Farming in Changing Production Conditions: Agricultural Technology, Climate Change and Adaptation in Vietnam

Nguyen Duc Kien

A thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy

Agricultural and Resource Economics

Faculty of Agriculture and Environment

THE UNIVERSITY OF SYDNEY

2017

STATEMENT OF ORIGINALITY

This is to certify that the content of this thesis is a product of my own research, and has not been submitted for the requirements of any other degree. I hereby certify that to the best of my knowledge, all the sources, materials and assistance received in preparation of this thesis have been acknowledged.

Nguyen Duc Kien

ACKNOWLEDGEMENTS

I would like to express my deep thanks to my supervisors, Associate Professor Tihomir Ancev and Professor Alan Randall, for their constant support and guidance during my study at the University of Sydney. This thesis is not possible without their exceptional supervision and valuable contributions, which I deeply appreciate.

Parts of the thesis have been presented at conferences and working groups such as the 2016 Australian Agricultural and Resource Economics Society (AARES) Annual Conference and the Microeconometric and Public Policy (MPP) working group in the School of Economics at the University of Sydney. I would like to thank discussants and participants for their numerous constructive comments, particularly Associate Professor Shyamal Chowdhury and Dr David Ubilava. I would also like to thank Dr Rhonda Daniels and Dr Evarn Ooi for their support during the editing process. I also appreciate the Australian Awards for financial support and AUSAID coordinators for their constant help during my study in Australia.

This thesis is dedicated to my wife, my daughter and all other family members for their endless love and sacrifice.

Nguyen Duc Kien

Farming in Changing Production Conditions:

Agricultural Technology, Climate Change and Adaptation in Vietnam

Abstract

In an era when enormous challenges to food security are imposed on humanity through phenomena such as global climate change, it is important to understand how farming households adapt and respond to a changing production environment. This is particularly relevant for developing countries that are heavily dependent on agriculture, like Vietnam. The primary research objective of this study is to determine how smallholder rice farmers in Vietnam respond to changes in the production environment driven by climate change over time, and the main driving forces behind farmers' responses. To explore different aspects of rice farmers' responses to changing production conditions, this thesis consists of three empirical studies at the intersection of development and environmental economics, with a special focus on rural farming households in Vietnam.

Technological change and its diffusion have become major factors contributing to the development of Vietnam's agricultural sector over many years as farmers have constantly adopted various agricultural practices to increase crop productivity and improve their standards of living. The first study of this thesis investigates the pattern and determinants of the use of four agricultural practices – new rice seed varieties, chemical fertilisers, pesticides and mechanisation – in small-scale rice farming across different agro-ecological regions of Vietnam. Probabilistic record linkage methods were used to find the best-matched observations from the two nationally representative surveys in Vietnam (VARH and VLSS) in order to create a 20-year panel dataset. Using a long panel dataset, the study applied a two-stage estimation strategy to determine how and to what extent the changes in agricultural technology have been affected by various factors, allowing for potential correlations among different practices used by rice farmers. There have been significant changes in the pattern and determinants of agricultural

practices applied by farmers in different regions of Vietnam. Prices of hired agricultural labour and rice, as well as macro-level socio-economic conditions such as the growing urban population and increasing agricultural wages, are the main factors driving the decision to use these practices and the intensity of their use. Since findings also confirm a simultaneous relationship among the use of agricultural practices, follow-up policy interventions need to account for those cross-correlations within a farmer's joint decisions to apply agricultural advances.

The second study examines the changes in climatological variables of temperature and precipitation since 1975 using a comprehensive dataset for a relatively long time period (1975 to 2014) and a high density of climatic records obtained from 112 meteorological stations across Vietnam. It first combines statistical methods with geostatistical techniques to graphically represent the distribution of climate patterns, identifying variations and trends over time and testing the statistical significance of those changes. Then, the evidence-based information is linked to rice production throughout the country to identify likely impacts of climate change on rice production. The findings show remarkable changes in the spatio-temporal distribution patterns of rainfall and temperature and confirm the statistically significant long-term trends of those changes in many areas, including areas with a very high proportion of agricultural land, particularly land used for rice production in the Red River and Mekong River deltas. The pronounced evidence of climate change at different scales across agricultural regions throughout Vietnam is likely to be especially challenging for agriculture, particularly for the key agricultural activity of rice growing given its direct exposure to variations in many climatic factors. The findings from this study provide a better understanding of underlying climate processes and impacts across regions of Vietnam and also provide a basis to develop effective climate-related policies for agricultural production, especially rice production, in response to changing climatic conditions.

The third study investigates whether or not farmers have altered their farming strategies over time in response to pronounced changes in the climate. This study uses a 20-year panel from nationally representative households in Vietnam, and thereby overcomes a major drawback in the previous published work due to the lack of extended time series cross-section data at the household level to investigate factors behind farmers' dynamic choices to adopt soil and water conservation techniques for the purpose of adaptation to climatic change. Since farmers' decisions to use certain farming techniques are inherently dynamic, I estimated a dynamic random-effects probit model, controlling for unobserved heterogeneity and state dependence. Weather shocks and long-run changes in temperature during the growing season are significant determinants of farmers' choices to apply adaptation practices. In addition, the decision to adopt in subsequent periods is strongly influenced by past adoption decisions. Results also indicate that farmers' experience, farm size and access to weather and output price information affect the decisions to apply conservation measures. This study provides better insights into farmers' decision-making process and its drivers in the face of changing climatic conditions, which is useful for practitioners and policy-makers in order to facilitate climate-resilient strategies to improve farmers' adaptive capacity under climatic uncertainty.

Vietnamese farmers have been operating their farms under a continuously transforming policy environment over recent decades, specifically since the Renovation Policy in the mid-1980s. Such policy transitions have created more favourable conditions for the development of the agricultural sector to meet the growing demand for food, both domestically and internationally. However, new challenges are emerging, climate change in particular, and their impacts on agricultural production have been increasingly pronounced. In an era with new and emerging challenges, further policy action is required to help the agricultural sector adapt to the ongoing changes in the production environment. The findings and policy implications drawn from the three studies will be useful in enhancing farmers' adaptive capacity to improve their overall wellbeing in fast changing production conditions.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AME	Average Marginal Effects
CIEM	Institute for Economic Management
CRE	Correlated Random Effect
DEM	Digital Elevation Model
FAO	Food and Agriculture Organization
FAOSTAT	Food and Agriculture Organization Corporate Statistical Database
GDD	Growing Degree-days
GDP	Gross Domestic Product
GIS	Geographical Information System
GSO	General Statistics Office of Vietnam
IMR	Inverse Mills' Ratio
IPCC	Intergovernmental Panel on Climate Change
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
SNHT	Standard Normal Homogeneity Test

SPC	State Planning Committee
SPI	Standardised Precipitation Index
SSWM	Sustainable Sanitation and Water Management
SUR	Seemingly Unrelated Regression
UNEP	United Nations Environment Programme
USGS	United States Geological Survey
VARHS	Vietnam Access to Resources Household Survey
VIF	Variance Inflation Factor
VLSS	Vietnam Living Standard Survey
VNCHMF	Vietnam National Centre for Hydro-Meteorological Forecasting
VNGP	Vietnam Government Portal
WB	World Bank

Chapter 1

Introduction

1.1 Overview

Agriculture plays a significant role in the development process, particularly in developing countries where much of the population depends on agricultural production as the main source of income. Agriculture can help developing societies by meeting the growing food demand, by increasing exports of agricultural products, by supplying labour to other expanding sectors of the economy, and by contributing capital for investments (Johnston and Mellor, 1961). However, the agricultural sector is highly vulnerable to changing production environments. Thus, at a time when global climate change and technology development are changing production conditions, it is important to understand how small farming households, specifically in developing countries, adapt and respond to those changes.

This thesis consists of three empirical studies at the intersection of development and environmental economics, with a special focus on rural farming households in a changing production environment in Vietnam. Development economics aims to understand the microeconomic foundations of households' behaviour (e.g. households' decision-making process) to deepen our understanding for the purpose of improving standards of living, especially for rural farming households in developing countries. Environmental economics studies, in turn, provide an insight into environment-related problems that could hamper development processes, particularly the advancement of vulnerable groups like small-scale farmers in the least developed countries. A better understanding of factors driving those development processes, and constraints deterring them, will be useful to improve smallholders' welfare and to enhance their adaptive capacity to changing production conditions.

Farmers around the world have a long record of constantly seeking to increase productivity and improve their wellbeing by finding new and better ways of farming. This includes the use of agricultural practices such as new seed varieties, fertilisers and agricultural machinery. Technological change and its diffusion have become major factors shaping the development process of the agricultural sector in many countries since the Green Revolution began in the 1960s (Hayami and Ruttan, 1970; Schultz, 1964; Sunding and Zilberman, 2001; Suri, 2011). Consequently, there is an increasing interest in agricultural technology changes, especially in less developed countries like Vietnam, because new agricultural technologies promise to substantially improve crop yields and income (Besley and Case, 1993; Feder et al., 1985; Suri, 2011). Also, it is often noticed that changes in agricultural technology at the farm level have been driven by various climatic, technological, economic, social and political forces, which could affect the agricultural development process.

Across the globe, climatic change has been manifesting through various channels such as increasing temperatures, heavier precipitation or prolonged periods with very little or no precipitation, as well as through more frequent and more intense weather-related extreme events (Below et al., 2010; Hisali et al., 2011). The Intergovernmental Panel on Climate Change notes that globally averaged surface temperature has increased by 0.85 °C between 1880 and 2012 (Stocker et al., 2014). Changes in average precipitation have not been spatially and temporally uniform, with decreases in mid-latitude areas and increases in other latitudes (IPCC, 2007). It is also very likely that weather-related extreme events are increasing in frequency and intensity on a global and local scale (Caesar et al., 2011; Pingale et al., 2014). In the case of Vietnam, the evidence of climatic change has been observed across regions. Observed changes in the climate system are having major effects on natural systems as well as on human activities, including agricultural production around the world.

In the face of climate change, adaptation is one of the options for reducing its adverse impacts, particularly in the agricultural sector (Deressa et al., 2009; Mendelsohn and Kurukulasuriya 2007). It could be argued that farming is about constantly adapting to external conditions through the process of behavioural and technological adjustments of individual farm households. This results in a wide range of response strategies for climate change that have been identified in many empirical studies (IPCC, 2007). These adaptation strategies can be classified in five categories: farm production management, farm financial management, farm diversification, external interventions, and management of social networks and governance (Below et al., 2010). Among those, practices that preserve land and water resources are promising approaches for adaptation of farming systems to various stresses (Kato et al., 2011; Sietz and Van Dijk, 2015).

1.2 The context of Vietnam

Household livelihoods in developing countries, in particular for smallholders in rural areas, depend heavily on agriculture as a predominant source of income. Despite Vietnam's rapid economic development, agriculture continues to play a critical role in the economy (GSO, 2014). Crop production in Vietnam is still dominated by rice as a major cash crop, using 39.8% of the total agricultural land (GSO, 2014). Since 1990s, the total output, consumption, export and productivity of rice have continuously increased in Vietnam (Figure 1.1). It is also obvious that the harvested area of rice has remained relatively stable over years and significant increase in productivity has been the main factor leading to increased export.

