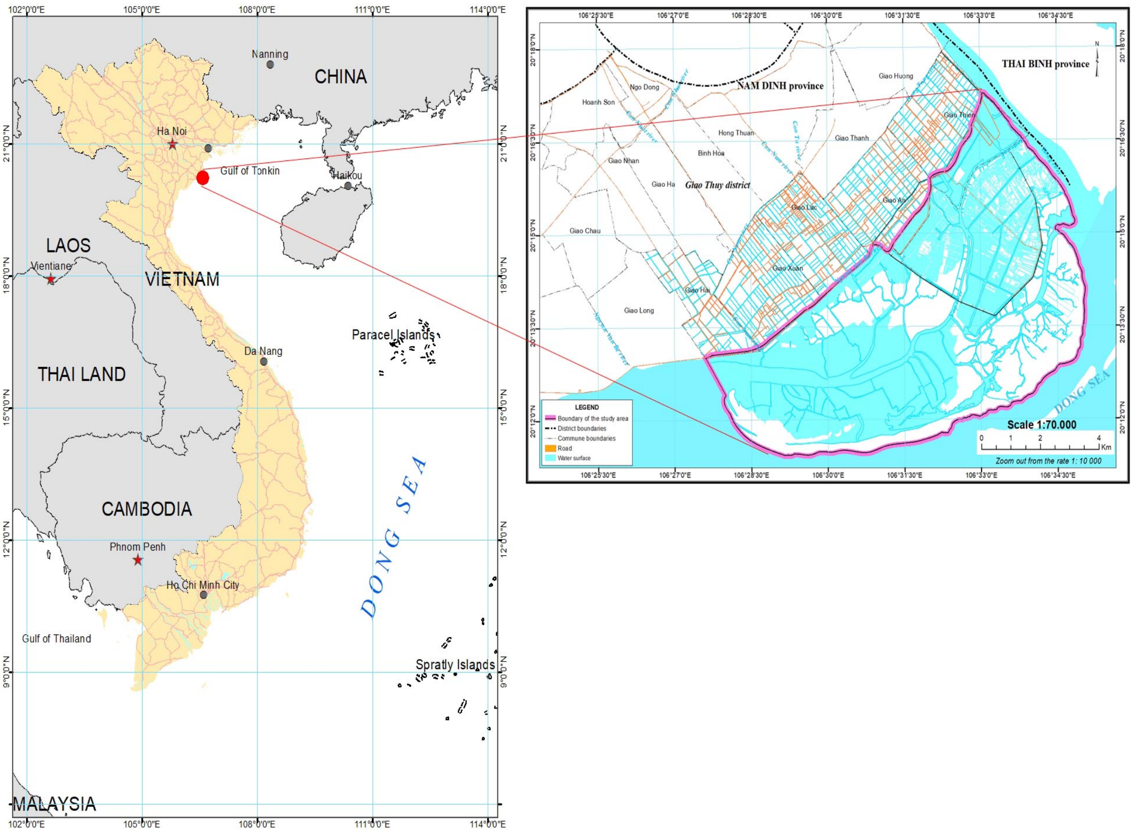
Xuan Thuy National Park (XTNP) is a special nature reserve with vast areas of mangrove swamps located in the coastal zone of the Red River Delta and Ba Lat estuary (Thanh and Yabar, 2015). The park is divided in two main areas: a core zone (7,100 hectares) where human activities are strictly prohibited and a buffer zone (8,000 hectares) where human activities are managed to mitigate adverse impacts on the core zone (Pham Hong and Mai Sy, 2015). Figure 3.1 shows the map of XTNP including the five communes in the buffer zone that were chosen as the study site: Giao Hai, Giao Xuan, Giao Lac, Giao An and Giao Thien.

XTNP was approved by the Bureau of the Convention on Wetlands of International Importance as the first Ramsar site in South-East Asia [2]. About 150 species of vascular plants, 111 species of floating aquatic plants, 500 species of benthos and zooplankton (shrimp, fish, crab, oysters, etc.) have been recorded at the park. This site is also internationally-recognized for many migrating birds with 219 bird species recorded. Many of them are listed in the Red List of Endangered species such as the Black-faced Spoonbill (*Platalea minors*), Spoon-billed Sandpiper (*Calidris pygmaea*) and Spotted Green-shank (*Tringa guttifer*). (Nguyen et al., 2011)

Nevertheless, there are a variety of issues that threaten wetlands in the area. Firstly, mangrove forests have been cleared and converted into agricultural lands for fish and shrimp

[2] The Convention on Wetlands is an intergovernmental treaty that provides the policy framework for national action and international cooperation for the proper management of wetlands and their resources.

Figure 3.1: Map of Xuan Thuy National Park and the study site



farming. Secondly, the future of mangrove forests is very sensitive to climate variability such as sea level rise, elevated levels of temperature, rainfall. The local government protects XTNP from being exploited by enforcing strict rules with respect to fishing, hunting and harvesting plants inside the reserve. International organizations are finding solutions to preserve the mangroves for future generations and for locals to make a sustainable living.

3.2.2 Survey methodology

Questionnaire development The questionnaire was developed through an iterative design process. We first consulted with researchers and economists in the field of natural resource valuation to review different versions of the questionnaire. We then had several meetings with the board of XTNP to identify the opportunities for mangrove management. We also conducted meetings with local representatives of villages to understand the local livelihoods in the buffer zone. We wanted to know the local representatives' view on climate change impacts and how the risk of flooding varied depending on the location.

In addition, the local representatives gave important suggestions on how community funding for mangrove rehabilitation program could be used properly to cope with climate change. Concrete missions such as the construction of dykes to protect mangroves against sea rise, ensuring the sediment supply, mangrove planting were suggested by the local representatives. The information was very useful for our selection of attributes with the levels associated in the choice design.

Furthermore, a pre-test survey was conducted with 20 households in the buffer zone to get some estimates of their minimum and maximum WTP for a mangrove conservation program. This preliminary survey was helpful in formulating the contribution rates for the improved scenarios in the choice sets.

In our choice experiment survey, respondents were presented with a series of scenarios or choice sets of mangrove preservation programs that described the hypothetical market for the attributes. The future climate change scenario provided by the Ministry of Natural Resources and Environment (MONRE), Vietnam in 2016 was built upon the 5th assessment report of the Intergovernmental Panel on Climate Change (IPCC). This report gave sea level, temperature rise trajectory, and minimum rainfall in 2030. The report by the XTNP's management board also provided the estimated rate of mangrove and biodiversity degradation(Tran et al., 2016; Management Board of Xuan Thuy National Park, 2014)

Attribute definition. The choice of attributes and their associated levels were based on many references. First, the report "The current state of biodiversity at XTNP" (Management Board of Xuan Thuy National Park, 2014) helped us gain a basic understanding of the mangroves at the study site and their benefits in the context of climate change. Initially, a list of 15 potential attributes characterizing mangrove conservation programs was introduced. These attributes included areas of mangroves planted at intertidal zone, areas of lagoons for aquaculture, average daily income from fishing in the wetland, number of fish species, number of the black-faced Spoonbill, number of bird species, number of tourists, and ability to prevent saline water intrusion, storms and coastal erosion. After several meetings with experts, local representatives in charge of mangrove conservation, and households, we decided to shorten the list of attributes to three (Table 3.1 gives their definitions and levels.). The first two are ecological attributes: the total area of tidal flat which has mangrove coverage being described in terms of hectares of mangroves protected, and biodiversity defined as the number of the black-faced Spoonbill preserved at the Ba Lat estuary. The third attribute was storm prevention ability measured in terms of expected economic losses from storm level, high or low. The avoided storm losses are linked to a recent event (Tropical Storm Mirinae) in order to tie an attribute of a hypothetical good to a real (consequential) event experienced by respondents.

The selected attributes were consistent with those chosen in other studies on wetland valuation (Brouwer et al., 1997; Do and Bennett, 2009; Tan et al., 2018). The number of attributes were also compatible with cognitive capacities of respondents at the study site. Indeed, all attributes represented important aspects of mangrove ecosystem services at Ba Lat estuary to respondents. Each choice option is based on a combination of attributes' levels and respondents' choices indicated how they valued these attributes. Last column of Table 3.1 gives the values corresponding to status quo.

Table 3.1: Wetland management attributes and levels in the CE.

Attribute	Description	Management levels	Status quo
Area	The total area of tidal flat which has mangrove coverage, providing a better habitat for animal species and increasing yields of eco-friendly shrimp ponds	Low : 1661 ha Average : 1900 ha High : 2100 ha	Low
Loss	The expected economic losses from storm level 10 (equivalent to tropical storm Mirinae in late July 2016) indicates the storm-prevention capacity	Low: losses of 300 billion VND [a] High: losses of 622 billion VND	High
Biodiversity	The number of endemic species (e.g. Black-faced Spoonbill) preserved at Ba Lat estuary	Low : 62 species Average : 80 species High : 100 species	Low
Payment	A one-off payment of each household goes to the Wetland Conservation Fund	4 payment levels: 200,000, 300,000, 400,000, and 600,000 VND [b]	0 VND

[a] 1 USD ≈ 23,245 VND Hence, 300 billion VND and ≈ 12,776,298 USD. 622 billion VND ≈ 26,488,318 USD.

[b] 200,000 VND ≈ 8.51 USD. 300,000 VND ≈ 12.77 USD. 300,000 VND ≈ 17.03 USD. 600,000 VND ≈ 25.54 USD.

A payment instrument was added to the list of attributes. Income tax is the most widely used payment instrument in developed countries. Nevertheless, this payment instrument could be inappropriate in Vietnam, and especially, in Nam Dinh province, due to a lack of transparency in tax system and low population coverage (Do and Bennett, 2009). Hence, household' donations to the Fund for Wetland Conservation of the Mangroves in the Ba Lat estuary was used as our payment instrument. Our survey targets households because community driven projects often require household contribution in Vietnam, especially for rural households that have low budgets. In addition, we did not conduct interviews with multiple members of the household because doing so would require multiple visits that might push up the cost of the survey considerably and the enumerators might have incentives to obtain information as quickly as possible.

Choice sets elaboration. The choice of attributes and their levels resulted in 72 potential choice options. Ngene software was used to implement a fractional factorial design for defining choice sets (ChoiceMetrics, 2018). A subset of complete factorials was chosen to capture efficiently the effects of interest according to the D-optimal criterion (Reynaud et al., 2018). 24 choice sets were constructed and grouped into four versions of the choice experiment presented to respondents. Each version contained six choice sets with varying levels of attributes in order to get a range of environmental goods and payments.

In each choice set, respondents were presented with two options. The first option was the status quo, keeping the entire mangrove forest intact (see last column in Table 3.1). All the attribute levels were kept at their current levels and required zero payment from respondents. The second option proposed improved levels of the restoration program but with some payments. An example where respondents were asked to choose between the status quo and the alternative scenario with an increase in payment for more mangrove coverage given the climate change projection is provided in Table 3.2.

Perception questionnaire. Another major part of the questionnaire consisted of questions about respondents' perception towards mangroves' role in fighting climate change. Respondents were explained clearly the potential threats for the mangroves in the Ba Lat

Table 3.2: Example of a choice set

Comparing the current scenario with the improved scenario, what is your selection?

Attribute	**Current scenario A**	**Proposed scenario B**
Mangrove coverage area	1661 ha	1900 ha
Biodiversity	62 species	62 species
Loss	622 billion VND	622 billion VND
One-off payment	0 VND	200,000 VND
I would prefer	☐ **Choice A**	☐ **Choice B**

estuary. Pictures of biodiversity degradation and coastal erosion were used as visual aid to help respondents understand the vulnerability of the wetland to climate change. Hence, our enumerators provided respondents with adequate information to evaluate non-market benefits that can be gained from the mangroves. Finally, standard socio-demographic information was collected (such as occupation, gender, household income, education level).

Sampling strategy The survey was conducted in Nam Dinh Province, which is located in the North East of Vietnam. Nam Dinh province has 72-kilometers coastline and is often affected by saline intrusion and tropical storms throughout the year (Leslie et al., 2018).

The sampling strategy was implemented as follows. We first chose Giao Thuy district to be the study site because this is the location of Xuan Thuy Wetland Nature Reserve. Then, 5 communes including Giao Thien, Giao An, Giao Xuan, Giao Hai and Giao Lac (out of 20 communes in Giao Thuy District) were selected because these communes constitute mostly the buffer zone at XTNP. Then, 145 households were chosen from the village listing of registered households. These representative households came from 74 hamlets in Giao Thuy District.

Multi-stage sampling was used to select villages and households. At the first stage, two villages were selected by random sampling from the list of villages in each commune. At the second stage, 145 households were surveyed by convenience sampling, i.e. surveying any household in each village without any prior notice given their proximity to enumerators.

Face-to-face interviews were carried out in March and April 2017. All enumerators were students from Hanoi University of Natural Resources and Environment (HUNRE) and Vietnam National University, University of Economics and Business (VNU-UEB), Hanoi, Vietnam. Before reaching the households, we contacted the head of the XTNP's management board for a formal approval for the survey. Our enumerators mentioned clearly the official approval of the survey at the beginning of each interview with the households. Most respondents in the survey were household heads or their spouses.

3.2.3 Discrete choice models

Random utility framework. Building upon the characteristics theory of demand (Lancaster, 1966), random utility models, or RUMs, have become the basis for the econometric analysis of DCE. These models assume that the utility for an alternative j in a choice experiment perceived by respondent i, or U_{ij}, can be decomposed into observed, or V_{ij}, and unobserved, or ε_{ij}, parts. Assuming that those parts are additive, RUM ends up with the following utility specification:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{3.1}$$

Most RUMs assume then that the observed part of utility V_{ij} can be expressed as a weighted sum of observed attribute levels of each alternative.

Conditional logit model. The most basic RUM is the conditional logit model, or CL, which assumes constant (homogeneous) weights for each attribute over all respondents (McFadden, 1974). CL model assumes that the random part of utility, i.e. ε_{ij}, is identically and independently extreme type 1 distributed. Omitting indexes for simplicity, the specification for the deterministic utility function for the CL model is:

$$V_i = ASC \cdot (\alpha) + Area \cdot (\beta) + Loss \cdot (\zeta) + Biodiversity \cdot (\mu) + Payment \cdot (\kappa) \tag{3.2}$$

where *Area* is a dummy variable equal to 1 for the area of tidal flat with average or high mangrove coverage respectively (reference category is low mangrove coverage), *Loss* is a dummy variable equal to 1 if a potential storm level 10 yields low economic losses (300 billion VND) in comparison to the high losses for the status quo, *Biodiversity* is a dummy variable equal to 1 if there are 80 or 100 individuals of endemic species preserved at Ba Lat estuary respectively (reference category is 60 individuals of endemic species), *Payment* is the one-off payment of each household (in thousand VND) for different conservation management levels (no payment is made for the status quo). An alternative specific constant (ASC), which is a dummy variable that equals to one when the alternative scenario was chosen and to zero when the status quo was chosen, was also added to the models (Hoyos, 2010; Reynaud et al., 2018; Adamowicz et al., 1998).

Random parameter logit model. More flexible models, such as random parameter logit model, or RPL, have been developed to overcome some restrictive assumptions of CL model: no random taste variation, restrictive substitution patterns and no correlation of unobserved factors as captured by ε_{ij} (Train, 2009). RPL model introduces taste heterogeneity by allowing for some or all utility weights to be individual specific, i.e. $\beta_i = \beta + \eta_i$ where η_i is a vector of individual i-specific deviations from the mean utility parameters β. These deviations vary with density $f(\eta_i|\theta)$, where θ is a vector of unknown parameters describing the distribution of β_i (for example their covariance matrix). RPL model allows modeling unobserved preference heterogeneity across respondents. The utility-specification of an RPL model can be written as

$$U_{ij} = \beta_i x_{ij} + \varepsilon_{ij} \text{ or, equivalently, } U_{ij} = (\beta + \eta_i)\, x_{ij} + \varepsilon_{ij} \tag{3.3}$$

The specification of the indirect utility function for the RPL basic and RPL with interactions is:

$$\begin{aligned} V_i =& ASC \cdot (\eta_i \cdot \alpha_1 + \alpha_2 \cdot z_i) + \text{Area} \cdot (\eta_i \cdot \beta_1 + \beta_2 \cdot z_i) + \text{Loss} \cdot (\eta_i \cdot \zeta_1 + \zeta_2 \cdot z_i) \\ &+ \text{Biodiversity} \cdot (\eta_i \cdot \mu_1 + \mu_2 \cdot z_i) + \text{ Payment } \cdot (\kappa_1 + \kappa_2 \cdot z_i) \end{aligned} \tag{3.4}$$

where z_i is a vector of individual specific social, economic and perceptional characteristics in the RPL with interactions. For each attribute and for the ASC, we have a mean preference parameter and a standard deviation coefficient to represent random taste variation for mangrove restoration services. For the sake of ease and accuracy of WTP computation, payments are not assumed to follow a normal distribution but only vary by respondent specific characteristics for the RPL with interactions.

Generalized Multinomial Logit Model. Although RPL models have shown their ability to capture taste heterogeneity in preferences across respondents in DCE, they were not designed to take into account potential scale heterogeneity or differences in the variance of the error term ε_{ij} across respondents. Scale heterogeneity might be interpreted as the consequence of variation of randomness in the decision-making process over respondents, i.e. the variance of the error term ε_{ij} (and hence the degree of certainty) may differ across individual decision-makers. This issue is especially important in DCE, where respondents could interpret choice situations differently and pay varying levels of attention to the tasks presented (Train and Weeks, 2005). Fiebig et al. (2010) proposed the Generalized Multinomial Logit Model, or GMNL, to tackle this issue. Unlike previous models, where the scale of the error term is normalized to 1, the GMNL model attempts to decouple taste and scale heterogeneities by nesting the RPL specification within a more general framework.

In the GMNL model, individual utility weights are defined as

$$\beta_i = \sigma_i \beta + (\gamma + (1 - \gamma)\, \sigma_i)\, \eta_i \tag{3.5}$$

where σ_i is the value of scale for respondent i, β is the vector of mean attribute utility weights, and η_i is the vector of respondent i's specific deviations from the mean.

Taking into account the constraint on γ, i.e. $\gamma \in [0,1]$, led Fiebig et al. (2010) to use a logistic transformation, or $\gamma = \exp(\gamma^*)/(1+\exp(\gamma^*))$ and to estimate γ^* instead of γ. But, recently, Keane and Wasi (2013) have shown that this transformation can lead to serious numerical problems and that there is no theoretical reason to impose the constraint. Behavioral patterns can also be meaningful with either $\gamma < 0$ or $\gamma > 1$. For instance, if $\gamma < 0$, it can be shown that the standard deviation of β_i increases more than proportionally as β is scaled up by σ_i.