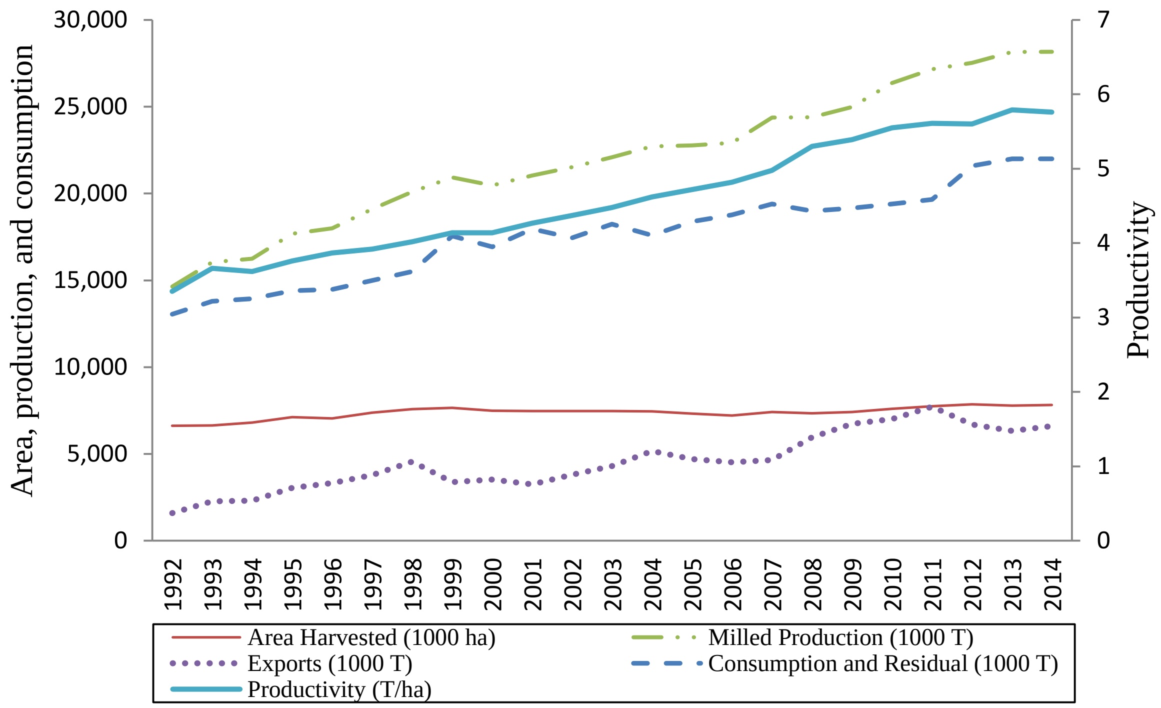


Figure 1.1 Long-term trend in rice production and consumption in Vietnam (1992-2014)

Source: Food and Agriculture Organization Corporate Statistical Database – FAOSTAT; OECD, 2015

Agricultural technology changes have been the main driver contributing to the development of Vietnam's agricultural sector over time, specifically for rice cultivation. From the introduction of the first high-yielding rice variety IR8 in 1966 in Vietnam, the Green Revolution has contributed significantly to the rice sector. Since then, the momentum of Vietnam's Green Revolution has continued based on the continuous release of new improved seed varieties and the increasing application of other technologies such as chemical fertilisers, pesticides and mechanisation (OECD, 2015; Ut and Kajisa, 2006).

However, significant changes in external conditions including climatic risks and technological, economic, social and political forces have posed numerous challenges for the farming sector. There is little doubt that Vietnam is being affected by climatic variability and change (Thomas et al., 2010). From the 1970s, the recorded average temperature of Vietnam has increased by 0.26±0.10 °C per decade, twice the rate of global average temperature for the same period (Nguyen et al., 2013). Also, total annual rainfall has been declining in five out of eight climatic zones of Vietnam over the same period (Nguyen et al., 2013). Climatic uncertainty has also intensified the incidence and magnitude of extreme events such as floods, droughts and typhoons across agro-ecological regions. It has been estimated that climatic change may directly affect about 10% to 12% of Vietnam's population and lead to the loss of approximately 10% of Gross Domestic Product (Vietnam Government Portal, 2011). More importantly, the country's most climate-dependent activity – agricultural production – still dominates Vietnam's economy, accounting for 22% of Gross Domestic Product and 54% of the labour force (GSO, 2014). Thus, it is expected that the impacts of climate-related changes will be particularly severe in fast changing environmental conditions and those effects could hamper the sustainability of Vietnamese farmers.

In the face of these risks, Vietnamese farmers have been constantly adapting to the changing climate by applying a broad range of adaptation practices. The most common adaptation practices for climate change include diversification of crops and income sources, adjustments of various farm management practices, and adoption of soil and water conservation measures. Of these, applying soil and water conservation practices are a key adaptation method to maintain soil moisture, alleviate growing water shortages and worsening soil conditions, and mitigate the negative impacts of higher temperatures and lower rainfall (Kurukulasuriya and Rosenthal, 2003). In Vietnam, farmers have been observed using rock bunds, soil bunds, terraces and grass lines as soil and water conservation measures.

1.3 Research questions and objectives

This research was motivated by the ongoing changes that are occurring in the agricultural sector in Vietnam. Technological change and its diffusion have become major factors contributing to the development of Vietnam's agricultural sector over many years. Over that time, farmers have been observed to be constantly adopting various agricultural technologies to increase crop productivity and improve their standards of living. Recently, however, there is pronounced evidence of climate anomalies at different scales across agricultural regions throughout Vietnam which is likely to be especially challenging for agriculture, particularly for the key agricultural activity of rice growing given its direct exposure to variations in climatic factors, such as temperature and precipitation. Thus, a primary research objective is to determine how smallholder rice farmers in Vietnam are responding to changes in the production environment driven by climate change over time, and what are the main driving forces behind farmers' responses. The three empirical studies in this thesis explore different aspects of farmers' responses by asking several research questions.

The first study, reported in Chapter 2, investigates the pattern and determinants of the use of four agricultural practices – new seed varieties, chemical fertilisers, pesticides and mechanisation – in small-scale farming during a transition period in Vietnam, specifically since the *Renovation Policy* in the mid-1980s. It addresses two research questions: How has agricultural technology changed over the last 20 years in Vietnam? What factors have contributed to those technology changes over time? Using a longitudinal panel dataset over 20 years from nationally representative surveys, the research first explores the pattern of agricultural technology changes across the study areas of six provinces across the country. It then investigates factors that may drive those changes based on the characteristics of farming households, the regional market conditions and macro-level drivers.

The second study, reported in Chapter 3, investigates changes in climatological variables of temperature and precipitation since 1975 to address two research questions: What is the empirical evidence of climate change across regions of Vietnam? What are the potential effects of those changes on the agricultural sector, particularly for rice production? The study uses a comprehensive dataset for a relatively long time period (1975 to 2014) and a high density of climatic records obtained from 112 meteorological stations across the country. The comprehensive approach of combining statistical testing with geostatistical techniques enables maping of climate patterns at a very fine resolution to identify changes and trends over time and statistically confirm their significance. Then, the empirical evidence of the spatio-temporal variations of climatic conditions is linked to rice production throughout the country to identify any likely impacts. Given the recently observed significant changes in climate conditions, it is reasonable to expect more negative climate-related consequences for agriculture due to the sector's direct exposure to the variations of climatic elements. The findings from this study will provide a basis for developing effective climate-related policies to respond to ongoing climate change and to help mitigate the adverse impacts of climate change on agricultural production in rural areas.

The third study, reported in Chapter 4, investigates whether or not farmers have altered their farming strategies over time in response to pronounced changes in the climate. Two research questions are addressed: To what extent have farmers used soil and water conserving techniques as adaptation practices in response to changing climate conditions? What are the main drivers influencing farmers' decision-making process of applying adaptation practices to cope with climate change? Findings drawn from this study can be used to strengthen the adaptive capacity of rural households and to inform policymakers in their agricultural policy-making activities to cope with future changes in climate.

1.4 Mind map

Figure 1.2 presents the general framework of the thesis showing the relationships between the three studies. These empirical studies focus on providing the evidence-base to develop policy recommendations to improve agricultural production in a changing production environment driven by climate change in Vietnam. Study 1 in Chapter 2 describes the general pattern of agricultural technology changes over 20 years in Vietnam. The second study in Chapter 3 focuses on climate change – one of the major constraints affecting agriculture. The third study in Chapter 4 investigates the strategies that have been applied by smallholder farmers to cope and adapt to the ongoing changes in climatic conditions.

It is important to note that Vietnamese farmers have been operating their farms under a continuously transforming production environment over recent decades, including changes in agricultural technologies, agriculture-related policies and more recently, climatic conditions. This study creates an analytical framework to deepen our understanding of agricultural production at the farm level under significant changing production conditions across Vietnam.

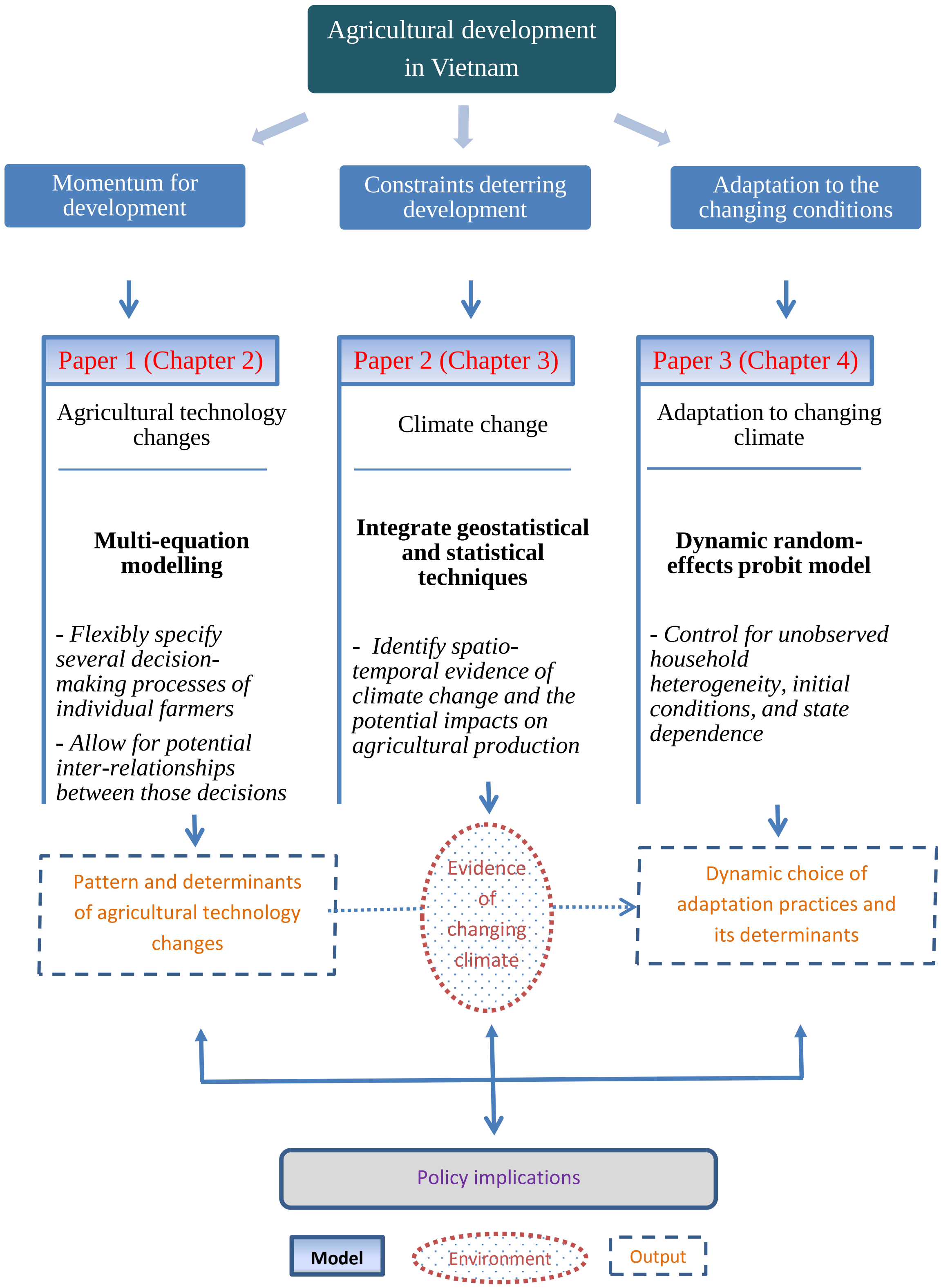


Figure 1.2 Mind map of the thesis

1.5 Contribution to the literature

Study 1 in chapter 2 extends existing approaches in the literature for investigating agricultural technology changes in several ways. It acknowledges that farmers regularly face decisions to simultaneously apply several agricultural practices. The approach used takes into account the simultaneity of the use of four major agricultural practices – the use of new seed varieties, chemical fertilisers, pesticides and machinery – that are applied by rice producers. This approach overcomes the limitation of many previous empirical studies that focus on a single specific practice. These decisions are modelled simultaneously in a multi-equation framework allowing for potential correlation between choices across space and time and, at the same time, controlling for potential endogeneity and unobserved household heterogeneity. The study deepens our understanding of the pattern and determinants of agricultural technology changes and provides new empirical insights related to possible factors driving, as well as constraints deterring, changes in technology by farming households.

The study employs an extensive cross-sectional time series dataset from nationally representative households in Vietnam from 1992 to 2012. Probabilistic record linkage methods were used to find the best-matched observations from the two original surveys, the Vietnam Access to Resources Household Survey (VARH) and the Vietnam Living Standard Survey (VLSS), to create a 20-year panel dataset. Such a long panel allows us to capture the dynamic patterns of technology changes and their determinants at the farm level. This represents a contribution of our study since studies using long time-series-cross-section data to investigate the dynamic behaviour are still lacking in the existing literature. This probability linked dataset is further explored in the third study on farmers' coping strategies in the face of a changing climate.

Study 2 in Chapter 3 improves previous studies by integrating statistical and geostatistical techniques to provide new evidence of ongoing climate change in Vietnam, both temporally and spatially. The comprehensive approach of combining statistical testing with geostatistical techniques enables climate patterns to be mapped at a very fine resolution to identify changes and trends over time and statistically confirm their significance. Using records of monthly precipitation and temperature for a relatively long time period (1975 to 2014) over a high density of 112 meteorological stations across the country provides superior spatio-temporal coverage and substantially improves data accuracy, particularly for interpolation techniques for climatic variables. Comparing evidence-based observed climate change with the spatial pattern of agricultural land use across Vietnam will help inform decision-makers and communities on the likely effects of the changing climate on agriculture.

Study 3 (Chapter 4) uses a relatively long panel dataset over 20 years, and thereby overcomes a major drawback in the previous published work due to the lack of extended time series cross-section data at the household level to investigate the dynamic choices that farmers make about adaptation practices to cope with changing climatic conditions. The approach also controls for methodological issues associated with dynamic modelling, such as unobserved household heterogeneity, initial conditions and state dependence, that could potentially lead to biased estimates. This study is among very few empirical studies globally that explain the pattern of adopting climate change adaptation practices in agriculture using long panel datasets, and is certainly the first such study for Vietnam. Findings from this study are critical for practitioners and policy-makers to facilitate climate-resilient strategies to improve small-scale farmers' adaptive capacity to cope with future changes in the climate.

1.6 Structure of the thesis

The thesis consists of three separate studies and is organised in five chapters as follows: Chapter 1 provides an introduction overviewing the motivation, research questions, research objectives, and approaches and methods applied for analysis. Chapter 2 presents the first study investigating the pattern of agricultural technology changes in rice-cultivating households in Vietnam. Chapter 3 presents the second study, which focuses on identifying empirical evidence of climate change in Vietnam and its implications for the farming in a changing production condition. Chapter 4 presents the third study on adaptation in farming, with lessons for adaptation to climate variability and change across regions of Vietnam. Chapter 5 presents some concluding remarks and policy implications, outlines some limitations and provides directions for further research.

Chapter 2

Pattern and determinants of agricultural technology changes: Evidence from rice-cultivating households in Vietnam

Abstract

Technological change and its diffusion have become major factors shaping the farming sector in many developing countries, including Vietnam. This study investigates agricultural technology change and its determinants at the farming household level using an extensive 20-year panel dataset of nationally representative surveys in Vietnam. The two-stage estimation strategy provides an efficient way to determine how and to what extent changes in agricultural technology (i.e. new seed varieties, chemical fertilisers, pesticides and machinery) have been affected by various factors, allowing for potential correlations among different technologies used by rice farmers. We find that there are significant changes in the pattern and determinants of agricultural technologies applied by farmers in different regions of Vietnam, with notable contributions from improved seed varieties and the rapid spread of agricultural mechanisation. Also, findings reveal that prices of hired labour and rice, as well as macro-level socio-economic conditions such as the growing urban population and increasing agricultural wages, are the main factors driving both the decision and the intensity of using agricultural innovations in the study areas. Findings also confirm correlations among decisions to use agricultural technologies. Follow-up policy interventions such as increasing access to credit that aim to facilite agricutltural technology need to account for the interrelationships in an individual smallholder’s decision-making process to apply agricultural advances.

Keywords: Agricultural technology, pattern changes, smallholders, panel data, Vietnam

JEL codes: D13, Q12, Q18

2.1 Introduction

Despite Vietnam's rapid economic development, agriculture continues to play a critical role in the Vietnamese economy, accounting for 22% of Gross Domestic Product and 54% of the labour force (GSO, 2014). The *Renovation Policy* ("*Doi Moi*") introduced in 1986 with a broad range of policy measures to shift Vietnam from a centrally planned economy to a market-oriented one by facilitating the private, household economy and agribusiness has generated remarkable results in the agricultural sector (Marsh et al., 2006). Total farm output more than tripled from 1990 to 2013, lifting rural incomes, reducing poverty and increasing agricultural exports (OECD, 2015). Over recent decades, Vietnam's agricultural sector has also outperformed all other countries in Asia (see Appendix 2A for details) (OECD, 2015). The *Renovation Policy* has resulted in substantial changes in land use and land ownership in Vietnam. Smallholder farmers have gained more flexibility in managing their plots, including applying appropriate agricultural innovations and altering investment levels of input technologies such as new seed varieties, chemical fertilisers and crop protection methods (Marsh et al., 2006).

There is an increasing interest in agricultural technology changes, especially in developing countries like Vietnam, because these innovations promise to substantially improve crop yields and income (Besley and Case, 1993; Feder et al., 1985; Suri, 2011). Technological change and its diffusion have become major factors shaping the farming sector over the last several decades (Hayami and Ruttan, 1970; Schultz, 1964; Sunding and Zilberman, 2001). As a result, there is a vast literature on agricultural technology changes. Extensive reviews on agricultural technology adoption include Feder et al. (1985), Besley and Case (1993), Sunding and Zilberman (2001) and Doss (2006).

Sunding and Zilberman (2001) specify a list of embodied technologies in agricultural production such as new seed varieties, fertilisers, pesticides and tractors. Farmers regularly make decisions to apply these technologies simultaneously, or sequentially, or as a portfolio. However, empirical studies considering the use of several embodied technologies as interrelated choices at a farm level are relatively sparse in the literature (Doss, 2006; Smale et al., 1995).

Most of the previous research using cross-sectional data on technological changes at the farm level takes a snapshot at a given point in time. Consequently, the dynamic nature of that process is not taken into account properly. Due to the lack of appropriate data, the number of studies on agricultural technology changes using longitudinal data remains limited, and the timescale of the technology applied is relatively short. Furthermore, Doss (2006) points out that econometric techniques dealing with endogeneity and simultaneity in applying new technologies have become increasingly sophisticated. Researchers are not only concerned with the decision to apply a technology but also the degree or intensity of use of the technology. Multi-equation modelling, which can specify more flexible equations for decision-making processes for the farmer’s decision problem and controls for potential interrelationships between those decisions, has been widely applied in recent empirical studies on the use of agricultural practices. This method of using multi-equation modelling is applied in this research.

The study aims to address two research questions: How has agricultural technology changed in the last 20 years in Vietnam? What factors have contributed to those technology changes over time? The pattern of agricultural technology changes is explored across the study area. The factors that may drive those changes based on the characteristics of farming households, regional market conditions and some macro-level drivers are investigated.

This study makes several contributions to the existing literature by addressing several gaps in the knowledge on technology changes in agricultural production. Firstly, the extensive 20-year panel data from a nationally representative sample of households of Vietnam allows us to take advantage of the longitudinal dataset, and control for potential endogeneity and unobserved heterogeneity. Since technology change is a long-term process, the cross-sectional time series data are useful for uncovering the inter-temporal dynamics of agriculture-related innovations. Secondly, based on this extensive dataset, we take into account various components of agricultural innovations implemented by rice producers such as new seed varieties, chemical fertilisers, pesticides and machinery. This approach overcomes the limitation of focusing solely on a specific innovation as in other empirical studies. More importantly, since farmers' use of new technologies could be characterised as several interrelated decisions, we model these decisions simultaneously in a multi-equation framework and also allow for potential correlation across space and time. The study deepens our understanding of agricultural technology applied by farmers and provides new empirical insights on possible factors driving agricultural technology changes by farming households.

The remainder of the chapter is structured as follows. Section 2.2 presents the literature review, followed by a brief overview of the agricultural sector and agricultural technology changes in Vietnam in Section 2.3. Section 2.4 describes the data used in the study. Section 2.5 describes the empirical model and estimation strategies. Section 2.6 discusses the empirical results, followed by the conclusion and policy implications in Section 2.7.

2.2 Literature review

Farmers around the world have a long record of constantly seeking to increase productivity and improve household welfare by applying new agricultural technologies. Technological change and its diffusion have become major factors contributing to the development of the farming sector over the last few decades (Barham et al., 2004; Hayami and Ruttan, 1970; Schultz, 1964; Sunding and Zilberman, 2001; Suri, 2011). Since the literature on agricultural technology changes has been extensively documented, this study focused on selected studies that highlight gaps in our knowledge that the present study is aiming to address.

Three aspects were considered: classification of agricultural technologies, empirical approaches, and advances in research methods dealing with technology changes.

Sunding and Zilberman (2001) distinguish between agriculture-related innovations that are embodied or disembodied in capital goods or products. Embodied technologies include biological innovations (such as new seed varieties), chemical innovations (such as fertilisers and pesticides) and mechanical innovations (such as tractors). On the other hand, disembodied technologies such as agronomic innovations are usually applied in packages such as integrated pest management, and soil and water management practices. Farmers, as producers, may decide to implement technologies simultaneously, or sequentially, or as a portfolio. As a result, researchers studying changes in agricultural technology must carefully consider the nature of the data, empirical approaches, and modelling methodologies such as using dichotomous or continuous variables, and modelling simultaneously or sequentially. Although implementation of embodied technologies such as seeds, pesticides and fertilisers can be characterised as several interrelated decisions, little of the recent literature focuses on the issues of endogeneity and simultaneity of these decisions of an individual farm (Doss, 2006; Feder et al., 1985; Smale et al., 1995).