The specification of the indirect utility function in this case is:

$$\begin{aligned} V_i =& ASC \cdot (\eta_i \alpha) + Area \cdot (\sigma_i \beta + (\gamma + (1-\gamma)\,\sigma_i)\,\eta_i) + Loss \cdot (\sigma_i \zeta + (\gamma + (1-\gamma)\,\sigma_i)\,\eta_i) \\ &+ Biodiversity \cdot (\sigma_i \mu + (\gamma + (1-\gamma)\,\sigma_i)\,\eta_i) + Payment \cdot \sigma_i \kappa \end{aligned} \tag{3.6}$$

Following Fiebig et al. (2010), the ASC is not scaled in our GMNL model because a model where all attributes are scaled including the ASC would result in a worse fit. *Payment* is fixed as in the RPL models but has scale heterogeneity across respondents in the GMNL model. For the scale parameter σ_i to be positive, Fiebig et al. (2010) proposed an exponential transformation:

$$\sigma_i = \exp\left(\overline{\sigma} + \delta z_i + \tau \nu_i\right) \tag{3.7}$$

where ν_i is assumed to be normally distributed with zero mean and variance equal to 1. Put differently, σ_i is thus assumed to be log-normally distributed, or $\log \sigma_i \sim N(\overline{\sigma}, \tau)$. To explain why scale differs across individuals, σ_i can be expressed as a function of individual specific characteristics z_i. Estimation of GMNL models can be achieved using maximum simulated likelihood techniques as shown in Fiebig et al. (2010).[3] Furthermore, it is noticeable that σ_i and β only enter the model as a product in Eq. (3.5). Some normalization on σ_i is therefore needed to identify β. A natural normalization is to set the mean of σ_i equal to 1 so that β can be interpreted as the mean vector of utility weights.

[3] See, for instance, the R package GMNL (Sarrias and Daziano, 2017).

The consequence of this normalization is to set $\overline{\sigma} = \tau^2/2$.

Willingness-to-pay. Coefficient estimates in the utility function do not have any real meaning, except for their significance and sign (Reynaud et al., 2018). To get a more concrete, interpretable result, it is important to compute the marginal WTP for a change in the attribute. The marginal WTP for an attribute is described as the marginal rate of substitution between this attribute and the monetary cost to maintain the same level of utility (Train, 2009). This is done by dividing the vector of non-price parameters by the price parameter, or [4] An estimate of marginal WTP specified this way is known as a preference space approach.

$$WTP_{attribute-level,i} = -\left(\frac{\beta_{\text{attribute}-\text{level},i}}{\beta_{\text{price},i}}\right) \tag{3.8}$$

Confidence intervals of the estimated marginal WTP can be computed by applying the non-parametric bootstrap technique proposed by Krinsky and Robb (1986) with a large number of simulations from the chosen distributions in the different models presented above.

3.3 Data

3.3.1 Individual characteristics

Table 3.3 displays the respondents' socio-demographic characteristics. In this sample, the number of female participants (50.3% of the 145 respondents) is almost equal to the number of male participants, ensuring that gender balance was represented in the survey. Almost 60% of the total sample aged over 45. This suggests that the middle-aged and elderly (over 45) people tend to work in the villages and were available for the interviews. Younger people might commute to work outside of the village and did not show up in the interviews. Married individuals account for 91.72 % of the sample. 76.6% of the respondents could

[4] There is a negative sign in the computation of marginal WTP because typically the price parameter is negative.

not complete high school, reflecting the fact that most people in rural areas obtain low education level [5]. In this study, farmers or fishermen constitute 57% of the total sample. The other main categories of jobs such as business owners, and hired employees at public or private sectors constitute about 29% of the sample. Students, retirees, housewives, and unemployed people constitute the remaining sample.

Table 3.3: Description of the sample

	Category	**Frequency**	**Percentage**
Gender	Female	73	50.30
	Male	72	49.70
Age	18-25	9	6.21
	26-35	27	18.62
	36-45	22	15.17
	46-55	45	31.03
	>= 56	42	28.97
Marital Status	Married	133	91.72
	Single	12	8.28
Education	Below high-school	111	76.55
	High-school or above	34	23.45
Career	Farmer/Fisherman	84	57.93
	Business owner/Self-employed	14	9.66
	Public sector employee	7	4.83
	Private sector employee	21	14.48
	Students	3	2.07
	Retired/Housewife	16	11.03
Household Size	1	5	3.45
	2	20	13.79
	3	18	12.41
	4	43	29.66
	5	42	28.97
	6	10	6.90
	7	5	3.45
	8	2	1.38
Monthly Income of household (million VND)	Low income (Up to 3)	48	33.33
	Lower middle (Between 3 and 6)	57	39.58
	Upper middle (Between 6 and 10)	19	13.19
	High income (Over 10)	20	13.89
Passion for environmental protection	No	3	2.07
	Like a little	19	13.10
	Like a lot	123	84.83
Mangrove dependency[a]	Yes	65	18.70
	No	282	81.30
Natural disaster impact [b]	Yes	111	76.55
	No	34	23.45

[a] Mangrove dependency refers to households that were direct beneficiaries of mangroves for their livelihood activities.
[b] Household agricultural activities and income affected by natural disasters in the past 5 years

Over one-third of the respondents (33.33%) reported to have a monthly household income lower than 3 million VND (about 129 USD). 39.58% of the respondents reported to receive a monthly household income between 3 and 6 million VND (about 129-258 USD).

[5] The comprehension or engagement in face-to-face interviews was independent of respondents' low education level. Respondents were intrinsically connected to the sea and their lives depend on it. Hence, they were keen on expressing personal concerns about climate change and their answers were important to our survey.

13.89 % of respondents said that they received a monthly income of over 10 million VND (about 430 USD). Furthermore, the majority of respondents (81.3%) said that mangrove ecosystem directly affected their income. There were about 1 to 8 people in the surveyed households. The mean household size of the sample was around 4.08, representing normal family size in Nam Dinh Province. Interestingly, most respondents (84.83%) were very passionate about environmental conservation activities. Finally, 76.6% of the respondents reported that their agricultural activities were affected to a certain degree by natural disasters in the past 5 years.

3.3.2 Local awareness about mangrove restoration in XTNP

Table 3.4 indicates the local subjective views of mangrove benefits. Over 67% of respondents believed that the mangroves in the XTNP played an important role in controlling flood, storms and soil erosion. The results also indicate that a major number of the respondents (37.9%) realized that mangroves have been a vital source of aquatic products, raw material for their production and consumption.

Table 3.4: Perceived benefits from mangrove forests

Benefits from mangrove forest	**Percentage**
Aquatic products, raw material for production and consumption	37.9
Recreation, tourism	0.7
Prevention of storms, floods, tides, and coastal erosion	67.6
Underground water protection, preventing salinization	7.6
Climate regulation, carbon dioxide absorption	18.6
Preserving silt, sea encroachment	6.9
Habitat for fish and animals	29.7
Biodiversity	2.1
Other	6.9
Do not know	10.3

Table 3.5 displays respondents' perceived reasons for mangrove degradation. 41.4% of the respondents perceived human activities such as aquaculture, fishery, etc. as the major threat to mangrove forests. 20% of them perceived that climate change posed threat to the survival of mangroves.

Table 3.6 shows perceived motives for mangrove protection in the Ba Lat estuary. In order to answer the questions, respondents were clearly explained how the mangroves in

Table 3.5: Perceived causes of mangrove degradation

Reasons	**Percentage**
Human activities: aquaculture, fishery, etc.	41.4
Pollution	12.4
Climate change	20.0
Other	11.0
Do not know	1.4

the Ba Lat estuary have been degraded overtime. Given various scenarios of the mangroves in the context of climate change, respondents were asked Likert scale questions to rate the importance of reasons to protect the mangroves, on a scale from 1 to 5, with "1 = Not at all important", "2 = Not so important", "3= Neutral" , 4= Important", and "5= Very important". Respondents could also choose “not able to evaluate” option. These results suggest preventing the coastal zone against floods, erosion, salinization and providing benefits for future uses were the two most important motives. Biodiversity preservation was the third most important motive for mangrove rehabilitation.

Table 3.6: Perceived motives for mangrove conservation

Reasons	**Not at all important**	**Not so important**	**Neutral**	**Important**	**Very important**
Providing wood, fish and raw materials	6.2	21.5	30.6	22.2	19.4
Providing recreation	1.4	8.3	20.1	40.3	29.9
Preventing floods, erosion, salinization	0	1.4	2.1	9.7	86.9
Conserving biodiversity	1.4	4.2	19.4	33.3	41.7
Benefits for future uses	0.7	2.8	4.1	17.2	75.2

3.4 Results

3.4.1 Sample size

Our multi-stage sampling ensures a statistically visible sample size for the choice experiment study. We excluded respondents who said they had a zero probability belief in all proposed options in most choice sets. It was not worth studying how much these respondents are willing to pay because they believed that the proposed conservation programs were not going to take place. That turned out to be about 13.7% of the sample excluded from our statistical analysis. The remaining 125 households were given 6 choice sets, making up a total of 750 observations in the statistical analysis. In addition, the random sampling guarantees that the sample is representative of Nam Dinh population that lived near mangrove forests and had some exposure to climate change impacts. There were around 13,000 households in the five surveyed communes, given the desired margin of error at 5%, a statistically visible sample size is about 380 observations [6]. By using experimental design theory, we have increased the statistical efficiency of the parameters estimated so that smaller samples may be used (Holmes et al., 2017). The minimum sample size necessary for choice studies is suggested about 50 decision makers for each alternative or about 300 observations for 6 choice sets (Hensher et al., 2015).

3.4.2 Estimation results

Different versions of the models presented in section 3.2 were estimated using a set of variables with descriptions given in Table 3.7.[7] Certain socio-demographic variables were thus grouped into a smaller number of classes with sufficient number of observations, while still being interpretable. In addition to a CL and a GMNL specifications, two RPL specifications were considered: a classical one with only individual parameters heterogeneity and another including interactions of attribute levels with some socio-demographic variables. Individual parameters heterogeneity was captured using normal distributions.

Estimation results are reported in Table 3.8. These results are discussed starting from the most commonly used specification in the literature, namely the CL model, and moving towards richer content models in terms of analysis of choice behaviors.

Conditional Logit. For the CL model, there were consistent preferences in the sample. The insignificant coefficient on the ASC means respondents had no preference for which program was chosen on average. The statistically significant, positive coefficients on

[6] The sample size n = $\left(\frac{N}{1+N*\varepsilon^2}\right)$

[7] The GMNL package in R was used to estimate the four models (Sarrias and Daziano, 2017). Following Train (2009), the distribution simulations in the RPL and GMNL models were based on 1000 sequence Halton draws .

Table 3.7: Description of variables.

Variable	Description	Value
Attributes of the CE		
AreaAverage	Total mangrove coverage (hectare) is average	1 = Average 0 = Low
AreaHigh	Total mangrove coverage (hectare) is high	1 = High 0 = Low
BioAverage	The number of endemic species preserved at Ba Lat is average	1 = Average 0 = Low
BioHigh	The number of endemic species preserved at Ba Lat is high	1 = High 0 = Low
LossLow	Total loss caused by storm level 10 (billion VND)is low	1 = Low 0 = High
Payment	Payment levels (thousand VND)	Level= 0; 200; 300; 400; 600
Respondent's characteristics		
Education	Respondent was educated to high-school level or above	1 = High-school or above 0 = Otherwise
Knowledge	Respondent has knowledge about benefits of mangroves [a]	1 = Yes 0 = No
Depend	Household income partially or totally depend on the mangrove's ecosystem	1 = Yes 0 = No
Income	Total household income per month on a scale going from 1 to 10 (with 1 for being up to 3 million VNDs and 7 for being over 30 million VNDs)	1 = On a scale going from 4 to 7 0 = On a scale going from 1 to 3
OccupFarmer	Respondent's main activity is agriculture	1 = Yes 0 = No

[a] Respondents have knowledge about the mangroves when they could tell the interviewer what benefits the mangroves have. No knowledge of mangrove benefits means respondents could not give a clue.

mangrove coverage attributes indicate that respondents wanted to have more mangroves preserved either at the medium (1991 ha) or high management level (2100 ha). There are positive and significant coefficients on total loss incurred by a storm at low level (losses of 300 billion VND). Therefore, if respondents were given a choice with a high flood prevention ability, everything else being held constant, they were more likely to say yes to the alternative program. Interestingly, there was no preference for the medium or high management level of biodiversity (80 or 100 individuals of endemic species, respectively). Hence, the lack of interest in biodiversity benefits indicating that biodiversity conservation plan might not be prioritized by households in the coastal area since it might only affect their livelihoods in the short-run. The negative coefficient on payment makes general sense. As respondents disliked the higher cost, they were less likely to pick the alternative program.

Random parameter logit. The RPL adds unobserved random variation in preferences between individuals to the classical CL specification. Random effect is demonstrated by normal distribution, the most commonly used distribution within RPL literature (Train, 2009). By knowing the mean and standard deviation for each attribute level, it is then possible to know what percentage of respondents likes or dislikes it.

It should be noted firstly that the RPL model nests the CL model. Then, the null hypothesis that the standard deviation coefficients are all equal to zero in the RPL model can be tested using classical log-likelihood test comparing log-likelihoods of the two models. The null hypothesis is then rejected at 5% significance level, implying that improvement in the model fit is achieved with the inclusion of unobserved individual heterogeneity when using the RPL model.

Secondly, taking into account unobserved individual heterogeneity in preferences does not modify the direction of the effects of attribute levels. Indeed, the signs and significance of the mean utility parameters in the RPL model are similar to those in the CL model. But now, the analysis of these mean effects is enriched by the knowledge of the standard deviations associated with them.

Standard deviations are not statistically significant in the effects of storm prevention capacity as well as mangrove coverage and biodiversity at the average management levels. Nonetheless, there was a considerable preference heterogeneity among respondents in the effects of mangrove coverage and biodiversity at the high management levels. Some people might like high management level of biodiversity and high level of mangrove coverage because they discerned a great deal of positive benefits. Some people, on the other hand, might dislike high levels because they might prefer more mangroves to be converted to short-term profitable alternatives like shrimp ponds, or they simply could not discern the ecological and social benefits of having high management levels for these attributes. It is noted that the mean coefficient of having high management level for biodiversity is negative and not statistically different from zero. For the CL model without accounting the variances of tastes, we would conclude that having biodiversity at high level of management is irrelevant to people's choices. However, it is still relevant to respondents' choices in the presence of taste variation. Some respondents really wanted biodiversity while other respondents did not see the benefits of having more biodiversity. On net, the negative and positive effects average each other out and the mean coefficient of high biodiversity level was close to zero. The same case is for the coefficient on the ASC given its significant standard deviation but insignificant mean coefficient. The statistically insignificant ASC means that WTP is not statistically different from zero in the status quo scenario. In addition, this is another instance where the random parameters model finds heterogeneity across respondents since the ASC standard deviation is greater than the mean.

Random parameter logit with interactions. The usual RPL model can be modified by interacting some individual specific covariates with attributes levels. Respondents are then assumed to have heterogeneity in their preferences stemming from individual socio-demographic characteristics. Different models with interactions were estimated and we selected those whose estimation results are reported in Table 3.8, using BIC criterion as recommended by Keane and Wasi (2013). Here, the RPL model with interactions also nests the simple RPL presented above. Log-likelihood ratio test of the null hypothesis of no interactions is clearly rejected at 5% significance level.

Similar to simple RPL model, the RPL model with interactions results in the same

Table 3.8: Maximum likelihood results

Variable	**CL**	**RPL basic**	**RPL interactions**	**GMNL**
Coefficients				
ASC	0.167(0.25)	0.378(0.297)	1.538(0.444)***	0.594(0.287)**
AreaAverage	0.767(0.194)***	0.876(0.211)***	0.747(0.288)***	0.494(0.193)**
AreaHigh	0.565(0.197)***	0.569(0.254)**	0.692(0.275)**	0.322(0.185)*
BioAverage	0.068(0.191)	0.076(0.203)	0.264(0.233)	0.01(0.129)
BioHigh	-0.131(0.195)	-0.311(0.267)	-0.006(0.302)	-0.199(0.178)
LossLow	0.534(0.158)***	0.676(0.179)***	0.459(0.203)**	0.422(0.164)***
Payment	-0.004(0.001)***	-0.005(0.001)***	-0.005(0.001)***	-0.003(0.001)***
Standard deviations				
ASC	—	0.456(0.2)**	0.213(0.401)	0.024(0.242)
AreaAverage	—	0.011(0.778)	0.007(0.667)	1.152(0.739)
AreaHigh	—	1.213(0.403)***	1.241(0.406)***	2.182(0.918)**
BioAverage	—	0.005(0.437)	0.011(0.449)	0.248(1.13)
BioHigh	—	1.172(0.448)***	1.216(0.444)***	2.036(0.961)**
LossLow	—	0.015(0.369)	0.007(0.396)	0.075(1.077)
Interactions				
ASC x Knowledge	—	—	-1.246(0.352)***	—
AreaAverage x OccupFarmer	—	—	0.256(0.373)	—
AreaHigh x IncomeHigh	—	—	-0.744(0.592)	—
BioAverage x Education	—	—	-0.533(0.405)	—
BioHigh x Education	—	—	-0.863(0.544)	—
LossLow x Education	—	—	0.736(0.354)**	—
Payment x Depend	—	—	0.001(0.001)**	—
Payment x OccupFarmer	—	—	-0.001(0.001)*	—
Heteroskedasticity				
Knowledge	—	—	—	0.486(0.319)
Depend	—	—	—	-0.456(0.219)**
OccupFarmer	—	—	—	0.343(0.166)**
Scale heterogeneity	—	—	—	0.359(0.191)*
Scalar control	—	—	—	2.048(0.728)***
Observations	750	750	750	750
Log likelihood	-464.50	-457.51	-436.39	-447.58
AIC	943.00	941.03	914.79	931.17
BIC	975.34	1000.29	1010.52	1015.83

Note: Standard errors are in parentheses, and *: p<0.1; **: p<0.05; ***: p<0.01.

significant mean preference parameters and no changes in their sign. The same is true for the estimated standard deviations, with the noticeable exception of those associated with the ASC. The most striking result is positive and significantly different from zero ASC mean coefficient. Respondents were more willing to choose the proposed program rather than status quo. A close look to interactions also shows that respondents with knowledge of wetland benefits were less likely to choose the alternative and more likely to stay with the status quo. Moreover, farmers were willing to pay on average, less while more educated respondents or those whose household activities relied on mangroves were willing to pay more. High income was not statistically significant in explaining demand for more mangrove coverage to be preserved. There are strong results for more educated respondents as they were more likely to be willing to pay for reduced flooding risks.

Generalized Multinomial Logit model. The usual RPL model can be also be generalized by modeling the scale parameter whose value was fixed to one when estimating CL and RPL specifications. After several modeling tests, we expressed scale heterogeneity as a function of of occupation, knowledge and dependence on mangroves as the background context.

As for the RPL model with interactions, the estimated GMNL model nests the simple RPL model. Here, log-likelihood ratio can also be implemented concluding in a clear rejection of the null hypothesis that scale parameter is constant, at 5% significance level. Such a test cannot be conducted to choose which is the most likely specification, between the RPL model with interactions and the GMNL model, these two models not being nested. The AIC and BIC criteria would indicate the RPL model with interactions as the preferred model. However, we preferred to make no choice between the two models and presented the conclusions to which they lead.