Besley and Case (1993) point out three different approaches for studying on technology changes in agriculture across space and time based on the type of data available: cross-sectional, time series and panel data analysis. Most previous studies were based on cross-sectional datasets (D'Souza et al., 1993; Diagne and Demont, 2007; Manda et al., 2016; Rahm and Huffman, 1984; Ransom et al., 2003; Shiferaw et al., 2013). These studies take a snapshot at a given point in time and therefore ignore some dynamic characteristics of the decision-making process. Time series studies can show the dynamics of changes in using various technologies by explaining how the rate of technology applied varies with time. However, these studies only use an aggregate measure of technology use, such as percentage of new technology adopted, and are unable to give insights into what might drive the dynamic process of applying new technology (Besley and Case, 1993).

Longitudinal analyses take advantage of both cross-sectional and time series data to investigate technology change and the drivers associated with that process across space and time. For instance, Barham et al. (2004) exploit the 1994-2001 panel dataset from the Wisconsin dairy sector to examine the dynamics of somatotropin rBST used by farmers and point out differences among non-adopters, dis-adopters, and early and late adopters.[1] Also, Moser and Barrett (2006) consider the dynamics of smallholders' use of high-yielding rice from 1993 to 1999 in Madagascar and find that seasonal liquidity constraints discourage application and learning effects exert significant influence over adoption decisions. A recent study by Suri (2011) uses 1997-2004 panel data for over 1,200 Kenyan households. The study takes advantage of the longitudinal dataset to examine how farmers' decision to implement improved agricultural technology is affected by the heterogeneity in net returns of the technology adopted. Unfortunately, the fundamental limitation of using panel data for studies on agricultural technology changes is the lack of appropriate datasets, especially in developing countries like Vietnam. Thus, the number of studies using longitudinal data is sparse in the literature, and also the timescale of the technology applied is relatively short.

In terms of methodological advances, Doss (2006) indicates that recent studies on agricultural technology focus on developments in modelling methodologies to further understand the implementation decision-making process. Feder et al. (1985) indicate that many of the previous empirical studies on technology changes have relied on probability models (probit or logit) to analyse the effects of independent variables on dichotomous choices. However, researchers are not only interested in the decision to adopt technology but also the

[1] rBST, a genetically engineered, productivity-enhancing hormone that is injected in cows.

degree or intensity of application. Thus, Tobit estimation, originally developed by Tobin (1958), has been widely applied in many empirical studies using continuous but limited (or censored) variables to quantify the degree of technology applied. There is increasing interest in new modelling approaches to address issues of endogeneity and simultaneity in the decisions to use new technologies (Doss, 2006). For example, Smale et al. (1995) simultaneously model the choice of whether or not to adopt and the decision of how much input to use. Josephson et al. (2014) apply Seemingly Unrelated Regression (SUR) using an Ethiopian household panel dataset to identify the effects of rural population density on input demand and households' welfare. Another recent promising approach focuses on multi-equation modelling, which is able to specify more flexible equations for multiple decision-making related to farmer's decision problems and controls for potential interrelationships between those decisions. However, the number of empirical studies applying this approach in the literature on investigating changes in agricultural innovations is still relatively limited (Doss, 2006; Josephson et al., 2014).

Drawing from the literature on agricultural technology changes, some gaps were identified and further explored in our study to deepen our understanding of technology use at the farm level. Our 20-year panel dataset provides a means to examine farmers' changes in using agricultural practices such as new seed varieties, fertilisers and mechanisation, and control for potential endogeneity and unobserved heterogeneity. It is also possible to consider various components of agricultural practices such as new seed varieties, chemical fertilisers, pesticides and machinery applied by producers simultaneously, which allows for modelling the correlation between choices across space and time.

2.3 Background: Agricultural sector and technology change in Vietnam

2.3.1 Agricultural production

The Vietnamese economy is dominated by agricultural production (GSO, 2014). Since 1986, following the *Renovation Policy*, Vietnam has shifted from a centrally planned economy — where the State took control of agricultural production — to a socialist-orientated market economy where individual farms have more flexibility over their production activities (Marsh et al., 2006). The structural transition has allowed farmers flexibility to alter their production systems in response to technological changes and market signals, and cope with risks associated with variations in the production environment. As a result, total agricultural output more than tripled in volume between 1990 and 2013, leading to higher farmers' incomes and reduction of poverty (Figure 2.1). Vietnam has maintained a higher growth rate in agricultural production than most countries in the region (see Appendix 2A for details) (OECD, 2015).

Note: Gross Agricultural Output (GAO); Taking indices for 1990 as 100.

Figure 2.1 Growth in the volume of agricultural output in Vietnam (1990-2013)

Source: Food and Agriculture Organization Corporate Statistical Database – FAOSTAT; OECD, 2015

Crop production in Vietnam is still dominated by rice as a major cash crop, using 39.8% of the total agricultural land (GSO, 2014). Rice farmers are typically smallholders and their livelihoods depend heavily on agriculture as the predominant source of income. Agricultural production, particularly rice cultivation, is inherently vulnerable to climate-related risks due to the large cultivated areas and the direct exposure to climatic conditions. Rice production in Vietnam combines areas with irrigation and rain-fed spreading across several agro-ecological regions. Large cultivated areas in the deltas are mainly irrigated, however the irrigation systems are not well-constructed. Hence, rice production is still sensitive to climate exposure.

2.3.2 Agricultural technology changes

From the introduction of the first high-yielding rice variety IR8 in 1966 in Vietnam, the Green Revolution has contributed significantly to rice production. High yielding rice varieties allow farmers to grow not only one crop per year like before, but multiple crops with high productivity (Soong, J., 2006). In order to maintain soil fertility in that intensive rice production system, fertilizers have been widely used to supply additional nutrient needs for warranting high crop yield. Also, the momentum of Vietnam's Green Revolution has continued based on the continuous release of new improved varieties and the increasing application of other technologies such as chemical fertilisers and pesticides (OECD, 2015; Ut and Kajisa, 2006). However, in recent years, a decline in demand for some input technologies in agricultural production, especially chemical-related inputs like chemical fertilisers and pesticides, has been observed in Vietnam (see Figures 2.2 and 2.3 for details).

2.4 Data and descriptive analysis

2.4.1 Household data

The study exploits a rich longitudinal dataset from a nationally representative sample of households from six provinces (Ha Tay, Lao Cai, Phu Tho, Nghe An, Khanh Hoa and Long An) across various agro-ecological regions of Vietnam.[2] A panel dataset was created by combining data from two separate national representative surveys: the Vietnam Living Standard Survey (VLSS 1992-1993, 1997-1998) and the Vietnam Access to Resources Household Survey (VARHS 2006, 2008, 2010, 2012). The VLSS was first carried out in 1992-1993 by the State Planning Committee (SPC) and the General Statistics Office (GSO), with technical support from the World Bank. The sample was selected based on a three-stage sampling strategy to represent various geographic regions of Vietnam. The second VLSS was implemented in 1997-1998 with the sample including most of the households surveyed in the VLSS 1992-1993. Further, the VARHS surveys were designed to be complementary to the VLSS and were conducted by the Vietnam Institute for Economic Management (CIEM) and the University of Copenhagen. The VARHS was implemented in 12 provinces across all regions of Vietnam. All surveys collected information about household and farm-level characteristics, agricultural production, non-farm employment, expenditure, assets, and savings and credit. Commune-level data on regional input and output prices have also been collected in parallel with household surveys and were deflated using the consumer price index published by Vietnam General Statistics Office.

It is often argued that farmers who perceive changes in production conditions tend to look for ways to respond to the changes by applying various practices (Maddison, 2007; Megersa et al., 2014). Because adapting to changing production environments is an ongoing process over a long period of time, data with a relatively long time frame are needed for studies on changes in agricultural practices applied by farmers. However, since the VARHS only provides short panel data for relatively recent years, it is necessary for the current temporal study to find and match these data with observations from the earlier VLSS to create a long panel dataset over 20 years. A combined panel dataset with a length of 20 years based on the two sets

[2] The original household dataset includes 12 provinces across Vietnam. However, after matching the records over time as discussed in detail further below, we retain data from six of these provinces for further analysis.

of surveys allows us to take advantage of the longitudinal dataset to investigate changes in agricultural practices at the farm level over a relatively long time period.

However, the absence of unique and identical identifiers between the datasets of the two separate surveys makes the simple merging of the data from the two sources impossible. The key obstacle was that these surveys may not have interviewed the same households in various years due to the differences in the sample, although they used an identical three-stage sampling strategy. The root of the problem is that, in Vietnam, all national representative surveys, such as the two household surveys VARHS and VLSS, rely on a core sample, which is drawn from the Population Census. However, the sample of that census is altered every ten years. Consequently, the core sample that can be used to select interviewees for any national representative survey like VARHS and VLSS has to be changed accordingly. Therefore, constructing a long panel using the same set of households surveyed consecutively over many years is not possible in our case.

To address this problem, a probabilistic record linkage method has been used in the literature to identify and link observations from independent sources with no unique identifiers (Blasnik, 2010; Gomatam et al., 2002; Gu et al., 2003; Ong et al., 2014; Wasi and Flaaen, 2015; Winkler, 2006). This record linkage method was applied to construct a linked panel dataset containing observations from the two sets of surveys by way of finding the best-matched observations from the two original surveys. The theory behind probabilistic record linkage methods is based on 'employing a combination of approximate string comparators and probabilistic matching algorithms to identify the best matches and assess their reliability' (Blasnik, 2010). While the statistical foundations of this matching method were suggested by Newcombe (1959), the formal mathematical concept was developed and further applied in various fields (Fellegi and Sunter, 1969; Grundy and Jitlal, 2007; Jenkins et al., 2008).

Following Blasnik (2010), suppose that a 'master' dataset (in our case data collected by VARHS) has n_a records, and a 'using' dataset (data collected by VLSS) has n_b records. Each of the n_b records in VLSS is a potential match for each of the n_a records in VARHS. The match/non-match status of $n_a \times n_b$ record pairs needs to be evaluated (Gomatam et al., 2002). Fellegi and Sunter (1969) use the ratio of probability for each pair as a matching score. The matching scores were calculated as the likelihood that observations from the two original surveys refer to the same household, based on a specified list of matching variables. Depending on how well each variable matches for each pair of observations, it is assigned a score (Dusetzina et al., 2014). Then, for each pair, the matching score is calculated as the sum of the scores generated from matching individual variables in the specified list. That matching score is then used to define whether two records are matched or linked by comparing it to a specified threshold (Baldwin et al., 2015). Winkler (1999) suggests that even after matching, it is important to manually review each matched pair, especially for observations with lower matching scores.

In this study, the record linkage technique was used to construct a longitudinal dataset using the following procedure:

(1) Identify those households that were surveyed in the VLSS 1992-1993 (N=3824) and then re-surveyed in VLSS 1997-1998 (N=4305) using a common identifier – Household identifier number (HID). The resulting panel dataset, which is called a 'using' dataset, consists of records on 3480 households.

(2) Identify households that were surveyed in VARHS 2006 (N=2324), and re-surveyed in any of the VARHS 2008 (N=3269), VARHS 2010 (N=3203), and VARHS 2012 (N=3247) using the common identifier – HID. The resulting panel dataset, called a 'master' dataset, consists of records on 2024 households.