Estimation results from GMNL display no differences with those of RPL model with interactions, when assessing the significance and sign of mean attribute level preference parameters and the associated standard deviations. Estimated mean ASC parameter still indicate respondents' tendency to choose the alternative program.

GMNL also allows for an explicit analysis sources of randomness in decision making over respondents, disentangling scale heterogeneity from residual taste heterogeneity. Results for the estimated standard deviations, commented above, relate mainly to this last source of randomness. Notice that, due to the estimated value of parameter γ, comments must take into account that residual η_i is weighted by $2.048 - 1.048\,\widehat{\sigma}_i$ in Eq. (3.5). Thus, the larger the estimated individual scale parameter $\widehat{\sigma}_i$, the smaller residual taste heterogeneity.

Scale heterogeneity. Consider scale heterogeneity as measured by σ_i. First, the estimated variance τ is statically significant, suggesting that there is some heterogeneity in choice behaviors among respondents. The estimated variance $\tau = 0.359$. Two variables have a significant impact on the mean of scale heterogeneity: dependence (negative impact, or -0.456) and farmer occupation (positive impact, or 0.343).

Table 3.9: Marginal WTP (in thousand VND) for conservation attributes

Variable	CL	RPL basic	RPL interactions	GMNL
AreaAverage	213.126	190.884	169.861	264.412
	[123.539, 319.080][a]	[-76.133, 474.889]	[-85.979, 447.431][b]	[-99.564, 889.727]
AreaHigh	157.816	122.123	155.874	169.221
	[64.873, 258.865]	[-347.245, 593.129]	[-340.887 , 663.799]	[-465.989, 982.141]
LossLow	151.803	149.120	104.790	208.381
	[74.836, 248.224]	[7.520, 300.556]	[-62.802, 283.628]	[-24.920, 631.857]
BioAverage	20.222	16.759	60.717	23.602
	[-65.734, 110.495]	[-148.485, 184.129]	[-122.469, 247.973]	[-207.569 , 284.493]
BioHigh	-36.680[c]	-67.060	-1.766	-92.283
	[-132.494, 52.516]	[-544.966 , 383.357]	[-506.251, 484.757]	[-848.446, 545.727]

Notes:

[a] For the CL,CIs are computed with 1000 bootstrap replications (Krinsky and Robb, 1986).

[b] For the RPL with interactions and GMNL, means and CIs are only computed for the base groups.

[c] The negative values mean willingness to accept to abandon the proposed scenario.

[d] For the RPL-interactions and the GMNL models, the lack of precision in the WTP may be the results of the small sample size and large number of parameters. Reviewers were skeptical about the results for the RPL-interactions and the GMNL models due to the small sample size. In our survey, 125 households were given 6 choice sets, making up a total of 750 observations in the statistical analysis.

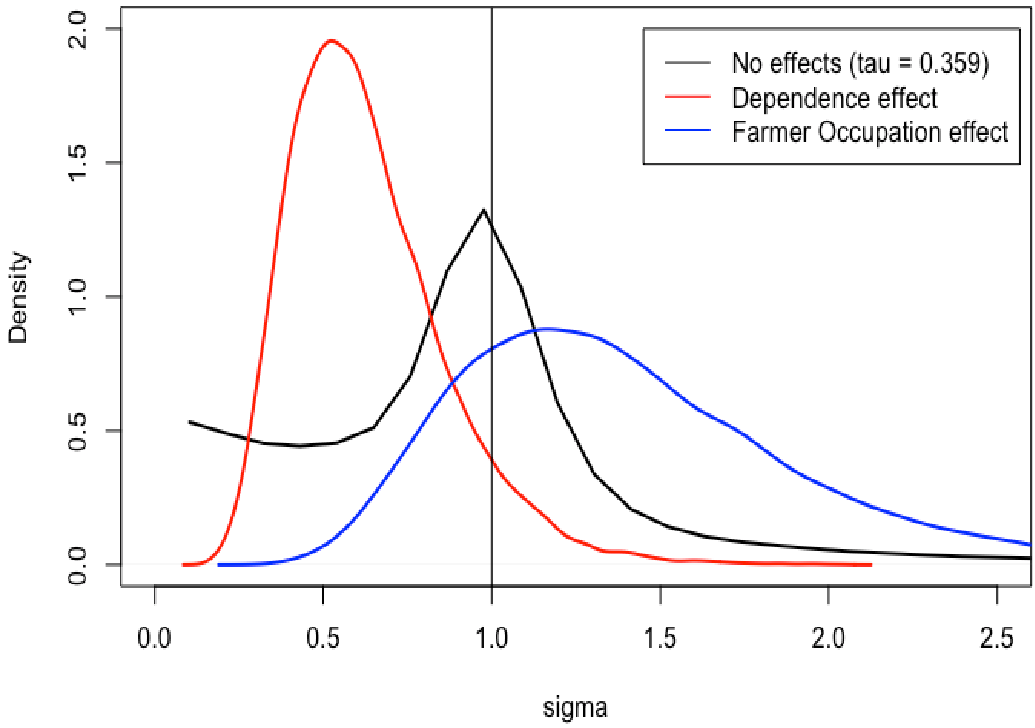
Figure 3.2 shows the corresponding distributions of scale heterogeneity. The figure implies that more randomness in choice for households that are dependent on mangroves (majority of sigma smaller than one) and less randomness in choice for household heads that occupy a farmer position (majority of sigma greater than one).

Results also indicate that a different level of knowledge of mangrove benefit is not a relevant scale factor for the choice context. However, having livelihood relied much on mangroves decreases scale heterogeneity. Less randomness seems to characterize the choice of farmers whose livelihood depends much on mangroves. Conversely, being mainly a farmer increases scale heterogeneity. As expected, larger randomness affects farmers' choice among mangrove restoration and status quo.

Willingness-to-pay estimates. Table 3.9 displays the marginal WTPs for conservation attributes for the four specifications, i.e. the WTPs to change from the status quo to the improved scenario given a change in each of the attribute level.

The estimation results for the attributes were found to be highly consistent for the four specifications. Furthermore, the results demonstrate fairly significant WTPs for households for mangrove coverage and flood prevention across the four specifications. In the CL specification, for instance, to move from low mangrove coverage (1661 ha) to medium coverage (1900 ha), households were willing to pay an additional 213,126 VND

Figure 3.2: Effects on scale heterogeneity distribution



(9.19 USD) per household. The confidence interval for this is the range of marginal WTP between 123,539 VND to 319,080 VND per household. This confidence interval potentially containing the true population parameter is fairly tight around the estimate, which is a good sign.

For a greater extension of mangroves, households on average were WTP 157,816 VND (6.81 USD) per household to have from 1661 ha to 2100 ha of mangroves preserved in the park. Surprisingly, household WTP for the highest level of mangrove coverage was lower than that for the medium level of mangrove coverage. Respondents would likely to vote against the proposed program for the greater coverage of mangroves due to higher payment. For protection against storms, the level of household WTP tied around 151,803 VND (6.55 USD). However, it should be stressed that there was no statistically significant effect from biodiversity, at the medium or the high management level across the four specifications. Confidence intervals that range from some negative numbers to large positive numbers indicate that there is no confidence about how precisely these estimates are. This could be explained by the fact that respondents were not aware of biodiversity benefits on their livelihoods or they paid more attention to other aspects of the ecosystem services.

In addition, the confidence intervals in the RPL basic, RPL interactions and GMNL models show a wider range around the mean WTP for all attributes than those in the CL model, implying a relatively inconsistent preference across the sample. For instance, in the RPL basic specification, the confidence interval indicates much variation of marginal WTP for for the highest level of mangrove coverage around the mean estimate from -347,245 VND to 593,129 VND. This is due to the preference heterogeneity among respondents over mangrove coverage obtained at a larger scale. The negative value implies some respondents were even willing to accept to abandon the proposed scenario, due to the higher cost associated with the higher attribute level. The widest rage of confidence interval in the GMNL was mainly driven by the scale effect of mangrove conservation preferences introduced into the model.

It is worth noting that the ranking of attributes with regards to household WTP was fairly consistent in the four specifications. In these four models, the highest marginal WTP was found for medium level of mangrove coverage based on the benefits and the costs associated with the attributes. There was a slight variation in the ranking of the marginal WTP for the highest level of mangrove coverage and storm protection attribute, reflecting how taste preferences were modeled differently across the specifications.

3.5 Conclusion

A choice experiment was employed for eliciting households' preferences for mangrove rehabilitation program at the Ba Lat estuary, Nam Dinh province. The survey consisted of choice sets in which respondents had to choose between two options: a status quo option and an improvement option based on different combinations of attributes such as the area of the restored mangrove forest, the number of preserved "Platalea Minor" birds, the total damages caused by storms, and the contribution rate. In addition to questions on socio-demographic characteristics of the respondents, various questions were asked about the awareness of the respondents with respect to mangrove ecosystem services in a climate change context.

Four econometric specifications were used to capture households‘ preferences: a) Conditional multinomial logit (MNL) which assumes homogenous preferences across respondents; b) Random parameter logit (RPL basic) which accounts for unobserved preference heterogeneity; c) RPL including interactions of respondent's social, economic and perceptional characteristics with choice attributes to explain sources of observed as well as unobserved heterogeneity; d) Generalized multinomial logit (GMNL) to capture scale heteroscedasticity and unobserved heterogeneity.

We found that mangrove coverage extension (at the medium or high management level), storm prevention ability, contribution rate were all statistically significant in explaining household WTP across the four specifications. Surprisingly, biodiversity conservation either at the medium or high management level was not statistically significant in explaining household WTP. Respondents might have incomplete understanding of the way biodiversity maintains the value of ecosystem services and were not willing to pay for this management attribute. If these respondents knew more about biodiversity aspects, they would value differently. Our results thus suggest scope for training and education in order to raise local awareness of biodiversity benefits.

The unobserved heterogeneity of tastes in the sample was found for the high mangrove coverage, and high management level of biodiversity. The observed heterogeneity of tastes for the alternative option was driven by different levels of knowledge about mangrove benefits. Taste variation for storm prevention ability could be observed by various education levels whereas taste variation for payment could be observed by mangrove dependency and occupation. Furthermore, the degree of certainty of choices differed across individuals. This could be explained by a scale heterogeneity that model the random source of heteroscedasticity in the utility function as well as socio-demographics of the individuals such as mangrove dependency and occupation. The results indicate that more randomness in choice for households that depend on mangrove and less randomness in choice for households with farming occupation.

Strong preference for the improvement option was found in the RPL interactions and GMNL models when a number of respondents' characterstics such as knowledge of mangrove benefits, education, mangrove dependency, occupation were considered. This calls for a careful assessment of respondents' motivations for adopting the proposed mangrove conservation policies. In order to increase the likelihood of mangrove conservation adoption, it is important to bring awareness, education, and knowledge exchange regarding mangrove values to local communities. Another solution is to develop sustainable conservation initiatives to benefit the communities and to take pressure off existing mangroves such as planting mushrooms, making various honey products, or ecotourism initiatives with part of the profits going straight back into a community conservation fund. These also help to generate an alternative livelihood and sustainable income for mangrove dependent households, farmers.

Marginal WTP per household for each attribute was estimated according to each specification. Our results reveal some different levels of WTP for mangrove conservation depending on the attributes and the management levels. The findings shed light on non-market values of wetland management attributes at Ba Lat estuary in the context of climate change, taking with caution the fact that people are different in their choice preferences.

We acknowledge that our study is subject to several shortcomings. Firstly, in order to expand the scope of the study, future studies could include additional improvement options in each choice set or incorporate other wetland management attributes such as the improvement of water quality, eco-tourism facilities. Another interesting avenue for further research is to examine whether these social norms or morals play an important role in determining households' WTP for mangrove conservation (Czajkowski et al., 2017). Secondly, more information on the project costs should be included in the current valuation so that policy makers can have a comprehensive cost benefit analysis of the coastal wetland restoration projects. Finally, a survey with large sample size should be conducted to improve the statistical analysis. The statistical uncertainty of the WTP estimates for the RPL-interactions and the GMNL models is largely driven by the small sample size. In our survey, 125 households were given 6 choice sets, making up a total of 750 observations in the statistical analysis.

Chapter 4

Adaptation of Rice Yields to Heat Stress in Vietnam: New Insights from Heterogeneous Slope Panel Data Modeling

4.1 Introduction

Rice is a staple crop in Vietnam's agricultural sector. It is a major socio-economic activity in Vietnam with around 7.9 million hectares (87.1% of total annual cultivation area), constituting of 42.75 million tons of paddy (89.46% of annual grain production) in 2013 (Trong and Napasintuwong, 2015). In 2017, Vietnam exported 5.79 million tons of milled rice, contributing 2.62 billion USD to national GDP, making the country the world's third largest rice exporter after Thailand and India. The Mekong Delta, the most important agricultural basin of Vietnam, is where 70% of Vietnam's rice is produced, contributing to more than 90% of total export volume (The Anh et al., 2020).

Rice farming activities take place throughout the country and face different climate risks. Any variation in occurrence of rainfall could affect rice production. In the Mekong Delta, annual rice production would decline by 0.2 t/ha for each 100 mm increase in precipitation beyond 250 mm, and 0.6 t/ha for each 100 mm decrease in precipitation below 50 mm (Nhan et al., 2011). Maintaining soil moisture in the Central provinces is often a major challenge for rice farmers due to heavy rain and floods. Furthermore, increased heat stress caused by climate change could delay flowering and reduce rice yield (Krishnan et al., 2011).

If rice yields falter due to climate change, this affects a great share of the nation's population. This has implications for the livelihoods of more than 60 million people, accounting for 70% of rural households that depend on rice as their main source of income. Furthermore, rice is a main food for domestic demand of more than 90 million people (Asian Development Bank, 2012). Rice and other cereals are essential food to meet daily calorie needs and constitutes 60% of total expenditure on food consumption for low-income households in Vietnam (Hoang, 2018).

Given the limited agricultural area and rising population growth, agricultural productivity has to increase to cope with escalating pressure on future food security. The future of the rice production system depends on its ability to build resilience through a wide variety of adaptation strategies. Diversifying farmers' income by growing other crops, altering the planting dates, changing sowing density are essential adaptation measures of rice cultivation (Shrestha et al., 2016). Smart irrigation systems like drip and sprinkler allow farmers effectively manage their limited irrigation water (The World Bank and Asian Development Bank, 2020) [1]. High grain quality rice varieties with heat or drought tolerance traits are adopted to maximize the plant's growth and productivity in the regions facing the risk of hot spells (Babel and Turyatunga, 2015).

This paper aims to contribute to the literature on the impact of climate change on Vietnamese rice production by investigating the evolution of rice yields over the period 1987-2015 as well as their variability between Vietnamese provinces, as a function of the climatic conditions which these provinces faced during this period. The focus is on the impact of periods of heat stress and potential adaptation of farmers to them at the provincial level. Then, following work on the impact of climate change on crop yields (see, among others, Roberts et al., 2013), the impact of temperatures is summarized in two indicators describing how much temperatures were favorable (growing degree days) or unfavorable (killing degree days) during the growth period of rice, for a given year in each province. Adaptation is captured by estimating a dynamic production function allowing spatial and temporal heterogeneity of rice yield responses to climate variations. The estimation of responses by province and varying in time is made possible by the application of the "mean-observation OLS" (MO-OLS) estimator recently proposed by Keane and Neal (2020a).

The paper is organized as follows. Section 4.2 provides an overview of the econometric approaches adopted to analyze the impact of climatic conditions on crop yields. Special attention is paid to approaches incorporating farmers' adaptation to these climatic conditions. We then introduce the panel model with heterogeneous slopes recently investigated by Keane and Neal (2020a). Section 4.3 introduces the data used. This section provides a detailed description of the temporal changes in rice yield distributions and the differences between provinces in these yields. A similar analysis is carried out for

[1] System of Rice Intensification (SRI), under Vietnamese government auspices, was widely applied by farmers in the Northern regions (Van Mai and Lovell, 2017). SRI practices include the use of young seedlings, transplanting 1 plant per hill (instead of 3 or 4), irrigating with a thin water layer of 1–2 cm deep, applying more organic fertilizers (Uphoff, 2012).

the climate indicators, i.e. growing degree days and killing degree days. Section 4.4 provides the results from estimation of a dynamic panel data model with heterogenous slopes and compare them with those resulting from the estimation of panel models classically used in the literature. This section then focuses on the spatial and temporal patterns of estimated heterogenous parameters associated with killing degree days, drawing new insights from adaptation to heat stress in rice production in Vietnam. Section 4.5 concludes. Appendices are devoted to the presentation of technical details involved in MO-OLS estimation, growing and killing degree days computation, as well as the formulation of a simple crop model with weather and adaptation.

4.2 Methodology

Measuring the impact of climate change on agricultural outcome (production, revenue per ha, yield. . .) is classically based on the estimation of a response function linking this outcome to various weather indicators (see Dell et al., 2014; Kolstad and Moore, 2020, for surveys). For instance, Chung et al. (2015) quantifies the impact of seasonal climate variability on rice yield in the Central Highland of Vietnam from 1986 to 2012. Using annual time-series of yield, temperature and precipitation for two rice growing seasons, they show the favorable impacts of an increase in average minimum temperature and average precipitation on rice yield, while an increase in average maximum temperature reduces rice yield by about 6% and 8% depending on the growing season. However, this approach relies only on short-run fluctuations in weather and, consequently, does not allow for estimation of a long-run climate response including adaptation, but rather a short-run weather response. The challenge is then to capture adaptive behavior not only at the extensive margin (e.g. increasing water use in the short run to fight against heat waves), but also at the intensive margin (e.g. adopting irrigated agriculture practices).

Two main approaches have been proposed in the literature to deal with this challenge. The first one, which was initiated by Mendelsohn et al. (1994), is called the Ricardian approach. This approach is based on the estimation of the impact of climate change on farmland value using cross-sectional data. Mendelsohn et al. (1994) measure variation in climate using 30-year average of weather conditions in different locations in the United States (US). Farmland values are known to reflect farmland profitability within a perfectly competitive market. They reflect farmers' optimization of their production technology or choice according to the climate they have faced. Thus, the main advantage of the Ricardian approach is to capture the long-run equilibrium effects of climate change, incorporating the net benefits of possible adaptation strategies. However, such approach would fail to control for many unobserved omitted variables that are correlated with the climate and also affect farmland values. For instance, lacking observations for factors such as soil quality or access to irrigation infrastructure would bias estimates of climate impacts on farm values.

Extensions of the Ricardian approach suggest using panel data (Schlenker et al., 2006; Massetti and Mendelsohn, 2011). Indeed, the inclusion of individual fixed effects plus region-by-year fixed effects in the regression model allows to control unobserved individual heterogeneity as well as unobserved region specificities and time shocks. To date, Trinh (2018) is the unique study that applies the Ricardian approach to study the impact of climate change on land value in Vietnam, using panel data. This paper uses four waves of household level data from Vietnam Household Living Standard Survey (VHLSS) over the period 2004-2014. Farmland values are approximated by net revenues, with net revenue defined as gross crop revenue (or total sales for each crop) less all cost, divided by agricultural land. Cross-sectional variation in climate is measured using time-average of monthly temperature and precipitation over 65 years (1950-2014). Results show that in the dry season, increases in temperatures are beneficial to all farms in the warmer Southern regions, while increases in precipitation damage only irrigated farms in the Central and Southern regions. The impact of higher temperature in the wet season is similar, except that it will negatively affect net revenue of irrigated farms in the long run. More rainfall in the wet season will increase net revenue only in the North region.

A limitation of the Ricaridan approach is that the classical panel data estimation method does not permit to estimate the effect of the long-run climate averages because these averages have no temporal variation. Indeed, transforming the panel data model using either within or first-difference operators makes it possible to get rid of individual fixed-effects, but at the cost of the disappearance of any time-unvarying variables such as long-run climate averages. Massetti and Mendelsohn (2011) propose the use of the two-step estimation method proposed by Hsiao (2014) to estimate the impact of time-unvarying variables in panel data models with fixed effects (see Trinh, 2018, for an application). This estimation method provides consistent estimates of the impacts of individually time-varying variables in its first step. Nevertheless, estimates of the impacts of time-unvarying variables (long-run climate averages) got in the second step are inconsistent even when the number of individuals tends to infinity, if individual fixed-effects and time unvarying variables are correlated. It is thus easy to imagine omitted variables, such as the location in a mountainous area, that can explain observed variability in farmland prices and are correlated with climate.

A second category of approaches has been recently introduced in the literature. Kolstad and Moore (2020) classify them as emerging hybrid approaches. One of these emerging approaches proposes to model the effect of weather and climate in two steps. First, the linear effect of weather variation is estimated for each location in the panel dataset, which allows the linear response to weather fluctuations to vary across space. Second, the coefficient on weather (from the first step) is modeled as a function of climate and other control variables. This approach exploits two sources of variation in the panel data: (1) the time-series variation from the natural variation of weather within each location, and (2) the cross-sectional variation in mean weather (climate) between locations. Hence, first step estimates measure short-run responses to weather variation in each location, while second step estimates capture the variation in these responses due to adaptation to climate. Indeed, in the long-term, we can think that each location has chosen a production technology adapted to its climate. For instance, hot locations have chosen a technology that performs well in hot temperatures but poorly in cold temperatures and cold locations have chosen the opposite.

A first application of this approach has been proposed by Butler and Huybers (2013). Their application deals with maize yields in US and makes use of county-level data observed from 1981 to 2008. Butler and Huybers (2013) uses the classical framework where the influence of temperature on yield is parametrized by growing degree days (GDD) and killing degree days (KDD) (see, for instance, Roberts et al., 2013). GDD are a commonly used measure for the cumulative warmth a crop has experienced and benefitted over the growing season. By contrast, KDD capture the detrimental effect of high temperatures by accumulating the total number of hours with harmful temperatures over the growing season. As a consequence, in a multiple regression of yields on GDD and KDD, the first measure generally enters positively while the second measure enters negatively. Thus, in a first step, Butler and Huybers (2013) estimate for each county:

$$y_{it} = c_{0i} + c_{1i}t + \beta_{1i}GDD_{it} + \beta_{2i}KDD_{it} + \varepsilon_{it}, \ t = 1, \ldots, T \tag{4.1}$$

where y_{it} denotes maize yield (in logarithm), and GDD_{it} and KDD_{it} denote growing degree days and killing degree days in county i in year t, respectively. The linear time term in t accounts for technological and other steady changes over the time period considered and ε_{it} is the residual error. β_{1i} and β_{2i} measure yield sensitivity of county i to GDD and KDD, respectively.

In a second step, Butler and Huybers (2013) put the focus on adaptation to warming climate and thus regress estimated county values of KDD sensitivities, or $\widehat{\beta}_{2i}$, on average county values of KDD over the period considered, or $\overline{KDD}_i$, i.e.

$$\widehat{\beta}_{2i} = \alpha_0 + \alpha_1 \log \overline{KDD}_i + \eta_i, \ i = 1, \ldots, N \tag{4.2}$$

This specification with the regressor expressed in logarithm appears to be the best in terms of fit quality when compared with other linear specifications with transformed covariates. County time-average value of KDD is used as an indicator of the long-run spatial heterogeneity among counties in terms of climate.

The estimated value of parameter α_1 shows a significant negative impact of county time-average value of KDD (in logarithm) on county KDD sensitivity. The relationship between these two variables appears to be concave, i.e. county KDD sensitivity increases up to a given threshold for time-average KDD, from which it starts to remain stable or even to decrease. Or, in other words, hotter counties exhibit significant adaptation to climate over the considered time period, these counties are becoming less and less sensitive to yield losses from heat.

The two-step approach originally proposed by Butler and Huybers (2013) has been recently applied to the measure of the impact of climate change on residential electricity and natural gas consumption in California (Auffhammer, 2018), and on mortality in the U.S. (Heutel et al., 2020). Although the two-step approach uses the temporal and individual dimensions to identify short and long term climate impacts, it does not fully exploit the panel dimension of the data. Moreover, this approach does not allow to investigate adaptation over time within counties. As recently emphasized by Keane and Neal (2020a), due to adaptation to climate, we could expect the function mapping weather conditions into crop yields to exhibit regional and time fixed effects in both intercepts and slopes. Keane and Neal (2020a) then propose an estimation strategy in panel data modeling that addresses adaptation across regions and time in a flexible way. More precisely, they consider estimation of the following panel data model:

$$y_{it} = c_i + \tau_t + \beta_{1it} GDD_{it} + \beta_{2it} KDD_{it} + \beta_{3it} Prec_{it} + \beta_{4it} Prec_{it}^2 + \varepsilon_{it}, \quad (4.3)$$
$$i = 1, \ldots, N, \; t = 1, \ldots, T$$

where y_{it} denotes crop yield (in logarithm), and GDD_{it} and KDD_{it} denote growing degree days and killing degree days in county i in year t, respectively. They add precipitations in county i in year t, denoted by $Prec_{it}$, and its squared value, or $Prec_{it}^2$, in order to investigate a potential nonlinear impact of precipitations on crop yield (see, among others, Burke and Emerick, 2016). This model generalizes the classical two-way fixed effects specification, with c_i and τ_t denoting the individual and time fixed effects, respectively, by considering both spatial and temporal heterogeneity in the slope coefficients, or β_{kit}, $k = 1, \ldots, 4$. This approach is more general and flexible than those proposed by Butler and Huybers (2013). This approach does not assume a specific form of non-linearity for the KDD coefficient such as Eq. (4.2). Instead, slope heterogeneity is allowed to be correlated with the regressors. The nature of the relationship between β_{2it} and KDD_{it} can be assessed in a second step by regressing estimates of β_{2it} provided by estimation of Eq. (4.3), on KDD_{it}.

Restrictions must be imposed in order to estimate coefficients in Eq. (4.3). Indeed, this equation involves more coefficients to be estimated than data points. Keane and Neal (2020a) then recommend to restrict attention to additive heterogeneity across the region and time dimensions, i.e.

$$\beta_{kit} = \beta_k + \lambda_{ki} + \theta_{kt}, \; k = 1, \ldots, 4 \tag{4.4}$$

As a consequence, each region's relative sensitivity to weather is assumed to be fixed over time. Moreover, time effects shift all region's sensitivities up or down to the same degree.

The panel data model defined by Eq. (4.3) and (4.4) can be estimated using the "mean observation OLS" (MO-OLS) procedure developed by Keane and Neal (2020a). The MO-OLS estimator is constructed by first running pooled OLS to obtain $\widehat{\beta}$, then running regressions by region to collect $\widehat{\beta}_i$, $i = 1, \ldots, N$, and lastly a set of regressions by year to collect $\widehat{\beta}_t$, $t = 1, \ldots, T$. A biased preliminary estimator for each β_{it} is given by $\widehat{\beta}_{it} = \widehat{\beta}_i + \widehat{\beta}_t - \widehat{\beta}$. Keane and Neal (2020a) show how the bias can be calculated to arbitrary accuracy and removed using an iterative procedure. Specifically, they show that the expression for the bias is a Cauchy sequence such that the new bias introduced in each iteration gets smaller and smaller. Details on MO-OLS estimation are provided in Appendix B.1.

Keane and Neal (2020b) compare the predictive performances of MO-OLS estimator with two other approaches: classical two-way fixed effect panel data estimator and the nonparametric technique of deep neural networks (DNNs). They show that both DNNs and MO-OLS estimators outperform classical two-way fixed effect panel data estimator for predicting yields, both in an exercise using the US county-level corn yield data from 1950 to 2015 and a Monte-Carlo cross-validation exercise. Moreover, MO-OLS estimation substantially outperforms the two other approaches in forecasting yield in a 2006-2015 sample.

4.3 Data

4.3.1 Rice data

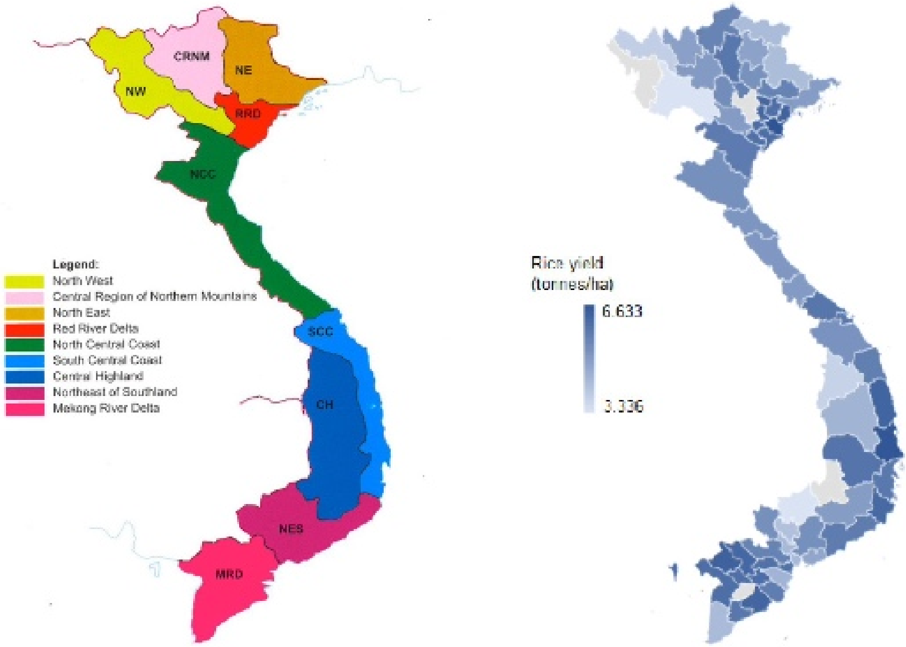
The rice yield database is obtained from the International Rice Research Institute[2], containing information on annual agricultural statistics such as rice production, area harvested, rice yields across 64 sub-national units nationwide from 1987 to 2015. In this period, Vietnam embarked on major structural reforms, or Doi Moi reforms, which gradually converted the country from a highly centralized planned economy to a socialist-oriented market economy with more openness to international trade.

The sub-national units refer to the first tier administrative units that are made up of municipalities and provinces in Vietnam. Our time period of study involved splitting of divisions with high population density and merging of geographically adjacent units. From 1987 to 2003, Vietnam was made up of 61 administrative units. In 2003-2004, Dien Bien was set apart from the remainder of Lai Chau province; Dak Lak was subdivided into Dak Lak and Dak Nong; Hau Giang was seperated from Can Tho city. Hence, from 2004-2007, there were 64 administrative units in Vietnam. Since 2008, the government incorporated Ha Tay province into Hanoi city, resulting in 63 administrative units left in Vietnam. To have a consistent sample size, we construct spatially consistent geographic units over the study period. In split or merger cases, new geographical entities are created with the rice production and area harvested to be combined from the corresponding units split or merged. Rice yields for these new entities are obtained by dividing the modified rice production by the area harvested. Therefore, there are 60 administrative units presented in our panel data.

Figure 4.1 maps the rice productivity across the 60 provinces under study in 2015. Rice cultivation is mainly concentrated in Mekong River and Red River Delta. The most productive rice growing area is Thai Binh at a record of around 6.64 tons per hectare. Rice farming is also heavily concentrated along the coast with South Central Coast as another

[2] IRRI is a research organisation that promotes agro-research and development, faring in reviving rice seedlings and improving crop yield in the world. Information about the institute can be found at https://www.irri.org/

Figure 4.1: Map of rice yield distribution (tonnes/ha) in 2015

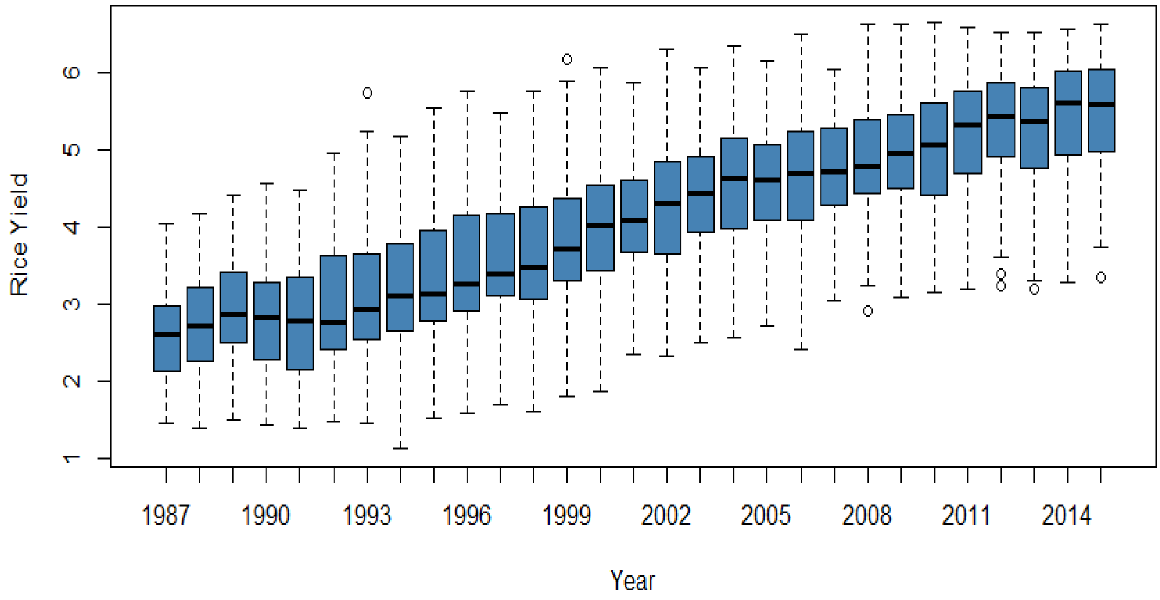


Note: The map on the left shows the nine agro-ecological zones of Vietnam marked by their particular types of soil, topography and climate context. The map on the right displays rice yields across 60 provinces in VN. The grey area is where rice yields were not available. (Source: Authors' own elaboration from IRRI's data).

rice production heartland of Vietnam. The area of light blue signifies poor productivity for rice in Vietnam and can be found in landlocked regions. The provinces with the lowest rice yield of Vietnam is Son La in the Northwest of Vietnam. Rice production in rural areas is apparently higher than that of the urban zones because the rural population still depends on the agricultural sector for livelihood.

Figure 4.2 shows the evolution of rice yields over the period from 1987 to 2015. After stagnation between 1987 and 1992, rice yields have grown steadily since 1992, and this growth has affected all Vietnamese provinces. It is then interesting to see if they have all progressed in the same way or if some of them have seen their yields increase while others have not. Figure 4.3 reports the distributions of rice yields for the 60 provinces. Provinces are ordered according to rice yields. Figure 3 shows a stability over time in order between provinces, the most productive remaining the most productive and so on, and this even if the respective positions of certain neighboring provinces in terms of yield may have changed certain years. This descriptive analysis therefore highlights a persistence in provinces' rice yields, i.e. provinces tend to "stick" with their previous position in the

Figure 4.2: Rice yield distributions from 1987 to 2015



ranking, which econometric modeling must take into account.

4.3.2 Climate data

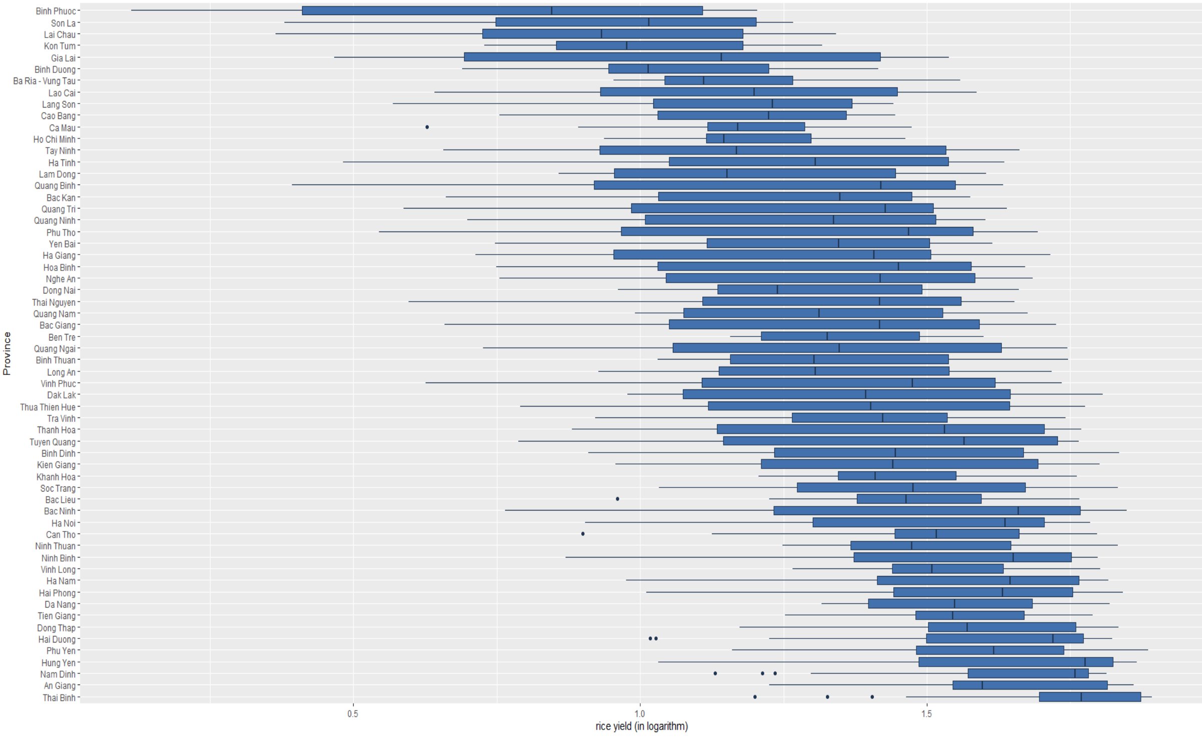
Weather data used in this study are daily temperatures and precipitations. Temperature data comes from the Climate Prediction Center (CPC) database developed by the National Oceanic and Atmospheric Administration (NOAA). It provides historical data on daily maximum and minimum temperature for a grid of 0.50 × 0.50 degree of latitude and longitude.[3] Precipitation data comes from Asian Precipitation-Highly-Resolved Observational Data Integration Towards Evaluation (APHRODITE) project.[4] The rainfall dataset has mean daily precipitation (millilitre per day) gridded at a 0.25 × 0.25 degree resolution used as a proxy for moisture conditions. The time units are days from January th1 1987 to December 3th1 2015.