(3) Perform probabilistic record linkage of households that are present in the 'using' dataset with those that are present in the 'master' dataset.[3] The matching was performed based on a specified list of comparison variables such as location (e.g. village), same primary sampling unit (e.g. commune), having rice production activity, characteristics of the household head (e.g. age, gender, experience) and of the farm (household size, farm size). All possible pairs of observations (a household from the 'using' and a household from the 'master' dataset) were evaluated, and a matching score computed for each pair. Then, each pair was assigned to one of four classes: true positives (the pairs refer to the same households and are classified as matches), false positives (the pairs are classified as matches even though they belong to different households), true negatives (the pairs, from different households, are classified as non-matches), and false negatives (the pairs are classified as non-matches even though they actually belong to the same households). The pairs were then sorted by the matching score and a cut-off threshold value for the score of 0.8 was applied. Selecting the cut-off threshold value was based on a method commonly applied in the literature through the process of manually adjusting that threshold in such a way that a minimum number of both false positives and false negatives was obtained (Christen, 2012; Gill, 2001; Guiver, 2011). The matched pairs that had a matching score of 0.8 or above were then put in a 'linked' dataset. This dataset consisted of observations on 661 households from six provinces (Ha Tay, Lao Cai, Phu Tho, Nghe An, Khanh Hoa and Long An).

(4) Review the records for each of the 661 households in the 'linked' dataset, with special attention to households with lower matching scores (scores closer to 0.8). Each pair of records in the 'linked' dataset were carefully checked and found errors and missing data in

[3] The user-written program RECLINK in STATA by Blasnik (2010) was used to perform the probabilistic record linkage.

variables of interest that led to inaccurate matching. As a result, a sample of 424 matching households was identified.

(5) Merge the household-level dataset with commune-level information. The information of each household is contained in the 'linked' dataset, while regional information such as average input and output prices was collected at the commune level. Hence, it is necessary to merge these data sources to obtain a dataset including all variables of interest. Due to missing data at some communes, the final longitudinal dataset with 316 matched households including all variables of interest is used for further analysis.

To control for factors influencing the decision-making process of individual farmers, several covariates measuring farm and household characteristics (H), information and market characteristics such as prices and access to extension services (M), and regional and macro-level socio-economic conditions (C) were included. The selection is based on reviewing previous studies on technology changes in agriculture using micro-studies (Chavas, 2001; Cragg, 1971; Doss, 2006; Lee, 2005; Mason and Smale, 2013; Moser and Barrett, 2006; Place and Dewees, 1999; Sietz and Van Dijk, 2015; Sunding and Zilberman, 2001; Xu et al., 2009).

Household and farm characteristics were first controlled for by using variables that best describe the features of the farms. Labour availability, represented by household size, could be a variable of interest in agricultural technology studies. Doss (2006) points out that where the labour market does not function effectively, particularly in developing countries, households must rely on their own labour for agricultural activities. In addition to household characteristics, some previous studies on technology use also consider the biophysical features of the farm. In general, the overall impact of landholding or farm size on technology changes is inconclusive (Maddison, 2007; Piya et al., 2013). In addition, land ownership or tenure has been considered in a number of empirical studies. However, Feder et al. (1985) confirm that there are conflicting empirical results on the relationship of tenure and decisions to apply improved agricultural technologies.

Furthermore, market characteristics such as prices and market access may influence agricultural technology changes. Commune-level input and output price information were controlled through labour and farm-gate average price variables. Furthermore, it is regularly hypothesised that access to credit eases the cash constraints of smallholders and allows them to invest more in farm production and management. Lack of access to credit may prevent farmers from applying innovations, in particular for practices that require high initial investment. Previous meta-analysis on changes in agricultural technologies applied by farmers around the world reveals that there is a positive relationship between technology use and credit availability (Knowler and Bradshaw, 2007).

2.4.2 Macro-level variables

Macro-level socio-economic trends may affect producers' decisions to apply a more advanced technology. The evolving labour market through the process of rural labour migrating to urban areas is a necessary condition fostering the use of agricultural technologies by farming households (Chavas, 2001). By constructing an integrated model of technological change and population density, Kremer (1993) indicates that high urban population spurs advanced technology in agriculture. Chavas (2001) also points out that meeting the growing food demand of the urban population could only be done by applying technological change in agriculture, which could lead to substantial increases in productivity. More labour-saving technologies such as mechanisation and yield-improving technologies such as chemical fertilisers and high-yielding varieties have been widely applied in agriculture across the world, particularly by Asian farmers since the Green Revolution (Hayami and Ruttan, 1970). The profound labour shifts from agriculture to other sectors pose significant stresses on the farm labour market, and thus affect the decision to apply more agricultural technologies (Chavas, 2001). In the study, the effect of macro-level factors such as agricultural wage and percentage of urban population on changes in agricultural technologies at the farm level was considered. Information on the real agricultural wage and percentage of urban population over the study period were collected from the Vietnam Statistical Yearbook published by the General Statistics Office (GSO). The real agricultural wage is calculated with a base year of 2010.

In addition, outcome variables representing agricultural technology changes, such as the decision to apply agricultural technologies and the intensity of use, at the household level were selected. A farmer's response on whether or not they use a particular agricultural practice is modelled as a binary variable. Following Feder et al. (1985), the intensity of technology use was defined as the total cost per hectare of a given technology used by farmers. The cost of technologies has been deflated using the Consumer Price Index (CPI) with the base year of 2010.

2.4.3 Descriptive analysis

Table 2.1 reports the descriptive statistics for the variables used in the study. The survey dataset covers a broad range of variables that may affect agricultural technology changes. The descriptive analysis shows relatively high rates of technology use reported by farmers in the study area over 1992 to 2012 period: 73% of total households under study use improved seed varieties, 86% use fertilisers, 79% use pesticides and 81% use machinery. Use of fertilisers and machinery is relatively higher than other practices. The dynamic patterns of agricultural technology changes from 1992 to 2012 are presented in Figures 2.2 and 2.3. There is a clear general increase in the percentage of households reporting use of improved seeds and machinery while use of pesticides and chemical fertilisers shows a slight decline in recent years (Figure 2.2).

Table 2.1 Full sample descriptive analysis

Variable	Description	Type of variable	Mean	SD
Outcome variables				
Adoption decisions				
Adopted improved seed	Household adopted improved seed *(1/0)*	Binary	0.73	0.19
Adopted chemical fertilisers	Household adopted fertilisers *(1/0)*	Binary	0.86	0.11
Adopted pesticides	Household adopted pesticides *(1/0)*	Binary	0.79	0.16
Adopted machinery	Household adopted machinery *(1/0)*	Binary	0.81	0.15
Intensity of adoption				
Improved seed used	Cost of improved seed *(Mill.VND/ha)*	Continuous	1.16	0.28
Chemical fertilisers used	Cost of chemical fertilisers *(Mill.VND/ha)*	Continuous	3.12	0.83
Pesticides used	Cost of pesticides *(Mill.VND/ha)*	Continuous	0.75	0.02
Machinery used	Cost of machinery *(Mill.VND/ha)*	Continuous	1.95	0.76
Household and farm characteristics				
Household size	Number of family members	Continuous	4.6	0.49
Farm size	Farmland operated by household *(ha)*	Continuous	0.405	0.84
Tenure	Farmland ownership *(1/0)*	Binary	0.87	0.11
Input and output market access				
Credit	Access to credit *(1/0)*	Binary	0.59	0.49
Labour wages $_{(t-1)}$	Average regional labour wages in previous season *(1000VND/day)*	Continuous	62.9	49.7
Farm-gate price $_{(t-1)}$	Average regional retail price of rice in previous season *(1000VND/kg)*	Continuous	3.29	3.52
Extension	Access to extension information (*1/0*)	Binary	0.44	0.50
Macro-level environment				
Real agricultural wage	Real wage in agriculture (*Mill.VND/month*)	Continuous	3.40	1.45
Urban population	% of urban population (%)	Continuous	26.42	4.22

*Note: *VND, Vietnamese Dong (approximately 16.015 VND/$U.S. averaged over 1992 to 2012)*

Figure 2.2 shows a constant increase in the use of agricultural machinery by rice producers in the study areas over the 20 years from 1992 to 2012. The percentage of farming households using tractors in their agricultural production has increased significantly from 42.3% in 1992 to 65.9% in 2006, 89.3% in 2008, 92.3% in 2010 and 97.9% in 2012. The rapid spread of farm mechanisation is associated with a sharp increase in land and labour productivity, and thus mitigates the adverse effects of rural labour migration to urban areas or to other sectors. For example, Ut and Kajisa (2006) notice a significant increase in productivity of rice from 2.5 tonnes per hectare in 1980 to 5.5 tonnes per hectare in 2002 across rice production regions of Vietnam. Also, in our dataset a positive shift in rice productivity with respect to mechanisation applied by farming households was found during the period of 1992 - 2012 (Appendix 2D).

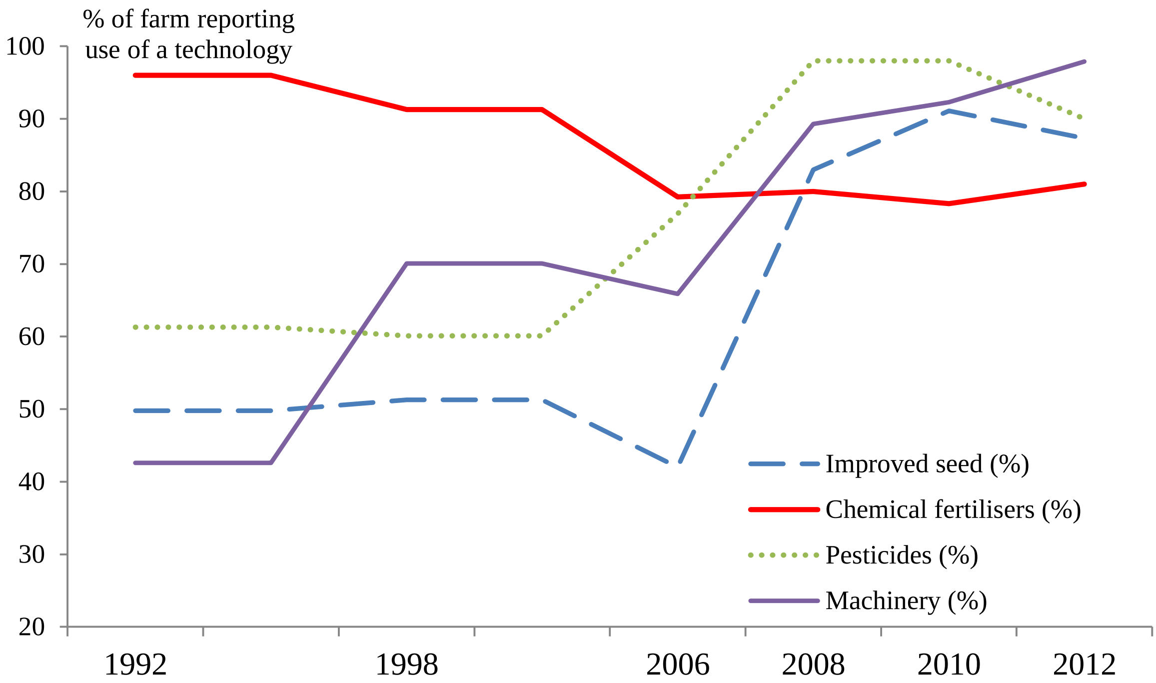


Figure 2.2 Long-term trend in the percentage of households reporting use of agricultural technologies (1992-2012)

In contrast, a slowdown in the percentage of farmers using chemical fertilisers is observed from 1992 to 2012. Starting from a relatively high rate of about 91.3% in 1992, the proportion of farmers using fertilisers decreases gradually to 81% in 2012 (Figure 2.2). A similar decrease is also observed in pesticide use in recent years, particularly from 2008 to 2012. The Vietnamese government has disseminated various environmentally friendly agricultural practices recently due to growing concerns about the negative impact of chemical fertilisers and pesticides on health and the environment. This has also led to a gradual decrease in chemical fertilisers and pesticides applied by many farming households.