Geo-spatial interpolation method was applied to have temperature estimates on a

[3]The Global Positioning System (GPS) coordinates utilized in our study range from 104.875 °E to 109.375 °E for longitude and from 8.625° N to 23.125 °N.

[4]Netcdf format data can be retrieved from https://www.cpc.ncep.noaa.gov and / http://aphrodite.st.hirosaki-u.ac.jp/

Figure 4.3: Rice yield distributions by province



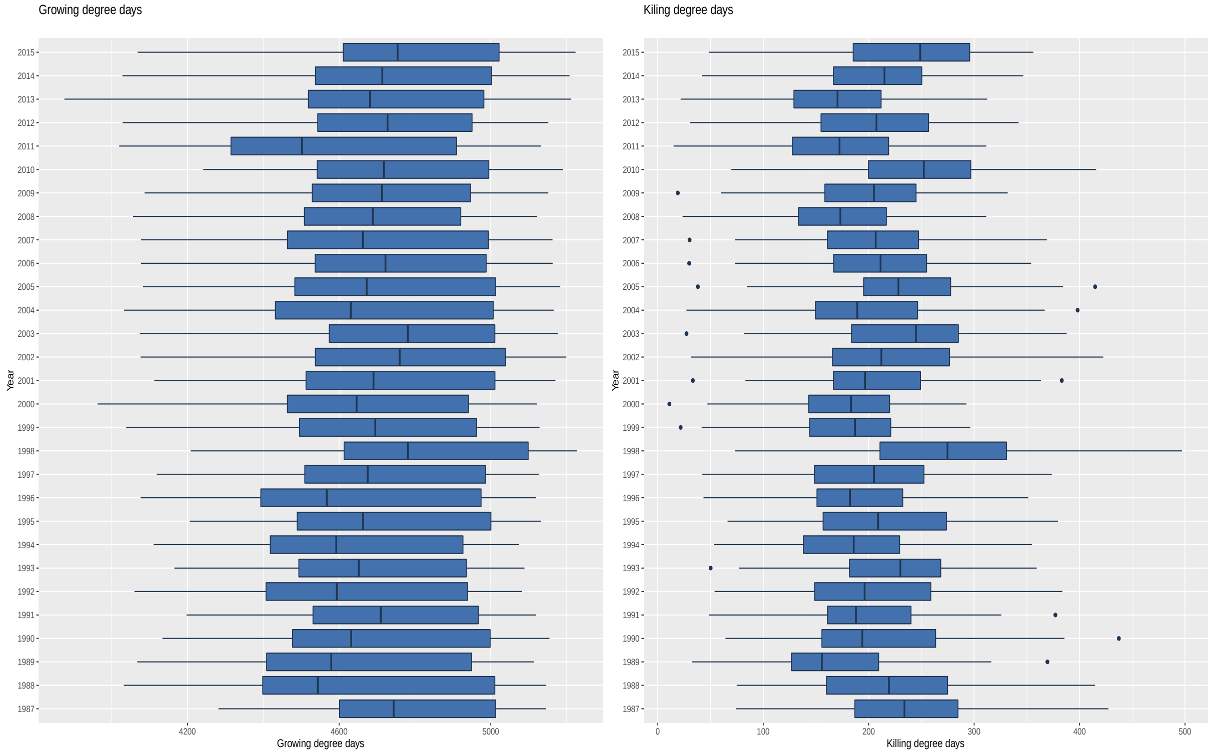
0.25x0.25 degree resolution grid. Indeed, the original data detailed on a 0.5x0.5 degree resolution grid does not sample all Vietnamese provinces. Generalized additive models (Wood, 2017b) were estimated in order to capture the complex nonlinear relationship between temperature and location using original data. Fitted models were used to predict temperature data over the finest grid.[5]

The interpolated weather data were then up-scaled to match the yield measurement spatial unit. Administrative boundaries were first overlaid with the gridded weather dataset. Then, for aggregated maximum (or minimum) temperature of a particular province, we found the maximum (or minimum) record of all observed maximum (or minimum) daily temperature values gridded within that province. We proceeded similarly for precipitation, i.e we took a simple average of observed precipitations within the provinces.

In line with the current literature on climate change impact on crop yields (Roberts et al., 2013), we finally computed growing degree days (GDD) and killing degrees days (KDD) for each province and year to assess the effect of weather conditions during the

[5]More information on the chosen interpolation strategy can be found at `https://swilke-geoscience.net/post/spatial_interpolation/`

Figure 4.4: GDD and KDD distributions by year

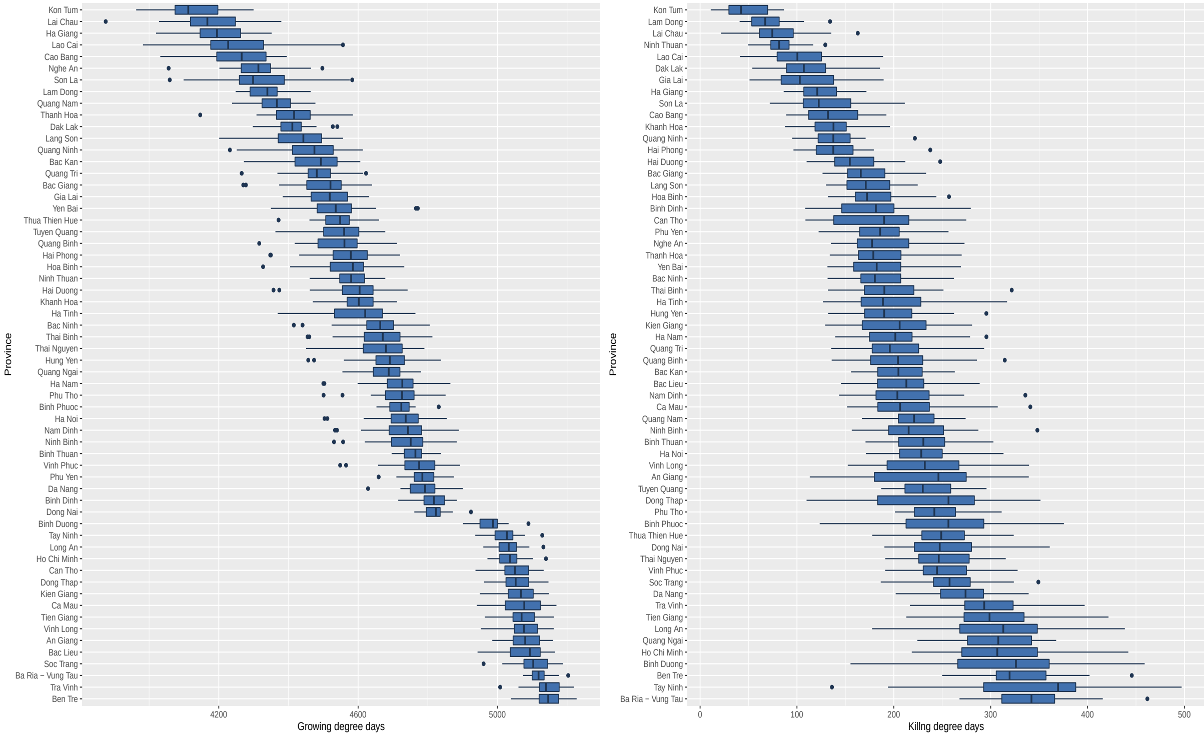


growing season on yields. Computational details on GDD and KDD computation are provided in Appendix B.2.

The changes in the distributions of GDD and KDD over the studied period do not appear to be characterized by any identifiable pattern as shown in Figure 4.4 . The year 1998 stands out from the others because several provinces show very high values for Killing Degree Days. Indeed, this year was characterized by a large decrease in rainfall during the dry season (only about 30-70% of the annual average), and prolonged heatwave, all this causing severe droughts in main rice producing provinces.

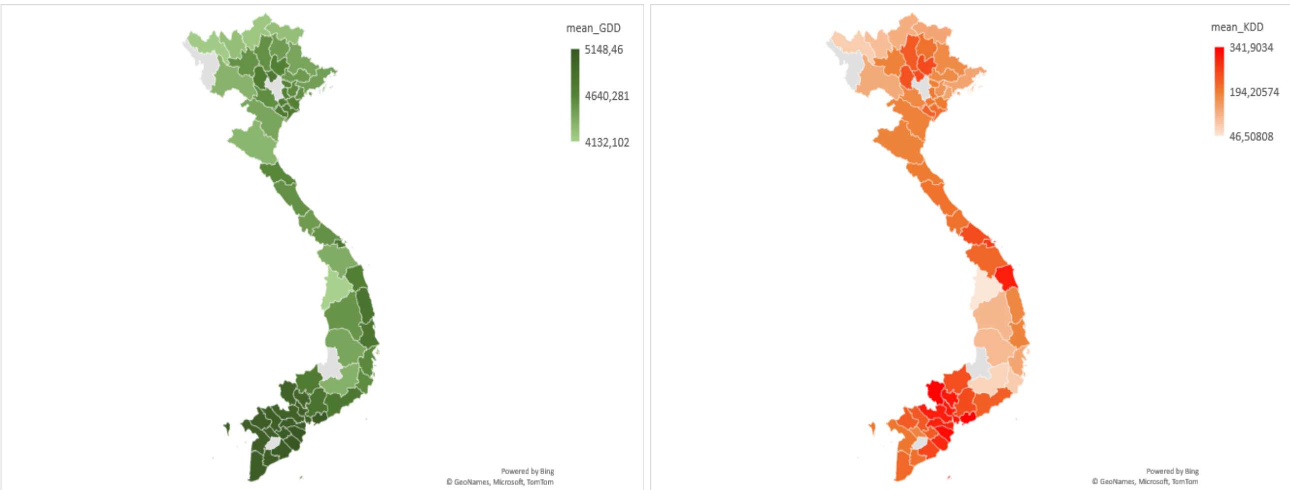
On the other hand, the analysis of the distributions of GDD by province (see Figure 4.5) shows a clear ranking of the provinces in terms of rice growing conditions. A similar fact is also observable for the distributions of KDD by province. Although the two rankings does not fit perfectly, the Spearman correlation between them is equal to 0.731 and is significantly different from zero with a p-value much smaller than usual significance levels. The Vietnamese provinces with the most favorable climate for the growth of rice are also those that experience the greatest risks in terms of unfavorable temperatures for this

Figure 4.5: GDD and KDD distributions by province



growth, and vice versa. This observation is corroborated when looking at the spatial distribution of average values of GDD and KDD (see Figure 4.6).

Figure 4.6: Spatial distributions of mean GDD and KDD in Vietnam



To sum up, Table 4.1 gives summary statistics for all the variables used below.

Table 4.1: Descriptive statistics for variables used for econometric analysis

Variables	Mean	Standard Deviation	Minimum	25% Percentile	75% Percentile	Maximum
Rice Yield	4.048	1.205	1.120	3.077	4.969	6.637
GDD	4,687.027	289.332	3,875.414	4,479.303	4,964.526	5,227.362
KDD	206.485	78.791	10.976	153.596	256.828	497.137
Precipitation	1,331.774	272.169	246.384	1,148.470	1,509.492	2,261.893
Crop acreage	118,296.000	121,029.900	5,400	43,775	150,025	770,400
Observations	1740					

Note: Precipitation is the simple average of precipitation values within province.

4.4 Results

4.4.1 Classical panel data models

Table 4.2 reports results from estimation of the three following models:

$$y_{it} = c + \rho y_{i,t-1} + \beta_1 GDD_{it} + \beta_2 KDD_{it} + \beta_3 Prec_{it} + \beta_4 Prec_{it}^2 + \varepsilon_{it} \quad (4.5)$$

$$y_{it} = c_i + \tau_t + \rho y_{i,t-1} + \beta_1 GDD_{it} + \beta_2 KDD_{it} + \beta_3 Prec_{it} + \beta_4 Prec_{it}^2 + \varepsilon_{it}, \quad (4.6)$$

$$\begin{aligned} y_{it} &= c_i + \tau_t + \rho y_{i,t-1} + \beta_1 GDD_{it} + \beta_{20} KDD_{it} + \beta_{21} \left(\log(KDD_{it}) \times KDD_{it} - KDD_{it}\right) \\ &\quad + \beta_3 Prec_{it} + \beta_4 Prec_{it}^2 + \varepsilon_{it}, \quad (4.7) \\ &\quad i = 1, \ldots, N,\ t = 1, \ldots, T \end{aligned}$$

These three models integrate the lagged rice yield value (in logarithm) in addition to classical weather variables, i.e. KDD_{it} and $Prec_{it}$, in the set of regressors. The objective is to capture the strong temporal dependence observed in rice yields highlighted in the descriptive presentation of the data. In other words, the lagged rice yield value captures state dependence as the assumption that rice yield is redrawn randomly in each period is inconsistent with evident shown in the data.

Model (4.5) is the classical Pooled-OLS model that does not take into account any unobserved individual or time heterogeneity while model (4.6), or Fixed-Effect model, captures it by adding individual and time fixed effects in its specification. As shown in Keane and Neal (2020a) (see also Appendix B.3), this last specification can be deduced

Table 4.2: Classical panel data estimates of the impacts of temperature and precipitation on rice yields in Vietnam

	Pooled-OLS	**FE-OLS without adaptation**	**FE-OLS with adaptation**
Lagged rice yield (in logarithm)	0.93707*** (0.00575)	0.65740*** (0.02516)	0.65998*** (0.02514)
GDD	0.00003*** (0.00001)	-0.00006 (0.00004)	-0.00002 (0.00004)
KDD	-0.00011*** (0.00003)	-0.00005 (0.00009)	-0.00211** (0.00094)
log(KDD) × KDD - KDD	—	—	0.00037** (0.00017)
Precipitation	0.19831** (0.07591)	0.17185* (0.08930)	0.17533* (0.09014)
Precipitation^2(÷1000)	-0.08174*** (0.02803)	-0.08213*** (0.03073)	-0.08396*** (0.03102)
Constant	-0.10187 (0.06997)	—	—
Observations	1680	1680	1680
R squared	0.928	0.912	0.912
Fixed Effects	No	Province, Year	Province, Year

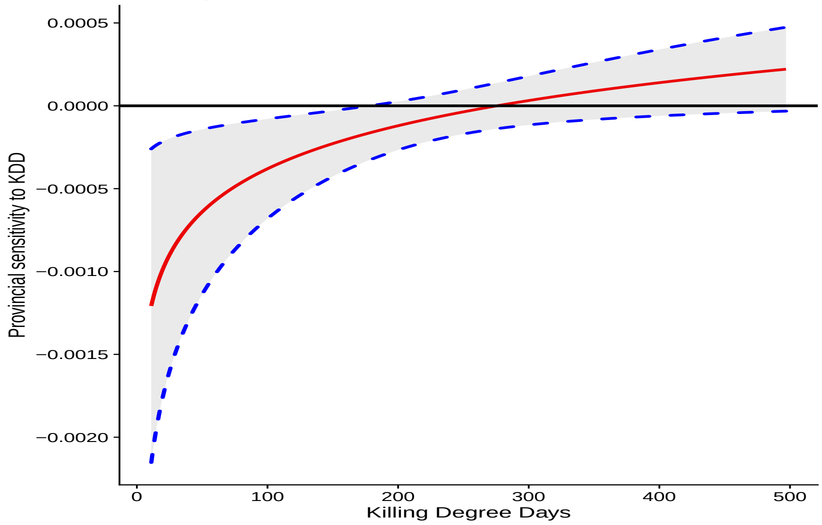
Note: Standard errors are reported in parentheses, and are clustered at the province level.

from a simple formalization of the rice production function that does not take into account any adaptation to climate change from farmers. This simple modeling can be generalized in order to incorporate adaptation behavior of farmers to extreme temperatures. The resulting prediction of a log linear relationship in farmers' high temperature response to KDD leads to the model (4.7) which includes as an additional regressor a nonlinear function of KDD to capture adaptation to high temperatures. β_{20} is thus expected to be negative and β_{21} positive.

A first striking result appears in Table 4.2: the coefficient associated with lagged rice yield value is found to be positive and significantly different from zero (at 1% significance level), regardless of the estimated model. The expectation that Pooled-OLS estimator overestimates the true coefficient on the lagged rice yield value, whereas the Fixed effects estimator will underestimate it (Bond, 2002), is satisfied. Hence, the true value of ρ lies between 0.66 and 0.94. As a consequence, rice yields exhibit large state dependence, even when unobserved individual heterogeneity is taken into account.

The results of the estimation of the three models show a positive and significant effect of precipitation on rice yield. However, this effect becomes less and less pronounced as

Figure 4.7: Estimated marginal effect of KDD on rice yields using FE-OLS with adaptation estimates
(with 95% confidence interval)



the amount of precipitation increases. The results regarding the effect of precipitation are similar whether or not we take into account the presence of individual and temporal fixed effects or the possibility of farmers' adaptation.

The two Fixed-Effect models (4.6) and (4.7) do not exhibit a significant and positive relationship between rice yield and GDD, while Pooled-OLS model (4.5) does. Results regarding the impact of high temperatures are more mixed. A significant and negative impact is shown when estimating the Pooled-OLS model, while the impact cannot be disentangled from zero when estimating the Fixed-Effect model without adaptation. The introduction of the nonlinear regressor in model (4.7) makes the direct impact of KDD negative and significant, as expected. In turn, the added regressor is positive and highly significant. Accordingly, as KDD increases, the total marginal effect of KDD on rice yield gets smaller as follows:

$$\frac{\partial y_{it}}{\partial KDD_{it}} = -0.00211 + 0.00037 \ln\left(KDD_{it}\right). \tag{4.8}$$

Figure 4.7 reports this estimated marginal effect drawn as a function of KDD. In accordance with the economic modeling of adaptation behaviors proposed by Keane and Neal (2020a) (see Appendix B.3), this function is increasing and concave. As the climatic conditions for rice production worsen in terms of high temperatures, farmers are making an increasing effort to adapt to these conditions. This effort seems sufficient to annihilate any impact of high temperatures from a threshold of KDD around 200 degree days.

4.4.2 Heterogeneous slope model (MO-OLS)

It should be noted that this result is closely related to the parametric specification chosen in Eq. (4.7). It is therefore interesting to investigate it in more detail using a more general specification that allows for both province and time heterogeneity in parameters on temperature and precipitation, or

$$y_{it} = c_{it} + \rho_{it} y_{i,t-1} + \beta_{1,it} GDD_{it} + \beta_{2,it} KDD_{it} + \beta_{3,it} Prec_{it} + \beta_{4,it} Prec_{it}^2 + \varepsilon_{it} \quad (4.9)$$
$$i = 1, \ldots, N, \; t = 1, \ldots, T$$

Table 4.3 reports results from the estimation of Eq. (4.9) using MO-OLS presented above. This table gives unweighted and weighted means of the estimated coefficients, using crop acreage of each province as weight, as well as their standard deviations, medians and 25% and 75% percentiles. Due to the asymptotic normality of the distribution of the unweighted mean, it is possible to associate a standard error with it and therefore to test its significance, which cannot be done for each province and time varying parameters.

The unweighted mean parameter on lagged rice yield is equal to 0.369 and is significantly different from zero, showing existence of true persistence in rice yield. High rice yields in current years are driven by high rice yields in past years, and vice versa, after controlling for observed and unobserved heterogeneity among provinces. Nevertheless, this average effect is smaller than the marginal effect of 0.660 obtained in the last column of Table 4.2 where we adaptation is modelled parametrically using the nonlinear KDD parameter. Unobserved factors seems to play a greater role in explaining persistence in rice yield when spatial and time heterogeneity are considered in production function modeling. Finally, the variation coefficient, or 0.539, is small and shows a concentration of individual estimates around their average values.

Results further highlight an inverse U-shaped relationship between rice yield and

Table 4.3: MO-OLS estimates of the impacts of temperature and precipitation on rice yields in Vietnam

	Mean	Weighted Mean	Median	Standard Deviation	25% Percentile	75% Percentile
Lagged rice yield (in logarithm)	.369017*** (.0304878)	.3732414	.3797735	.1989875	.2411912	.5178423
GDD	.0005283*** (.0000946)	.0004151	.0003268	.0007192	.0000527	.0008113
KDD	-.0006413*** (.0001617)	-.0003812	-.0003281	.0011987	-.0009688	.0000899
Precipitation	.3980065** (.1991514)	.3239101	.236618	1.477125	-.5835178	1.408696
Precipitation^2(÷1000)	-.1718048*** (.0755211)	-.134721	-.0927474	.563858	-.5249135	.2224721
Constant	-1.750997*** (.4387644)	-1.193757	-1.186775	3.300954	-3.578941	.601102
R squared	.9737651		Observations	1680		

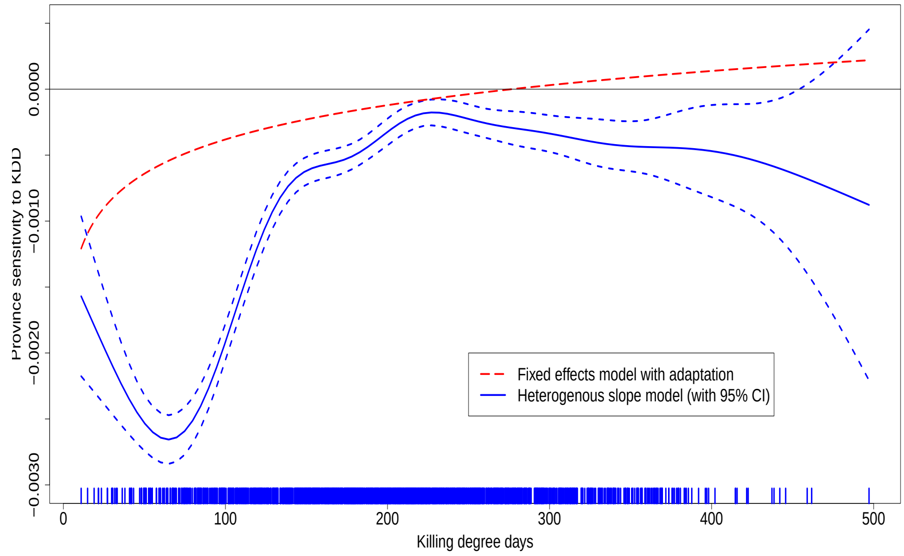
Note: Standard errors are reported in parentheses.

precipitation. The rice yield increases as the precipitation increases but this positive effect gradually diminishes until it is canceled or eventually begins to decrease. Furthermore, this effect appears more pronounced when the spatial and temporal heterogeneity are taken into account in the modeling of the production function. Indeed, the mean values of the parameters associated with precipitation shown in Table 4.3 are twice as large as the estimated values shown in Table 4.2. Nevertheless, the statistics summarizing the distribution of estimated individual and temporal values show a high variability of the responses of rice yield to precipitation with respect to geography and time.

The unweighted average parameter on GDD is equal to 0.00053 and is significantly different from zero, implying that one extra degree days of temperature between 7°C and 29°C causes a 0.053% increase in rice yield. Note that no significant and positive effect of GDD appears when estimating production function models with only individual and temporal fixed effects. Here too, individual responses to GDD do not appear to be widely dispersed around their mean.

The unweighted mean parameter on KDD is negative, as expected, and is significantly different from zero, showing that one extra degree days of temperature above 29°C causes a −0.064% decrease in rice yield. The standard deviation of the KDD parameter, or 0.00120

Figure 4.8: Estimated marginal effect of KDD on rice yield as a function of KDD



is twice as large as the estimated mean value, with a 75/25 percentile range of 0.00009 to −0.00969. The MO-OLS estimates display thus substantial heterogeneity in estimated KDD sensitivity. Moreover, estimated KDD sensitivities appear to be positive for some provinces and some years. Such positive values contradict the expected results with respect to the sign of KDD sensitivities. Nevertheless, in the absence of any result pertaining to the asymptotic distribution of the estimated heterogeneous slopes, it is impossible to say whether these values are statistically significantly positive.

It is therefore interesting to investigate the shape of the relationship linking KDD sensitivity to KDD. Figure 4.8 reports the nonparametric regression of estimated heterogeneous KDD sensitivities, or $\widehat{\beta}_{2,it}^{\text{MO-OLS}}$, on corresponding values of KDD, or KDD_{it} and the corresponding 95% confidence interval.[6] First, the estimated curve shows that, on average, KDD sensitivity is always negative and significantly different from zero.[7] Second, the estimated curve suggests a more complex relationship between yield response and KDD that the parametric models fail to capture (Figure 4.8 also reports the estimated marginal effect in FE-OLS model with adaptation). Therefore, as KDD moves from 0 to 60, rice

[6] Nonparametric estimation is based on recent advances in estimating generalized additive models from splines (Wood, 2017b).

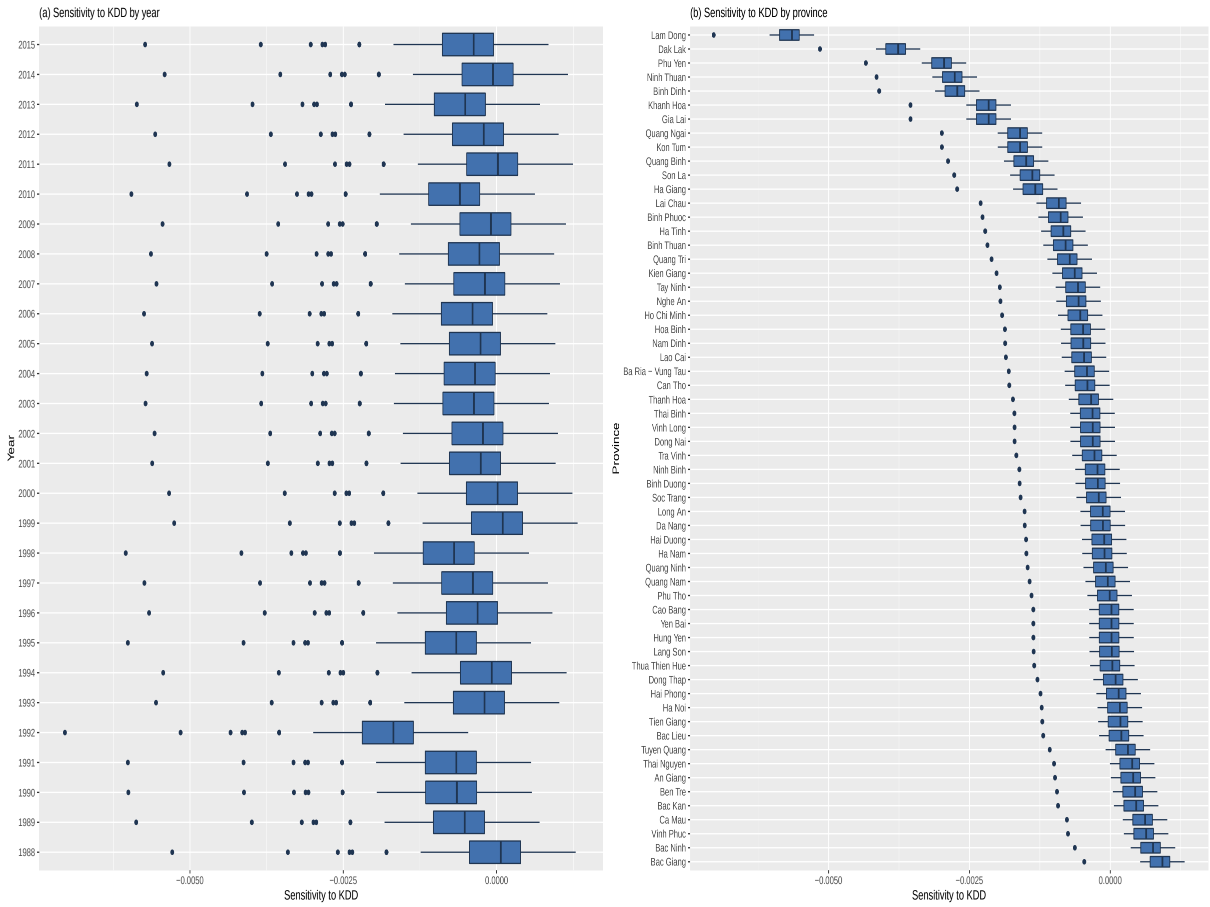
[7] Estimated degrees of freedom associated with the estimated curve are equal to 8.549. They are larger than 1, indicating the nonlinearity of the curve. Moreover, the null hypothesis of joint nullity of all the parameters involved in the spline basis approximation of the smooth function is clearly rejected. Indeed, a low p-value, beyond classical significance levels, is associated with the estimated value of the F-statistics involved in the test.

yields respond more negatively to heat stress. Adaptation seems to be overlooked in cooler regions. These regions are not the ones with the best conditions for rice growth as shown in the description of the data. The costs of adapting to high temperatures may therefore not be offset by yield gains in these regions. As KDD moves from 60 to 220, rice yields are less and less sensitive to high temperatures. Adapting to high temperatures is becoming increasingly profitable. The increase in KDD is accompanied by an increase in GDD for the provinces concerned. They are therefore experiencing increasing incentives to adapt to high temperatures and to limit the resulting losses in terms of yield. For KDD values exceeding 220, the estimated curve shows a slow decrease and even stabilization in the yield response. Although the provinces concerned are those which experience the best conditions in terms of rice cultivation, their efforts to adapt to heat stress seem to be less and less effective, this stress becomes a great concern. For KDD values exceeding 400, the curve estimate becomes increasingly imprecise due to the scarcity of available observations (see the rug of observations on the x-axis of Figure 4.8).

No clear trend appears regarding the evolution of the distribution of provincial responses to KDD over time, as shown in left panel of Figure 4.9. The beginning of the period, 1988-1992, is characterized by a deterioration in these responses. Subsequently, from 1993 to 1998, the evolution is characterized by wide fluctuations. These fluctuations diminish considerably from 1999 to 2009 and pick up again in the last years studied. We do not therefore see an increasingly pronounced adaptation process to heat stress over the period, as observed for wheat in the US by Keane and Neal (2020a).

However, a very clear pattern appears when looking at the differences between the distributions of responses to KDD of Vietnamese provinces. The right panel of Figure 4.9 clearly shows a ranking of Vietnamese provinces from the most KDD sensitive to the least. The descriptive analysis of the climatic condition distributions revealed a clear ranking of the Vietnamese provinces, showing that the more they experience favorable conditions for rice growth, the more they face the risk of heat stress. So, is there a link between this classification and that regarding sensitivity to heat stress? The Spearman correlation coefficient between the ranking of provinces relative to GDD and that relative to KDD

Figure 4.9: Distributions of $\beta_{2,it}$



sensitivity is 0.246 and is not significantly different from zero. The correlation coefficient between now the ranking of provinces relative to GDD and that relative to KDD sensitivity, or 0.380, is higher and significantly different from zero at classical significance levels. This clearly reflects an adaptation to heat stress which is getting stronger as this stress is high. Despite being significant, this correlation remains weak because there is no perfect fit of the two rankings. A perfect fit would have resulted in a linear relationship between KDD sensitivity and KDD value. However, as shown in Figure 4.8, this relation appears to be log-linear for a part of the potential values of KDD, and even decreasing for the low or very high values of this climatic indicator.

4.5 Conclusion

Our paper contributes to the growing literature of climate change impact in Vietnam's agricultural sector in several ways. There have been many discussions around agricultural communities about the potential effects of climate change related to changes in both temperature and rainfall at the national scale. Nevertheless, the literature has treated the yield response without accounting for adaptations to get a full measure of climate damage. The need for large-scale adaptive measures to vulnerability to increased warming might be overlooked. Vietnamese farmers have engaged in all kinds of adaptations to protect their crop against heat stress over the half past century. Models that do not allow for adaptation might result in biased estimates of the effects of high temperatures on plant growth.

In addition, the conventional empirical models treated the country as one region which implies that climate change adaptation remains the same everywhere. The panel data model with heterogeneous slopes recently proposed by Keane and Neal (2020a) provides us a tool to investigate how the responsiveness of rice yield to climate conditions varies over time and across Vietnam's regions. Indeed, heterogeneity in the parameters of the production function linking the rice yield to climatic conditions makes it possible to infer different impacts on heat stress tolerance under different environmental conditions and adaptation measures. This heterogeneity takes a fixed effect form not only in intercepts, as in classical linear panel data models, but also in slopes. In addition, as a byproduct, this approach makes it possible to infer the link between heterogeneous responses and heat stress, without fixing its form as in the fixed effects model with adaptation also proposed by Keane and Neal (2020a) following Butler and Huybers (2013).

A dynamic version of the production function capturing not only heterogeneity in slopes but also state persistence in rice yields is estimated using panel data for the 1987-2015 period across 60 sub-national units. We use the MO-OLS estimator proposed by Keane and Neal (2020a). Results clearly show strong temperature effects on rice yield. We find that rice yield is magnified when beneficial temperatures (warming to the 7–29 °C range in a growing season) increase. Extreme heat (average temperatures exceed 29 °C) intensifies yield loss. Rice yield also relies heavily on rainfall for growth, but excessive rainfall can bring significant damage.

Results also show that the heat stress response function is nonlinear in extreme heat. This function seems to have a natural logarithm form when using parametric specifications, as shown by Butler and Huybers (2013) and Keane and Neal (2020a) when dealing with wheat yield in the U.S. There is good evidence from the parametric models that adaptation increases plant heat stress tolerance. However, whether crop is still resilient beyond an extreme climate threshold is questionable. We thus estimate nonparametrically the function, in order to overcome the caveats of classical parametric specifications. Results then suggest that rice yield sensitivity to heat stress is maximized in the middle range of killing degree days, but declines significantly if they rise above an upper threshold. Put differently, farmers adapt all the more to heat stress as it becomes important. And this holds true up to a threshold beyond which the gain resulting from their adaptation effort is exceeded by the losses due to heat stress.

From a policymakers' perspective, location is very important to consider when thinking about developing food security and sustainability solutions. There are big disparities, yet well-defined spatial patterns in sensitivity across regions. In general, moving towards colder environments, the impact of higher temperatures on yield is more severe. There is a significant difference between crops in rice production hubs such as Mekong River Delta, Red River Delta and other parts of the country in their response to heat stress. The finding also implies that increases in temperature in the coming decades could have even more disruptive effects on agriculture in the coastal part.

This paper constitutes a first step in the analysis of the impact of climatic conditions, and, more specifically, heat stress, on rice yields in Vietnam. Further studies could be undertaken to separate the rice data into spring and winter rice because these crops have different climates requirements. Climate variables could also be further divided for distinct phases of crop (sowing, tillage, anthesis, grain-filling). Moreover, further studies should be conducted to assess the effect of cold condition on yields because plants adapted to higher temperatures might not be able to perform optimally under low temperatures.

Chapter 5

Conclusion

Climate matters a great deal for the economy and the well-being of societies. We are well aware that humans have a large footprint impact across our planet, on forests and aquaculture (IPCC, 2013; Food and Agriculture Organization of the United Nation, 2017). The greatest economic costs of climate change will fall hardest on the poor as they are least equipped to deal with these changes (World Bank, 2018). The thesis provides empirical investigations to understand how local communities along the northern coast and rice growers in Vietnam might adapt to the climate change. Findings would help policy makers in Vietnam think strategically about how to encourage economic development while also managing national climate.

5.1 The economic valuation of mangrove ecosystem services

The first two chapters contribute to the current knowledge database regarding the valuation of mangrove ecosystem services. The scientific evidence related to environmental conservation efforts in Red River Delta is not very adequately known. The studies used multistage stratified random sampling to select sample households in the buffer zone of XTNP, Nam Dinh Province. [1] Contingent valuation and discrete choice experiment were implemented to elicit local willingness to pay for a mangrove restoration project to help coastal ecosystem resilient to sea level rise and other climate hazards. For the contingent valuation, the double bounded dichotomous choice question survey was utilized to elicit the total non-use value of mangrove estimation (Hanemann et al., 1991). By employing log-logistic, log-normal, and Weibull regressions, determinants of the local's willingness to undertake the environmental cost have been identified. People with higher income, better understanding of the mangrove benefits and strong environmental preferences would be willing to pay more for the conservation programs.

[1] Many thanks to my co-author, Dr. Thanh Viet Nguyen, the Assistant Professor at the University of Akureyri, Iceland and students from Hanoi University of Natural Resources and Environment, Vietnam for the design of the questionnaires, surveys, household sampling, pilot tests and face-to-face interviews conducted in 2017 that I did not participate in. My main responsibilities include data wrangling, statistical analysis and writing up the chapters based on the raw data collected from the survey site.

The discrete choice experiment was applied to infer the multidimensional non-use values of mangrove ecosystem services (Holmes et al., 2017). The environmental program was broken down in its component attributes: area of the forest, avoided storm damage losses, and price. In additon to the classical CL model, RPL and GMNL were used to address preference heterogeneity by looking at respondents' socioeconomic demographic characteristics, people's subjective perceptions, and their responses to different options. The results suggest that the local communities can be expected to generate higher WTP for preserving more mangroves areas and avoiding flooding event. There was widespread biodiversity degradation, yet people were not fully aware of this because humans have been doing many things to protect themselves more effectively than wild life populations. The GMNL results indicate that heterogeneity or heteroskedasticity was a big driver of the error variance. More heteroskedasticity was driven by mangrove dependency, occupation variables. Preference for alternative programs over the status quo was also linked with local knowledge of elevated environmental program.

5.1.1 Policy implication

The two studies inform policy-makers as to what coastal communities value and provide an economic justification of conservation policies based on estimates about non-use values of alternative management practices. The findings would help design compensation mechanisms (payment for ecosystem services) for the local communities to contribute to a more sustainable management of mangrove ecosystems in Red River Delta.