The use of new seed varieties has increased remarkably in recent years, especially from 2006. The use of improved rice seeds has more than doubled from around 40% in 2006 to 87.3% in 2012. The continuous release of modern varieties of rice has been a critical factor maintaining the momentum of agricultural growth in Vietnam, even after the Green Revolution (Ut and Kajisa, 2006). Thus, agricultural technology changes across the study areas in Vietnam are due mainly to better genetics from plant breeding and the rapid spread of agricultural mechanisation.

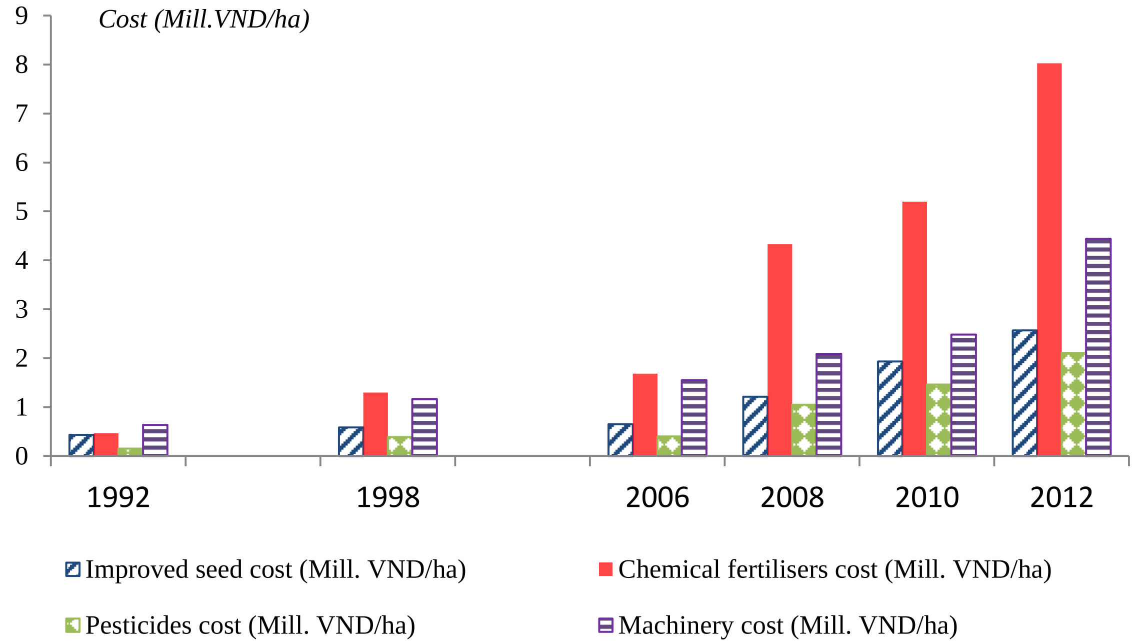


Figure 2.3 Long-term trend in the cost of agricultural technologies in the study areas (1992-2012)

Figure 2.3 shows that the cost of the four practices has increased over time, but at different rates. Chemical fertiliser is the most costly, at approximately 8 million VND per hectare in 2012. That significant cost is likely one of the factors that can explain the slowdown in the growth rate of fertiliser use in recent years (Figures 2.3 and 2.4). For other practices, increases in the cost of improved seeds, pesticides and machinery are also notable over 1992 to 2012 (Figure 2.3). Especifically, mechanisation has maintained increasing trends in both average cost per hectare and the annual growth rate of that cost in recent years (Figures 2.3 and 2.4). Labour mobility from rural to urban areas over time is likely the main driver behind farmers' shift to labour-saving technology like mechanisation with a constant increase in its growth rate from 1992 to 2012 (Figure 2.4).

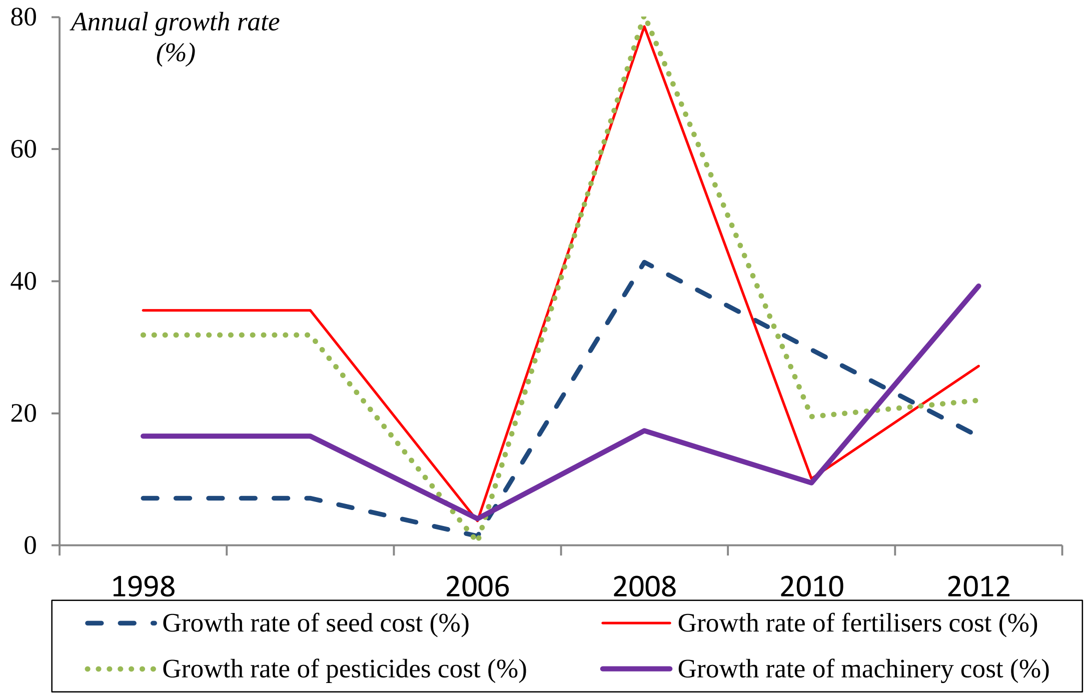


Figure 2.4 Long-term growth rate in the cost of agricultural technologies in the study areas (1992-2012)

2.5 Empirical model and estimation strategies

To identify possible factors associated with agricultural technology changes in the study areas, a two-stage empirical model considering both the decisions to apply agricultural practices and the intensity of their use was applied. Using the approach of Cragg (1971), Byrne et al. (1996), Alene et al. (2008) and Mason and Smale (2013) of an input consumption framework, the household's decision to apply agricultural practices (T) can be specified in the two following steps: (1) farmer's decision is made on whether or not to use a new practice, known as the participation decision; and (2) farmer decides the extent of using that practice, known as the expenditure-level decision. In the literature, three main groups of factors have been identified in studies on agricultural technology changes in developing countries: farm and household characteristics (H), information and market characteristics such as prices and access to extension services (M), and regional and macro-level socio-economic conditions (C) (Chavas, 2001; Doss, 2006; Mason and Smale, 2013; Moser and Barrett, 2006; Sunding and Zilberman, 2001; Xu et al., 2009).

It can be observed from the data that many of the surveyed households have not made any input purchases: 14.4% of the total sample have not used fertiliser, 14.6% have not used pesticides, 20.5% have not used improved seeds and 7.1% have not used machinery; in other words, the data is left-censored (Bellemare and Barrett, 2006; Burke et al., 2015; Tobin, 1958). Left-censored data may be associated with the issue of sample selection, which potentially leads to biased parameter estimates (Heckman, 1977). The issue exists because the sample is non-random when it only observes the input purchases from farmers who reported use of a particular technology. So, while considering the subsample of only technology users, it is very likely that some unobservable factors such as farmer's management ability would influence both their participation decision and their expenditure-level decision. Thus, there may be some correlation between the residuals of the two stages that can lead to sample selection bias. A popular approach for addressing selection bias is to follow a two-step procedure, with the first step identifying determinants behind the decision to apply the technology and the second analysing factors associated with input technology use given the decision to apply the technology, which is referred to as conditional probability (Cragg, 1971; Heckman, 1977; McIntosh et al., 2013). Applying this approach, the first step in the participation decision is linked to the second step of the expenditure-level decision by using the inverse Mills' ratio (IMR), which is able to account for any correlations between residuals of the two stages and thus, avoids biased estimation (Beltran et al., 2013; Byrne et al., 1996). If the estimated parameter of the inverse Mills' ratio is found to be statistically significant, it can be concluded that sample selection bias is present in the sample. Consequently, including that ratio in the estimation model corrects selection bias (Byrne et al., 1996). In this study, that strategy to analyse decision-making to use agricultural practices in connection with the degree of applying those practices was applied.

(1)Step 1: Factors associated with the decision to apply new technology

A pooled cross-section probit model of the decision to use a given agricultural practice was first estimated. The inverse Mills' ratio (IMR) is then generated and used in a second-stage regression to explain the level of input used by producers. The inverse Mills' ratio for each technology equation is calculated as $IMR = \phi(F(X'\alpha))/\Phi(F(X'\alpha))$ to account for sample selection, where ϕ is the probability density function, and Φ is the cumulative distribution function.

$$\begin{aligned}\Pr(T_{adopt\,s,i,t}=1) &= F(X'\alpha) \\ &= \alpha_0 + \alpha_1 H_{s,i,t} + \alpha_2 M_{s,i,t} + \alpha_3 C_{s,i,t} + \mu_{s,i} + \varepsilon_{s,i,t}\end{aligned} \tag{2.1}$$

$$i = 1,2,...N;\ t = 1,2,...6,$$

where T_{adopt} takes the value of one if the farming household purchased an input technology and is zero otherwise; an unknown vector of parameters α to be estimated; s is the type of input technology (improved seed, chemical fertilisers, pesticides, machinery); $\Pr(T_{adopt})$ is the probability of input technology s; vectors of explanatory variables X include H, M and C; $\mu_{s,i}$ is an unobserved individual-specific effect, which captures the unobserved heterogeneity, such as farmers' management ability and farmers' attitude towards new agricultural practices. To take into account the unobserved effects, the composite error term was decomposed into individual-specific time-invariant $\mu_{s,i}$ terms and $\varepsilon_{s,i} \sim i.i.d.(0, \sigma^2)$.

$$T_{adopt_i} = \begin{cases} 1 & if \quad T_{adopt}*_i > 0 \\ 0 & if \quad T_{adopt}*_i \leq 0, \end{cases} \qquad (2.2)$$

where $T_{adopt}*$ is a latent response formulation of the observed decision to apply a technology.