The enabling condition for sustainable ecosystems requires public participation and people's willingness to change behavior. This is often hindered by the low scientific understanding, especially with respect to ecological consequences of biodiversity loss. Therefore, research, outreach and education campaigns together with a major participation of local governments can help increase ecological knowledge and the awareness of biodiversity benefits.

The preferences of local communities in the protected areas in Vietnam are fairly heterogeneous. Some people were very passionate about biodiversity conservation while others were not. Some respondents were sensitive to changes in the quantity of mangrove coverage while others would see the additional hectares of mangroves as a bad. Hence, it is also essential to have empirical evidence at the local level to make any specific policy suggestions based on community contexts.

5.1.2 Future research

Mangrove ecotourism at XTNP can induce positive impacts on household welfare by providing employment, income and business opportunities (Management Board of Xuan Thuy National Park, 2014; Thanh and Yabar, 2015). It is crucial to examine the linkages between local tourism participation, socio-economic development and environmental conservation to see if the benefits derived from the protected areas channel to households through the medium of ecotourism.

Personality traits are becoming more relevant as determinants of preferences in the choice experiment literature. The notion of rationality is often used in conventional discrete choice models where the decision maker is assumed to solve an optimization problem and ends up choosing the alternative with the highest utility (McFadden, 1999). However, there are several evidences that human beings may not necessarily respond rationally in the way assumed by random utility models (Kahneman et al., 1993). For instance, framing effect, i.e. how decisions can be framed (Tversky and Kahneman, 1986), means the way the question is asked will change the way people respond and the values that people have found are very context-specific, depending on how the scenario is described. In addition, impulsiveness, which essentially refers to people's thinking without acting, making quick judgments, is also relevant to decision-making (Mariel and Meyerhoff, 2016). A hybrid choice model, which is a discrete choice model with latent variables, can take these psychological aspects into account. This involves latent concepts such as perceptions and attitudes that cannot be observed and needs indirect measurements, the so-called psychometrics indicator (Ben-Akiva et al., 2002; Hoyos et al., 2015). Indirect measurements about an attitude can be done by adding psychometric questions to other people's survey. Respondents are presented with a series of Likert-style questions about environmental concerns, about their views on public policies to categorize people based on their degree of agreement with the statement.

A household survey with a large sample size should be conducted to improve the statistical reliability. The lack of precision in the reported WTP estimates could be due to the small sample size. Given a small sample, there is not enough variation to sufficiently pin down estimates of all the parameters in the RPL-interactions and the GMNL. The survey design also needs to be modified to suit the context of community relationships and kinship in developing country setting.

Respondents' insensitivity to the scope of environmental goods has been a subject of strong concern in the stated preference literature. The conventional economic theory states that WTP is increasing with more quantity or quality of a good, however, this might contradict the notion of scope insensitivity in real world settings (Kahneman and Knetsch, 1992; Czajkowski and Hanley, 2009; Whitehead, 2016). A split-sample design could be conducted to assess how respondents value different segments of the protected areas presenting different characteristics. In doing so, we can investigate if households' preferences for mangrove management policy vary across geographical segments which differ in terms of size of mangrove coverage, the speed of coastal erosion or mangrove degradation.

There is relatively scant information about people's willingness to pay for mitigation projects especially in developing countries. We know very little about people's willingness to migrate from coastal communities suffering extreme weather events. The World Bank stressed the great effects of climate change on human migration as 140 million people will be displaced by climate change by 2050 (Rigaud et al., 2018). Further studies should enhance understanding of migration as an adaptation strategy for coastal communities.

5.2 Climate change adaptation in rice production

The study examines the effect of average temperatures, precipitation over the growing season on rice yield loss risks in Vietnam. The data includes national data set on rice yield and gridded weather records assembled at the sub-national level from 1987 to 2015. The focus is on rice because it is a major socio-economic activity, covering 7.9 million hectares (87.1% of total annual cultivation area) in Vietnam (Trong and Napasintuwong, 2015).

The study looks for evidence of adaptation that reduces the rice yield sensitivity. The methodological contribution of this paper is that we allow the temporal and spatial variation of the parameters on climate variables to measure long term changes in the yield response function, based on farmers' underlying level of adaptation (Butler and Huybers, 2013; Schlenker and Roberts, 2009). The "mean observation OLS" (or "MO-OLS") approach proposed by Keane and Neal (2020a) was utilized to allow unit and time fixed effects in both intercepts and slopes in panel data models. This approach gives a more accurate assessment of the relationship between rising temperature and crop productivity than those with linear fixed effect panel models that neglect the long-run yield response under adaptation (Dell et al., 2014).

Main findings suggest that most regions of Vietnam experienced heightened yield due to higher GDD, i.e. the total beneficial heat units for crop growth over the growing season. Locations that tend to be very hot, with a large number of KDDs in which the annual temperature was above 29 ° C on average, would experience high yield losses on those hottest days. Precipitation and rice yield had an inverted quadratic relationship. Results from the MO-OLS model further indicate that major agro-climatic zones such as Red River Delta, Mekong River Delta, and North East remained less sensitive to KDD. Farmers in these locations realize benefits from investing in the adaptive technologies and were able to protect themselves against those extreme degree days that may damage their yields. There are many parts of the country that ended up being net beneficiaries because the losses of hot days were outweighed by the benefits accruing from the adaptation efforts. Moreover, every province in Vietnam experienced negative yield changes over the time period. However, the effect of these hot days was declining and then roughly stabilized. This indicates that there were adaptation efforts occurring over time because farmers are somehow protecting themselves from these hot day events, yet, the trend has not been persistent recently.

5.2.1 Policy implication

Our study helps populations be aware of the more subtle impacts as something that are more salient. Most people are not aware of forgone earnings due to a heat wave happened in the past. It is a much more difficult thing cognitively to track, and what we see is no evidence of adaptation in certain regions. Hence, policy makers will face difficulties in designing regulations to protect the populations, because things that are of subtle damages. With business as usual going on, it will be a significant cost to the poor and defeat poverty reduction programs in Vietnam. The study helps farmers and local decision-makers realize that it makes sense to invest heavily in irrigation or other types of adaptation.

The chapter represents a roadmap for how to think about the effects of adaptation around the country, which then can be used to support regular regulation and and policy making in the future, for instance, the distributional schemes of grants. The study also calls for spatially explicit information about where different activities could occur in order to develop future zoning schemes in the management plan of the agriculture sector.

Furthermore, the projected yield loss could help the government understand the actual social cost of carbon, given the adaptation efforts. How should adaptation be costed and monetized? Taxing too much might take away resources from other investments we should be making, but taxing too little means we would not be investing enough in the climate. Besides, private funding is another importance source of climate finance. Private companies might see something happening and they might be willing to pay to support the food and agricultural industries.

5.2.2 Future research

To expand the study, I will estimate different independent sets of future projections that provide heterogeneity of rice yield responses at the scale of cities in Vietnam. I would do a large number of simulations considering all sorts of uncertainty from climate models. In particular, I track those costs over time and across provinces in each of different simulations in order to give a sense of how much adaptation matters. There is a range of important projections for stakeholders in the rice sector to appreciate the amount of uncertainty in this type of economic calculation.

The study leaves us with many possible weather variables that could be determining crop yields and many possible drivers of adaptation. Another idea is to aim to quantify the relationship between the soil conditions and crop growth at these sites. This is often constrained by lack of data due to high cost and time demand. We need to figure out what are measuring across farms, at a fine spatial scale that can be used to drive management decisions.

The current analysis ignores many technical aspects: how climate impacts on productivity are, depending on future novel cropping systems that are resilient in the face of climate change and rural demographics. It is also important to examine the seed variety farmers are selecting, water management, fertilizers, tillage activities, planting schedule, the equipment that is used, the pests, the disease outbreaks.

Further study should figure out which constraint is binding technology to adapt and in which setting. There exists some technology to adapt but it is too expensive to be worth, or not really cost-effective. Most of the rural regions today live on much lower incomes and do not have access to the technological frontier; for instance, computing, cellphones, some types of seed that are not always available. High income populations tend to be better protected. They have the resources to deploy irrigation or find better agricultural insurance that is protecting themselves. Policymakers might loosen those constraints by fostering innovation that bring the costs of adaptation technology down. Understanding the obstacles to technological diffusion is essentially relevant from a policy perspective.

The yield sensitivity maps may look entirely different if we incorporate the natural migration as climate change occurs. There should be more active research on that questions: how farmers mobilize, who will mobilize, where they might go and why they go there. It turns out to be a very difficult problem to crack by rigorous quantitative approaches because the data for tracking people around Vietnam, particularly in the regions that are most likely to produce migrants, is very limited.

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Appendices

Appendix A

Chapter 2

A.1 Questionnaire survey used in the contingent valuation study

This session provides a sample of questions on WTP developed as part of the household questionnaire survey.

Future climate scenario

Climate change is a major challenge for coastal areas in Vietnam. According to the future climate change scenario that the Ministry of Natural Resources and Environment released in 2016, the average temperature in Ba Lat estuary would increase by about 0.6C by 2030 compared to the period of 1986-2005. Meanwhile, maximum rainfall per day would increase from 20 to 30 ml and sea level would likely rise by an additional 20 cm in Ba Lat estuary. Climate change and sea rise could result in a large area of the mangrove degraded, which in turn lead to severe losses of biodiversity. According to the board of directors at XTNP , if appropriate preservation measures are not taken, biodiversity value of the park would be declined by about 5% each year in comparison to the present.

Supposed a project is conducted from now to 2030 to implement new measures for planting, protection of the mangroves, protecting birds and biodiversity in the mangrove forest. This project would raise awareness and capacity of the locals on planting, mangrove rehabilitation as well as provide training courses, seminars on the mangroves. It is noted that the project would help develop alternative livelihoods for the locals and encourage communities to actively participate in the conservation. The exploitation of natural resources for fisheries would be reduced and replaced by eco-tourism services, hence offering new opportunities for economic development as well as conservation of natural biodiversity resources. Local authorities would play a role in mobilizing financial resources necessary to fund the project. If this project is supported by the majority of the locals, all households living in 5 communes including Giao Thien, Giao An, Giao Lac, Giao Xuan and Giao Hai would make a lump sum payment to the Fund for Biodiversity Conservation (Fauna and Flora) of the Mangroves in Ba Lat estuary.

1. Please tell us, are you ready to make a financial contribution to the Fund for the Conservation of Fauna and Flora Diversity of the mangroves in Ba Lat estuary?

   ☐ Yes ☐ No ☐ Not sure

2. (If YES) Please tell us the reason

   ☐ For my own sake

   ☐ For the next generation

   ☐ Preservation of culture, religion

   ☐ For the benefit of society

   ☐ Other (please specify) ....

   → Go to question 4

3. (If NO or NOT SURE) Please tell us the reason

   ☐ My family has no money to contribute

   ☐ The diversity of species in this area does not mean much to my family

   ☐ I am afraid my household contribution shall not be used properly

   ☐ I do not believe in the success of the project

   ☐ Biodiversity conservation is the sole responsibility of the local government

   ☐ The person who is beneficiary should finance

   ☐ Other (Please specify) ....

   → Go to question 7

Applicability of the WTP

We know that this is just a survey for research purposes, so your WTP answers may not reflect the real payment. In surveys, people sometimes response that they are willing to pay a larger amount than they will actually do. For example, 70% of respondents say they are willing to pay the money. Nevertheless, when the project is actually implemented, only 50% of the households contribute to the fund. Therefore, we would like you to answer as if this is a real payment, i.e. imagine that you are required to contribute to the funds for implementing the project on request of local authorities and most people agree to make financial contributions.

4. Are you willing to pay <**first bid**> to implement the project?

   ☐ Yes ☐ No → go to question 6 ☐ Not sure → go to question 6

5. (If YES) If your contribution is <**second higher bid**>, would you be willing to pay the amount for the implementation of the project?

   ☐ Yes → go to question 9 ☐ No → go to question 7 ☐ Not sure → go to question 8

6. (If NO or NOT SURE) If the contribution is <**second lower bid**>, would you be willing to pay the amount for the implementation of the project?

   ☐ Yes → go to question 9 ☐ No → go to question 7 ☐ Not sure → go to question 8

7. Please tell me the reason you are not willing to contribute this sum

   ☐ It is not necessary to contribute so much money

   ☐ The biodiversity in this area does not mean much to my family

   ☐ I do not believe in the success of the project

   ☐ I must spend money on more important things

   ☐ My household does not have enough money to contribute this much

   ☐ Other (please specify) ....

8. Could you please show the reason that you are not willing to contribute this sum? (*the interviewer should not give a clue*)

   ☐ I must discuss with other family members / I have no right to decide

   ☐ I wait to see whether others contribute or not

   ☐ Other (please specify) ....

9. Assuming that the project is not implemented, how will biodiversity be affected in the mangroves in Ba Lat estuary by 2030?

   ☐ Very much

   ☐ Much

   ☐ Average

   ☐ Little

   ☐ Not affected

   ☐ Do not know

10. When the project is implemented, how better will the biodiversity of the mangroves in Ba Lat estuary than that when the project is absent?

    ☐ Very much

    ☐ Much

    ☐ Average

    ☐ Little

    ☐ Not different

    ☐ Do not know

Appendix B

Chapter 4

B.1 The MO-OLS estimator

Recently, Keane and Neal (2020a) consider the estimation of a linear panel data model with heterogeneous coefficients like:

$$y_{it} = \boldsymbol{\beta}_{it}'\boldsymbol{x}_{it} + u_{it},\ i = 1,\ldots,N \text{ and } t = 1,\ldots,T, \tag{B.1}$$

where $\boldsymbol{x}_{it} = (1, x_{1it}, \ldots, x_{Kit})'$ is a $(K+1)\times 1$ vector of regressors, $\boldsymbol{\beta}_{it} = (\beta_{0it}, \beta_{1it}, \ldots, \beta_{Kit})'$ is a $(K+1)\times 1$ vector of coefficients that vary across individuals and overtime, and u_{it} is the idiosyncratic error term. The vector of regressors $\boldsymbol{x}_{it}$ includes a constant term, which allows for intercept heterogeneity across i and t, and it may also include lags of the dependent variable or any of the regressors as needed. Regressors are assumed to be weakly exogenous and the idiosyncratic error term to have finite conditional second order moment given $\boldsymbol{x}_{it}$.

Linear panel data model with coefficients varying both over individuals and periods are in general overparameterized, having $N\times T$ coefficients and disturbance second order moments. This by far exceeds the number of parameters estimable from one panel data set. Keane and Neal (2020a) propose then the parsimonious alternative where:

$$\boldsymbol{\beta}_{it} = \boldsymbol{\beta} + \boldsymbol{\lambda}_i + \boldsymbol{\theta}_t.$$

$\boldsymbol{\beta} = (\beta_0, \beta_1, \ldots, \beta_K)'$ is the vector of the constant effects across all observations, $\boldsymbol{\lambda}_i = (\lambda_{0i}, \lambda_{1i}, \ldots, \lambda_{Ki})'$ are the individual effects that vary across every unit in the panel, and $\boldsymbol{\theta}_t = (\theta_{0t}, \theta_{1t}, \ldots, \theta_{Kt})'$ are time effects that vary between each time period.

Keane and Neal (2020a) propose an iterative estimation procedure, they call "mean observation OLS" (MO-OLS), to get consistent estimates of $\boldsymbol{\beta}_{it}$. This procedure consists in running a series of feasible regressions and then removing the resulting biases. Three preliminary sets of regressions are initially run. First, pooled OLS estimation is applied to Eq. (B.1) rewritten as:

$$y_{it} = \boldsymbol{x}_{it}'\boldsymbol{\beta} + v_{it} \text{ with } v_{it} = \boldsymbol{x}_{it}'\boldsymbol{\lambda}_i + \boldsymbol{x}_{it}'\boldsymbol{\theta}_t + u_{it},,\ \ i = 1,\ldots,N \text{ and } t = 1,\ldots,T$$

to obtain $\hat{\boldsymbol{\beta}}$, or

$$\widehat{\boldsymbol{\beta}} = \left(\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\boldsymbol{x}_{it}\boldsymbol{x}_{it}'\right)^{-1}\left(\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\boldsymbol{x}_{it}y_{it}\right)$$

Second, regressions by individual using Eq. (B.1) rewritten for each indivudual i as

$$y_{it} = x_{it}'\left(\boldsymbol{\beta} + \boldsymbol{\lambda}_i\right) + v_{it} \text{ with } v_{it} = \boldsymbol{x}_{it}'\boldsymbol{\theta}_t + u_{it},\ t = 1,\ldots,T$$

are run to get $\hat{\boldsymbol{\beta}}_i$, or:

$$\widehat{\boldsymbol{\beta}}_i = \left(\frac{1}{T}\sum_{t=1}^{T}\boldsymbol{x}_{it}\boldsymbol{x}_{it}'\right)^{-1}\left(\frac{1}{T}\sum_{t=1}^{T}\boldsymbol{x}_{it}y_{it}\right)$$

Third, Eq. (B.1) is rewritten for each year t as:

$$y_{it} = x_{it}'\left(\boldsymbol{\beta} + \boldsymbol{\theta}_t\right) + v_{it} \text{ with } v_{it} = \boldsymbol{x}_{it}'\boldsymbol{\lambda}_i + u_{it},\ i = 1,\ldots,N$$

and estimated in order to get:

$$\widehat{\boldsymbol{\beta}}_t = \left(\frac{1}{N} \sum_{t=1}^{N} \boldsymbol{x}_{it} \boldsymbol{x}'_{it} \right)^{-1} \left(\frac{1}{N} \sum_{t=1}^{N} \boldsymbol{x}_{it} y_{it} \right)$$

A preliminary biased estimator of $\boldsymbol{\beta}_{it}$ is then given by $\widehat{\boldsymbol{\beta}}_{it}^{\text{Prel}} = \widehat{\boldsymbol{\beta}}_i + \widehat{\boldsymbol{\beta}}_t - \widehat{\boldsymbol{\beta}}$. Indeed, using matrix calculus, it can be shown that:

$$\widehat{\boldsymbol{\beta}}_{it}^{\text{Prel}} = \boldsymbol{\beta} + \boldsymbol{\lambda}_i + \boldsymbol{\theta}_t + R(\boldsymbol{\lambda}_i, \boldsymbol{\theta}_t) + Q(\boldsymbol{x}, \boldsymbol{u}) \tag{B.2}$$

where the first bias term $R(\boldsymbol{\lambda}_i, \boldsymbol{\theta}_t)$ that depends on unknown values of parameters in $\boldsymbol{\lambda}_i$ and $\boldsymbol{\theta}_t$, arises from correlation between the regressors and the heterogeneity, and the second bias term $Q(\boldsymbol{x}, \boldsymbol{u})$ only involves the regressors and the errors. The latter vanishes asymptotically given the weak exogeneity assumption for regressors.