(2)Step 2: Factors associated with the level of agricultural technology used

Four components of agricultural practices (new seed varieties, chemical fertilisers, pesticides and machinery) applied by rice producers were considered. Since farmers' decision-making to use new practices could be characterised as several interrelated decisions, a farmer's joint decision was modelled simultaneously and also allowed for potential correlation between them across space and time. In doing so, the level of use of the four agricultural practices was estimated using the Seemingly Unrelated Regression (SUR) approach. These models include the relevant inverse Mills' ratios from Step 1 to correct for sample selection bias (Bellemare and Barrett, 2006; Burke et al., 2015; Wooldridge, 2010). The regression models can be specified as:

$$T_{used\ s,i,t} = \beta_{0,s} + IMR_{s,i} + \beta_1 H_{s,i,t} + \beta_2 M_{s,i,t} + \beta_3 C_{s,i,t} + \mu_{s,i} + \varepsilon_{s,i,t} \qquad (2.3)$$

where *s* is the type of input technology (improved seed, chemical fertilisers, pesticides and machinery) and their corresponding error terms $\varepsilon_{seed,i,t}$, $\varepsilon_{fertilisers,i,t}$, $\varepsilon_{pesticides,i,t}$ and $\varepsilon_{machinery,i,t}$ are assumed to be *i.i.d.*$(0, \sigma^2)$; an unknown vector of parameters β to be estimated. In addition, ordinary least squares estimation assumes: cov($\varepsilon_{seed,i,t}$, $\varepsilon_{fertilisers,i,t}$, $\varepsilon_{pesticides,i,t}$, $\varepsilon_{machinery,i,t}$) = 0 for all *t*. That is, at any time period *t*, the cross-equation errors are uncorrelated. However, in reality, some factors may influence all error terms and are likely to have similar effects in each equation. In our study the errors (residuals) from these four models are suspected to be correlated because these decisions are made by the same household simultaneously. This suggests correlated error terms as cov($\varepsilon_{seed,i,t}$, $\varepsilon_{fertilisers,i,t}$, $\varepsilon_{pesticides,i,t}$, $\varepsilon_{machinery,i,t}$) = $\sigma_{s,i}$, for all *t*. In this case, a Seemingly Unrelated Regression system including a set of equations that has contemporaneous cross-equation error correlation is preferred. Here, the set of equations seems unrelated at first glance, but their error terms are, in fact, correlated between the equations.

(3) Controlling for unobserved heterogeneity μ_i

It could be assumed that unobserved heterogeneity μ_i is independent of the explanatory variables, but that assumption would be perhaps too strong since some correlations may exist between observable and unobservable characteristics within a farming household. Mundlak (1978) proposed an approach to relax this assumption by allowing for correlations between unobserved heterogeneity (μ_i) and the vector of explanatory variables across all time periods, called Correlated Random Effect (CRE). In practice, the Correlated Random Effect estimation procedure is performed by adding an extra set of explanatory variables to the model (Bezu et al., 2014; Mundlak, 1978; Pesaran, 2006; Wooldridge, 2010). That set includes the mean of the time-varying variables (e.g. $\overline{H_i}, \overline{M_i}, \overline{C_i}$). The Correlated Random Effect estimator was applied for both Step 1 and Step 2 to properly handle the issue of unobserved heterogeneity.

2.6 Empirical results and discussion

2.6.1 Estimation results of the two-stage procedure

This section presents the estimation results for the two-step procedure proposed in the previous section. The procedure allows us to determine factors that may be associated with agricultural technology changes over time in the study areas. The probability that farmers report use of any of the four agricultural practices: new seed varieties, fertilisers, pesticides and tractors, was first estimated. Then, the intensity of using those technologies is modelled in a multi-equation framework, conditional on the probability of a farmer reporting use of the practices in the first step.

(1) Factors associated with the decision to apply new technology

The probability of a farmer's use of a particular technology is estimated using a probit model, using various covariates such as farm and household characteristics, input and output market features, access to extension services and macro-level conditions associated with farmers' decisions. The results are shown in Table 2.2.

There is statistically significant evidence of the effect of farm and household characteristics on agricultural practices used by farmers. Not surprisingly, farmers with more farmland and land ownership are generally more likely to apply new practices. It is clear that producers who own their land have more incentive to invest in their farms because they can benefit from those investments in the future (Beltran et al., 2013). Moreover, households with more farmland are also willing to use new practices due to the promise of substantially increasing crop yield, particularly for large-scale production (Besley and Case, 1993; Suri, 2011).

However, the role of household size on agricultural practices used by farmers is insignificant for most of the technologies adopted, except for agricultural machinery. Agricultural mechanisation is an interesting technology because our finding indicates that the larger size of households is associated with a significantly lower probability of being machinery users. Since rural labour migration to urban areas has increased dramatically, the use of mechanisation in agricultural production is an important way to overcome the rural labour deficiency.

Table 2.2 Factors associated with the decision to apply agricultural technologies

Variable	Improved seed	Fertilisers	Pesticides	Machinery
Household size	0.01974	0.03774	0.00384	-0.10068**
	(0.0390)	(0.0690)	(0.0395)	(0.0504)
Farm size	0.00003***	0.00003**	-0.00001	0.00003**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tenure	0.47844**	1.32934***	0.53476**	0.17180
	(0.2290)	(0.2110)	(0.2499)	(0.4773)
Credit	0.11878	0.21936	-0.19861	0.16205***
	(0.1008)	(0.1225)	(0.1001)	(0.0289)
Labour wages$_{(t-1)}$	0.00165	0.00038	0.00873***	0.00940***
	(0.0018)	(0.0020)	(0.0028)	(0.0028)
Farm-gate price$_{(t-1)}$	0.03506*	0.05622**	0.03343**	0.00420
	(0.0179)	(0.0230)	(0.0151)	(0.0170)
Extension	0.19091*	0.46376***	0.09641	-0.07836
	(0.1047)	(0.1909)	(0.2170)	(0.1236)
Real agricultural wage	1.94952***	0.30591*	0.11458	0.97172***
	(0.1995)	(0.1428)	(0.2048)	(0.2753)
Urban population	0.51238***	-0.17959	0.15638***	0.18765**
	(0.0544)	(0.090)	(0.0202)	(0.0389)
Constant	14.6284	-17.4936	-7.61281	21.5870*
	(11.229)	(12.256)	(11.125)	(10.627)
Year dummy[4]	Yes	Yes	Yes	Yes
Within-household means	Yes	Yes	Yes	Yes
N	1376	1525	1375	936
Pseudo R^2	0.2757	0.3394	0.2350	0.2576

*Notes: 1. Standard errors are presented in parentheses 2. *, **, *** significant at 10%, 5%, 1% level*

[4] The estimated results of year dummy and within-household means variables are provided in Appendix 2C.

Input and output prices are strongly associated with agricultural technology changes. Statistically significant evidence of the positive relationship between farm-gate price of rice and the decision to apply new seed varieties, chemical fertilisers and pesticides has been found. Undoubtedly, increases in output price could encourage farmers' use of technology since these new practices could increase yield (Timmer, 1988; Ut and Kajisa, 2006). Nevertheless, the decision to adopt a technology is also affected by input market conditions. More specifically, the higher the hired labour wage, the greater the likelihood of using modern agricultural practices.

Increasing demand for food and a favourable macro-level labour market are expected to foster agricultural technology (Chavas, 2001; Place and Dewees, 1999). In this study, very strong evidence of the effect of macro-level variables such as average agricultural wage and urban population on changes in the use of agricultural technologies was found. A higher percentage of people living in urban areas is positively and significantly correlated with the decision to apply improved agricultural technologies. Vietnam has a rapidly growing urban population, and increasing agricultural output through applying new technology is the primary way to meet the stronger food demand from urban areas. In addition, the agricultural wage is also likely to be a significant factor that affects the decision to apply new technology. Statistically significant correlation between real agricultural wage and the probability of farmers reporting use of an agricultural technology was found. This may be because the increasing average wage in the agricultural sector over time has forced farmers to switch to labour-saving technologies. The transition in the labour market has created more incentive to apply new technology in agriculture in the study areas in Vietnam.

(2) Factors associated with the level of agricultural technology used

When considering the application of a set of technology components within an individual household as interrelated decisions, the Seemingly Unrelated Regression model is a preferred approach in the literature because decisions to use those technology components are likely to be jointly made by an individual farming household (Smale et al., 1995). In that case, the Seemingly Unrelated Regression specification is relevant when it is able to capture the potential cross-correlation among different decisions which have been made by producers. Here, farmers' joint decisions were simultaneously modelled and also allowed for potential correlation across space and time using a system of equations.

A farmer's decision to apply improved technologies in Step 1 and the degree of use in Step 2 may occur sequentially or simultaneously in the decision-making process. Following Wooldridge (2010), Bellemare and Barrett (2006) and Burke et al. (2015), our approach is flexible in allowing separate mechanisms to determine the decision to apply a technology and the decision on the extent of application. To begin, the probit models in Step 1 above are estimated and obtained the inverse Mills' ratio of the probability of using a particular agricultural practice. Next, the inverse Mills' ratios are tested whether they are statistically significantly different from zero at this stage. If the hypothesis is rejected, the second step will be re-estimated excluding insignificant inverse Mills' ratios from the models. The final estimated results are given in Table 2.3.

Initially, the coefficient estimates of inverse Mills' ratios are 0.896 for improved seeds (p-value of 0.201), -5.84 for chemical fertilisers (p-value of 0.001), 1.48 for pesticides (p-value of 0.000) and 0.530 for machinery (p-value of 0.535). This means that the inverse Mills' ratio coefficients on the use of improved seeds and machinery are not statistically significantly different from zero and they are dropped before re-estimation.

Table 2.3 Factors associated with the level of agricultural technologies used

Variable	Seed used	Fertilisers used	Pesticides used	Machinery used
$\hat{IMR}$	-	-5.84236***	1.48399**	-
		(1.0760)	(0.4573)	
Household size	0.00499	0.05310	0.06619	0.08052
	(0.0299)	(0.0681)	(0.0310)	(0.0751)
Farm size	-0.00002***	-0.00008***	-0.00000	-0.00001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tenure	0.03490	2.52325*	0.55509	0.67575*
	(0.3037)	(1.1678)	(0.3791)	(0.3360)
Credit	-0.04507	-0.24663	0.03697	-0.09896
	(0.0867)	(0.2451)	(0.0730)	(0.2280)
Labour wages$_{(t-1)}$	0.00109	0.00950**	0.00308***	0.00202***
	(0.0015)	(0.0038)	(0.0010)	(0.0004)
Farm-gate price$_{(t-1)}$	0.02059*	0.02052	0.05071**	0.01978**
	(0.0100)	(0.0494)	(0.0204)	(0.0080)
Extension	-0.03564	-0.28170	0.15934*	-0.05287
	(0.1037)	(0.2547)	(0.0800)	(0.1970)
Real agricultural wage	0.55351***	0.83375***	0.36001**	1.71863***
	(0.1531)	(0.2730)	(0.1388)	(0.3173)
Urban population	0.03180	0.34816***	0.08426*	0.21565**
	(0.0380)	(0.0843)	(0.0440)	(0.0900)
Constant	21.5522*	30.4962***	6.79895	-5.26326
	(10.5570)	(11.3655)	(6.4063)	(1.2043)

Co-variance

cov(*e.y1 X e.y2*)	cov(e.y1 *X* e.y3)	cov(e.y1 *X* e.y4)	cov(e.y3 *X* e.y4)	cov(e.y2 *X* e.y3)	cov(e.y2 *X* e.y4)
1.2575**	0.1658*	0.0241	0.5607***	1.4084***	2.9110
(0.4139)	(0.0746)	(0.1670)	(0.1200)	(0.2628)	(1.5889)

Year dummy:[5]	Yes
Within-household means:	Yes

Notes: 1. Standard errors are presented in parentheses *2. *, **, *** significant at 10%, 5%, 1% level*

[5] The estimated results of year dummy and within-household means variables are provided in Appendix 2C.