Keane and Neal (2020a) show how the bias can be calculated to arbitrary accuracy and removed. This requires replacing $\boldsymbol{\lambda}_i$ and $\boldsymbol{\theta}_t$ by their estimates $\widehat{\boldsymbol{\beta}}_i$ and $\widehat{\boldsymbol{\beta}}_t$ to form a biased estimate of $R(\boldsymbol{\lambda}_i, \boldsymbol{\theta}_t)$. By replacing $R(\boldsymbol{\lambda}_i, \boldsymbol{\theta}_t)$ by its estimate corrected for its bias, we eliminate the original bias from $\widehat{\boldsymbol{\beta}}_{it}^{\text{Prel}}$, while introducing a new bias. Keane and Neal (2020a) show that this new bias is smaller than the original bias.

This process can be repeated using $\widehat{\boldsymbol{\beta}}_i$ and $\widehat{\boldsymbol{\beta}}_t$ to approximate the new bias. In turn, this generates a new bias which is smaller in magnitude. In fact, this process can be repeated L times to render the heterogeneity biases arbitrarily small and form the final estimates:

$$\begin{aligned} \widehat{\boldsymbol{\beta}}_{it} \;=\; & \widehat{\boldsymbol{\beta}}_i + \widehat{\boldsymbol{\beta}}_t - \widehat{\boldsymbol{\beta}} + \sum_{\ell=0}^{L} (-1)^{\ell+1} \Bigg(\boldsymbol{Q}_{xx,N}^{-1} \frac{1}{N} \sum_{i=1}^{N} \boldsymbol{x}_{it} \boldsymbol{x}'_{it} \Gamma_{1,\ell} + \boldsymbol{Q}_{xx,T}^{-1} \frac{1}{T} \sum_{t=1}^{T} \boldsymbol{x}_{it} \boldsymbol{x}'_{it} \Gamma_{2,\ell} \\ & - \boldsymbol{Q}_{xx,NT}^{-1} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(\boldsymbol{x}_{it} \boldsymbol{x}'_{it} \Gamma_{1,\ell} + \boldsymbol{x}_{it} \boldsymbol{x}'_{it} \Gamma_{2,\ell} \right) \Bigg) \end{aligned} \tag{B.3}$$

with $\boldsymbol{Q}_{xx,N} = \left(\sum_{i=1}^{N} \boldsymbol{x}_{it} \boldsymbol{x}'_{it} / N \right)$, $\boldsymbol{Q}_{xx,T} = \left(\sum_{t=1}^{T} \boldsymbol{x}_{it} \boldsymbol{x}'_{it} / T \right)$, and $\boldsymbol{Q}_{xx,NT} = \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \boldsymbol{x}_{it} \boldsymbol{x}'_{it} / NT \right)$. Moreover, $\Gamma_{1,\ell} = Q_{xx,T}^{-1} \left(\sum_{t=1}^{T} \boldsymbol{x}_{it} \boldsymbol{x}'_{it} \Gamma_{2,\ell-1} / T \right)$ and $\Gamma_{2,\ell} = Q_{xx,N}^{-1} \left(\sum_{i=1}^{N} \boldsymbol{x}_{it} \boldsymbol{x}'_{it} \Gamma_{1,\ell-1} / N \right)$ when $\ell > 0$, and $\Gamma_{1,0} = \widehat{\boldsymbol{\beta}}_i$ and $\Gamma_{2,0} = \widehat{\boldsymbol{\beta}}_t$. This is a Cauchy sequence in ℓ, so a suitable L can be chosen by terminating the sequence once it converges to a desired tolerance. In practice, small values of L are usually adequate. Eq. (B.3) is simple to construct as it is a function of only the preliminary estimates $\left(\widehat{\boldsymbol{\beta}}_i, \widehat{\boldsymbol{\beta}}_t, \widehat{\boldsymbol{\beta}} \right)$ and the covariates $\boldsymbol{x}_{it}$.

Keane and Neal (2020a) show consistency of $\widehat{\boldsymbol{\beta}}_{it}$ when N and T together tend to infinity. They then define the Mean Observation OLS (MO-OLS) estimate as the simple average of of estimates of the observation-level coefficients, or:

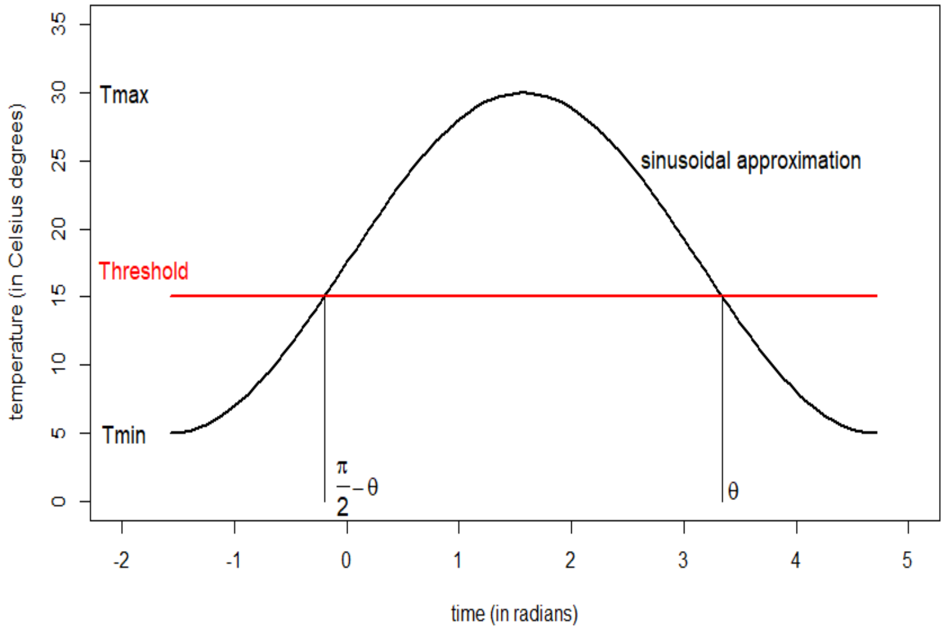
$$\widehat{\boldsymbol{\beta}}_{\text{MO}} = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{\boldsymbol{\beta}}_{it} \tag{B.4}$$

Finally, they provide results for consistency and asymptotic normality of $\widehat{\boldsymbol{\beta}}_{\text{MO}}$.

B.2 GDD and KDD computation

Calendar days do not provide reliable information about the timing of crop development because crop grows by the accumulation of heat over the growing season (Gilmore and Rogers, 1958).

Figure B.1: Graphical illustration of DD computation



When the air temperature exceeds the base temperature for a certain length of time, rice will grow. If the temperature falls below the base temperature, development slows. Degree day accumulations are used by growers to monitor the development of biological processes and thus are used in crop and pest management. Following Arnold (1960), Baskerville and Emin (1969) and Snyder (1985), degree days are usually computed from daily minimum and maximum air temperature, or T_{min} and T_{max}, using a sinusoidal approximation, or:

$$T = M + W\sin(t)$$

where t is time expressed in radians from $-\pi/2$ to $3\pi/2$, or $t = \pi(h-6)/12$ where h varies form 0 to 24 hours, $M = (T_{\text{max}} + T_{\text{min}})/2$, and $W = (T_{\text{max}} - T_{\text{min}})/2$. This approximation is depicted on Figure B.1 when $T_{\text{min}} = 5°\text{C}$ and $T_{\text{max}} = 30°\text{C}$.

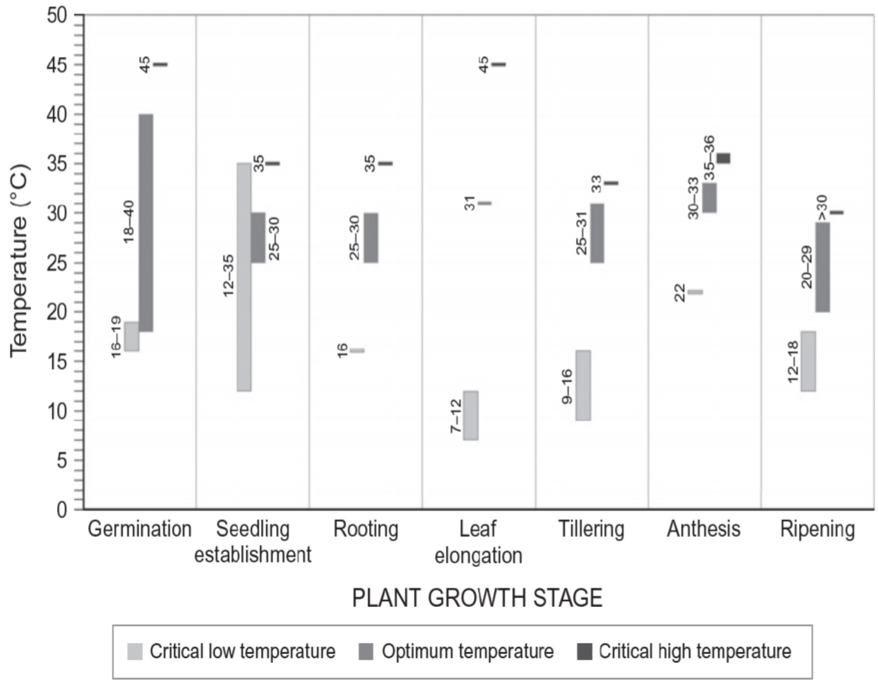
Degree days at a given threshold temperature are measured by integrating the aera under the sinusoidal curve above this threshold temperature. In Figure B.1, this area corresponds to the difference between the area under the sinusoidal curve for time between $\pi/2-\theta$ and θ, and the aera of the rectangle whose base goes from $\pi/2-\theta$ to θ and height is equal to the threshold temperature value. This results in the following expression of degree days as a function of the value C of the temperature threshold:

$$\text{DD}_C = \begin{cases} 0 & \text{if } C > T_{\text{max}} \\ T_{\text{avg}} - C & \text{if } C < T_{\text{min}} \\ \left((T_{\text{avg}} - C)\left(\pi - 2\sin^{-1}(\theta)\right) + (T_{\text{max}} - T_{\text{min}})\cos(\sin^{-1}(\theta))\right)/2\pi & \text{otherwise} \end{cases}$$

where $T_{\text{avg}} = (T_{\text{max}} + T_{\text{min}})/2$ and $\theta = (2C - T_{\text{max}} - T_{\text{min}})/(T_{\text{max}} - T_{\text{min}})$.

Figure B.2, which has been adapted fromYoshida (1978) by Krishnan et al. (2011), provides us a guideline for choosing the boundaries of the temperature for rice development.As shown in Figure B.2, rice crop only develops if there is adequate heat, i.e. if the minimum temperature for the day is above a base temperature. Rice Crop will develop faster with more heat between a base temperature and an optimum temperature. Growth will slow between this optimum and an upper temperature and eventually cease occurring outside the upper temperature range. We choose optimum growing temperature between 7°C and 29 °C to ensure our low and high temperature thresholds are within the acceptable range for the positive growth rate of rice in Vietnam [1]. Beyond this range, high temperature could reduce yield by delaying flowering and shortening the duration of grain-filling. Hence, growth and productivity would rapidly decrease.

Figure B.2: Rice plant response to varying temperature at different growth stages.



Cumulative beneficial temperatures ("growing degree days") are calculated by adding up beneficial temperature per day over a season to predict when rice crop will reach maturity, i.e. $\text{GDD}_{it} = \text{DD}_{7,it} - \text{DD}_{29,it}$ where $\text{DD}_{d,it}$ is the accumulation of degree days at temperature threshold d for province i over the growing season in year t. Harmful temperatures ("killing degree days") indicating the amplified warming that might be detrimental to crops are calculated as $\text{KDD}_{it} = \text{DD}_{29,it}$.

The rice yield data we have is annual. Accordingly, the different harvests that take place in North and South Vietnam during one year are summarized in only one growing season going from March to October (Wassmann et al., 2009).

B.3 A simple model of agricultural yield with weather and adaptation

This appendix replicates section 1 in Keane and Neal (2020a). In this section, they present a simple model of agricultural yield with adaptation. Their aim is to provide a coherent framework for the empirical work they present in their paper. This model starts with a production function

[1]The optimum growing temperature chosen in our study also counts for the fact that the temperature experienced by the crop itself is normally higher than the measured air temperature above the plant canopy as noted by Butler and Huybers (2013) and Keane and Neal (2020a). We also find that the other choices of threshold reduce the predictive power of the fit in our regressions.

that incorporates measures of temperature:

$$\frac{Y_{it}}{C_{it}} = A_t \mu_i I_{it} \left(1 + \beta_1 (GDD_{it} - GDD_{min}) + \beta_2 KDD_{it}\right) \tag{B.5}$$

Y_{it} denotes the crop output (in tonne) for farm i at time t, while C_{it} indicates the land area (hectare) planted. Thus, Y_{it}/C_{it} measures crop productivity or yield (tonne per hectare). Basic factors of production, denoted by I_{it}, are capital, labor, and fertilizers that vary across farms and time. μ_i is an indicator of unobserved soil characteristics pertaining to farm i, and A_t indicates total factor productivity that enhances crop productivity at time t.

The yield fluctuation associated with temperature variation is characterized by growing degree days, or GDD_{it}, and killing degree days, or KDD_{it}, as defined in Appendix B.2. $GDD_{\min}$ stands for the minimum level of GDD needed for crop to experience a positive yield. Intuitively, β_1 is expected to be positive whereas β_2 is expected to be negative. $(\beta_1(GDD_{it} - GDD_{min}) + \beta_2 KDD_{it})$ measures the percent shift in crop yield due to temperature factors.

Taking the log on both sides of Eq. (B.5), and making use of the approximation $ln(1+x) \approx x$ when x is small, we obtain:

$$y_{it} = \ln(A_i) + (\ln(\mu_i) - \beta_1 GDD_{min}) + \ln(I_{it}) + \beta_1 GDD_{it} + \beta_2 KDD_{it} \tag{B.6}$$

where $y_{it} = \ln\left(Y_{it}/C_{it}\right)$. Keane and Neal (2020a) then notice that Eq. (B.6) is akin that estimated in several recent papers (See, among others, Lobell et al., 2011; Burke and Emerick, 2016). In these papers, fixed effects over i and i are used to capture the A_t, μ_i, and I_{it} terms.The estimation of model (4.6) is part of this approach which neglects any adaptation to climate change by farmers.

Subsequently, the simple model is extended to present a more sophisticated adaptive farm management approach. Climate change imply that the weather experienced by a farmer would change. A farmer who deal with a potential loss of crop revenue due to increased temperatures would adjust production choices by adapting its production technology to the new climatic situation. For instance, in drier and hotter periods, yields may be lower than normal and seeds with heat or drought tolerance traits can be selected to better protect the crop. Farmers adapt crop production by adopting best practices that decrease sensitivity of yield to extreme heat or droughts at a monetary cost.

Let now the coefficient that indicates yield response to KDD varying across farmer an time according to $\beta_{2it} = s/\left(1 + \alpha_{it}\right)$ where α_{it} denotes units of adaptation purchased in farm i in period t, and s, which is negative, indicates the adverse impact of heat stress on crop yield when $\alpha_{it} = 0$. Determining optimal responses to extreme temperature due to climate climate involves trading off the benefits of the adaptation choice against its cost. Profit for farm i in period t is total revenue minus total cost, i.e.

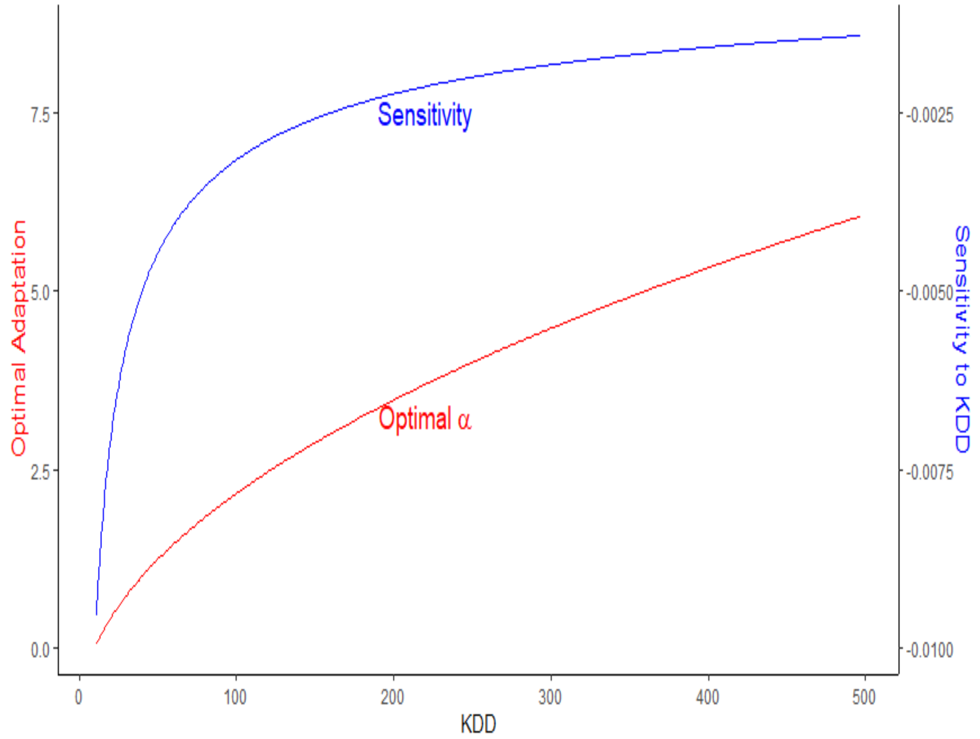
$$\pi_{it} = p_t Y_{it} - \gamma \alpha_{it} - r_t I_{it} \tag{B.7}$$

where p_t is the price of the crop,γ is the price of adaptation, and r_t is the rental rate per unit of production factor in period t. To maximize profit, farmers purchase the optimal level of adaptation. Setting $\partial\pi/\partial\alpha = 0$ leads to

$$\alpha^*_{it} = \sqrt{\frac{p_t (C_{it} A_i \mu_i I_{it})(-s) KDD_{it}}{\gamma}} - 1 \tag{B.8}$$

Hence, the optimal level of adaptation increases in correspondence with KDD_{it}. In hot-enduring regions, farmers have more incentive to protect their crop through investing in various adaptation activities. Figure B.3 displays the optimal level of adaptation α^*_{it} and the corresponding sensitivity

Figure B.3: Relationship between optimal adaptation, or α^*_{it}, yield sensitivity, or $\beta^*_{2,it}$, and KDD_{it}



to KDD $\beta^*_{2,it}$ as a function of KDD.[2] The relationship between KDD and $\beta^*_{2,it}$ looks like a log-linear function. Taken in absolute value, the sensitivity to KDD tends to become negligible when KDD increases, highlighting a better adaptation to the extreme temperatures of the hotter provinces. The prediction of this simple economic model is in line with the empirical findings of Butler and Huybers (2013). This prediction motivates the estimation of model (4.7) where the marginal effect of KDD_{it} on y_{it} approximates a log linear dependence, or:

$$\frac{\partial y_{it}}{\partial KDD_{it}} = \beta_{20} + \beta_{21} \ln \left(KDD_{it} \right). \tag{B.9}$$

The prediction assumes that β_{20} is negative while β_{21} is positive, assumptions that can be tested.

[2] As Keane and Neal (2020a), we fix $p_t(C_{it}A_i\mu_i I_{it}) = 1$ and $s = -0.01$.