Considering farm and household characteristics, it has been found that tenure or land ownership is still positively contributing to the level of agricultural technologies used by producers, with significant effects on machinery and chemical fertilisers. Compared with the estimated coefficients of other covariates, the effect of land ownership on technology use is relatively high. It is clear that landowners are often willing to invest more in their own agricultural land so they can benefit from those investments in the future. In contrast, land tenants often lack security of tenure due to short-term rent contracts which clearly affects their willingness to take risks with their investments (Banerjee, 2000). In addition, the negative coefficients for access to credit are implausible although their effects on the level of technology use are not statistically significant. It raises a concern about the effectiveness of the credit market in the study areas for smallholders with strict budget constraints. The ability for farm households to access commercial credit commenced in 1993 and has been further expanded with concessional interest rate loans to purchase machines, mechanical equipment and materials. However, the policy is not as effective as anticipated for many reasons, including the limited credit availability, complicated and inconsistent application procedures, and a high interest rate for agricultural credit (Marsh et al. 2006; OECD, 2015).

The effect of farm size on technology use, in general, is as expected with many of the estimated coefficients showing a very high level of significance. The adverse impact of farm size on the average level of input technologies use is consistent with the increasing returns to scale theory where producers with more farmland are often able to make better use of inputs than that are politically regulated or suggested by suppliers and government agencies (Banerjee, 2000). As a result, increasing returns to larger scale of production may bring an improvement in farming outcomes such as increases in productivity and household income as observed in the study (Appendices 2D and 2E).

Among the remaining variables, the factors associated with input and output markets such as labour and farm-gate prices for rice, in general, positively and significantly affect how much input technology a producer uses, given that the adoption decision has been made. Our finding confirms the positive relationship between sale prices and the level of agricultural technologies used by farmers in many previous studies (Bezu et al., 2014; Feder et al., 1985; Ricker-Gilbert et al., 2011). This result is plausible because farmers are willing to apply input technologies in their farms to boost productivity when they expect output prices to be higher. In contrast to expectations, producers' access to extension services is, in general, not significantly correlated with the amount of input technologies used. In Vietnam, the main channel providing information to farmers is the extension system, which was officially established in 1993, the first year of the panel dataset. Agricultural extension has a strong production focus associated with the introduction of new seed varieties, special production techniques and information related to new policies and market prices. However, due to resource constraints the role of extension services in Vietnam in supplying necessary information to producers is still quite limited (OECD, 2015).

In addition, better overall socio-economic conditions such as stronger food demand and a favourable labour market are expected to encourage farmers to invest more in their farmland. In the study, these macro-level factors including an increasing agricultural wage and a growing urban population have a strong impact on expenditure on agricultural technologies, as expected. The real wage growth in agriculture is highly significantly associated with increasing investments in agricultural technologies. Wage growth puts a great burden on agricultural production so that farmers have to rely on labour-saving technologies to maintain their returns from farming activities.

It is important to note that the two estimation stages introduce some degree of flexibility that allows us to distinguish between factors associated with the decision to apply a technology and those related to the level of technology use (Burke et al., 2015). It is evidence that landholding size is positively associated with decision-making to use agricultural innovations, but negatively affects the intensity of applying those technologies.

In general, combining the results of the first two steps, it is evident that farm size and prices of hired labour and output, as well as macro-level factors, are the main factors driving agricultural technology changes over time in the study areas. Not surprisingly, by using the Seemingly Unrelated Regression (SUR) approach, strong evidence of the cross-correlation among the decisions to use agricultural technologies has been found through the very high statistical significance level of their co-variances. That confirms our hypothesis of the simultaneous relationships among technology uses within an individual farm. Follow-up policy interventions should account for the interrelationships in the decision-making process of smallholders to apply agricultural advances, recognising household budget constraints.

2.6.2 Robustness check

Several model diagnostics, including statistical tests for multicollinearity and heteroskedasticity have been conducted in this study, because in the regression model various kinds of misspecification such as heteroskedastic errors or omitted variables could lead to biased or inconsistent estimators (Yatchew and Griliches, 1985). In our case, due to the significant spatial-temporal variations in farm and farmer characteristics and farming strategies it may be expected that there is correlation among explanatory variables and heteroskedastic disturbances in the sample. If the estimation models violate any assumption of those tests, the estimated results would be biased.

Firstly, potential correlations among explanatory variables were investigated using Pearson's correlation matrix. The Pearson's correlation coefficients show no perfect linear relationship between variables (see Appendix 2F for estimated results). The largest coefficient is 0.6189, at 1% significance level, representing the correlation between labour wages and predicted value of inverse Mills' ratio of machinery. Thus, the correlation among variables does not seem particularly high, but it is still necessary to test for multicollinearity. If a higher degree of multicollinearity presents in the dataset, the estimated coefficients and standard errors are more volatile, unstable and difficult to interpret.

To detect multicollinearity, two well-known indicators were used: Tolerance, which is correlation between variables, and Variance Inflation Factor (VIF), the level of estimated coefficients being inflated by multicollinearity.[6] Our estimated results confirm a low level of multicollinearity in the models as the largest value of VIF is 7.18 (equivalent to tolerance of 0.139) from the labour wages variable (Appendix 2C). After testing for heteroskedasticity, the results of the Breusch-Pagan test reject the underlying assumption of homoscedasticity at 1% significance level in the estimation models (Appendix 2C).[7] Thus, robust standard errors are applied when regression models are estimated. Also, correlation among the four practices used in the Seemingly Unrelated Regression model was allowed because it is suspected that the decisions may be interrelated. Consequently, the test results confirm the statistically significant interrelationships among these decisions to use agricultural practices (Table 2.4).

2.7 Conclusion and policy implications

This chapter examines the general patterns of agricultural technology changes and identifies factors that are likely to be associated with those changes in Vietnam. Using a rich 20-year longitudinal dataset from a nationally representative sample of households, four agricultural practices were investigated: use of new seed varieties, use of chemical fertilisers, use of pesticides and use of machinery by rice producers. Technology change and its

[6] The indicators are calculated using Stata user-written program 'collin' from Philip B. Ender, UCLA Department of Education.
[7] We apply Stata user-written program 'regcheck' from Mehmet Mehmetoglu, Norwegian University of Science and Technology. The test output is provided in Appendix 2C.

determinants were analysed by a two-stage procedure considering the probability of rice farmers being users of particular agricultural practices and also the intensity of the practice used by farmers, conditional on several factors that may affect that decision-making process. Sample selection bias and unobserved heterogeneity were controlled, as well as for endogeneity and simultaneity associated with the inter-temporal changes of those agricultural technologies.

The findings indicate that there have been significant changes in the pattern and determinants of the use of four agricultural practices applied by rice farmers across regions of Vietnam. A general increase over time in the percentage of farmers using improved seeds and machinery has been observed while use of pesticides and chemical fertilisers has been flat, with signs of a slight decline in recent years. Findings on the degree of use of these agriculture-related practices reveal increases at different rates in the use of those practices over time. In addition, a farmer's decision to apply agricultural practices is strongly affected by farm size, input and output prices and by macro-level socio-economic conditions such as average agricultural wage and urban population as a proportion of total population. Household size and access to credit show limited effects on rice producers' use of the four practices. Considering factors influencing the level of technology use, the results indicate that land ownership, farm size, and labour and farm-gate prices have statistically significant effects on the demand for agricultural technologies adopted. As expected, it is evident that macro-level variables such as the stronger food demand from growing urban population and the increasing agricultural wages are very likely to be associated with the level of agricultural advances used by farmers.

Overall, the study highlights that farm size, cost of hired labour and output prices, as well as macro-level variables, are the main factors driving agricultural technology changes in Vietnam over many years. Not surprisingly, it exists strong evidence of cross-correlation among decisions that have been made by individual farming households to apply various agricultural technologies.

It is important to note that Vietnamese farmers have been operating their farms under a continuously transforming policy environment over recent decades. Such policy transitions have contributed significantly to shaping the agricultural sector, increasing productivity and enhancing rural producers’ income. However, findings from this study also show weak and uncertain spillover effects from other government policies aimed at improving access to credit and extension services on agricultural technology changes in the study area. Focusing on improving the performance of the credit market, as well as access to technological information, could help promote agriculture-related technologies to improve farmers’ wellbeing. Developing land markets to allow larger-scale land acquisitions is necessary to facilitate labour-saving and productivity-improving technologies such as mechanisation in the agricultural sector. In addition, our findings confirm the simultaneous interrelationships among decisions to apply agricultural practices within an individual farm. Follow-up policy interventions should account for those correlations in an individual smallholder’s decision-making process to apply agricultural advances.

Chapter 3

Farming in changing production conditions: Evidence of climatic change in Vietnam

Abstract

Changes in climatic conditions can have a significant impact on both natural systems and human activities. This research provides a better understanding of the spatio-temporal variations in underlying climate processes and the potential effects on Vietnam's agricultural sector. In this study, statistical methods with geostatistical techniques were combined to graphically represent the distribution of climate patterns, identifying variations and trends over time, and testing the statistical significance of those changes. By using records of monthly precipitation and temperature for a relatively long-term period (1975 to 2014) over the high density of 112 meteorological stations across the country, robust visual and statistical evidence of climatic change throughout Vietnam were provided. The visual analytics show remarkable changes in the spatio-temporal distribution patterns of rainfall and temperature. The Mann-Kendall trend test confirms the statistically significant long-term trends in most of the 'hotspot' areas identified by geostatistical mapping. The long-term significant trends were in areas with very high proportions of agricultural land, particularly land used for rice production in the Red River and Mekong River deltas. The findings deliver a better understanding of underlying climate processes and impacts across regions of Vietnam and provide a basis to develop effective climate-related policies for agricultural production in response to changing climatic conditions.

Keywords: Climate change, spatio-temporal pattern, geostatistical and statistical methods, agricultural production, Vietnam

JEL codes: C25, Q12, Q54

3.1 Introduction

Climatic conditions are changing across the globe but vary in direction, frequency and intensity by location. The Intergovernmental Panel on Climate Change notes that globally averaged surface temperature shows an increasing linear trend of 0.85 °C between 1880 and 2012 (Stocker et al., 2014). But, changes in average precipitation have not been spatially and temporally uniform, with decreases in mid-latitude areas and increases in other latitudes (IPCC, 2007). It is also very likely that weather and climate extreme events have increased in frequency and intensity on a global and local scale (Caesar et al., 2011; Pingale et al., 2014). Observed changes in the climate system are having major effects on natural systems as well as on human activities.

Vietnam is being affected by climatic variability and change (Thomas et al., 2010b). From the 1970s, the recorded average temperature of the country has increased by 0.26±0.10 °C per decade, twice the rate of global warming for the same period (Nguyen et al., 2013). Also, total annual rainfall is dominated by a negative trend in five out of eight climatic zones of Vietnam (Nguyen et al., 2013). Changes in climate have also intensified the incidence and magnitude of extreme events such as floods, droughts and typhoons. It has been estimated that climatic change may directly affect about 10-12% of Vietnam's population and lead to the loss of approximately 10% of Gross Domestic Product (VNGP, 2011). More importantly, the country's most climate-dependent activity – agricultural production – still dominates Vietnam's economy, accounting for 22% of GDP and 54% of the labour force (GSO, 2014).

The primary goal of this study is to identify empirically evidence of climate change and potential effects of those changes on the agricultural sector of Vietnam, particularly for rice production. The comprehensive approach of combining statistical testing with geostatistical techniques enables climate patterns to be mapped at a very fine resolution to identify changes and trends over years and statistically confirm their significance. Comparing evidence-based observed climate changes with the spatial pattern of agricultural land use across Vietnam will help inform decision-makers and communities on the likely effects of the changing climate.

A better understanding of the pattern of climatic variability and change at various spatial and temporal scales is crucial to supply rigorous evidence-based information to policy-makers at all levels in the decision-making process and to guide the development and implementation of appropriate adaptation responses (Conway et al., 2015; Nam et al., 2016). At the global and regional scales, a substantial number of studies have investigated and documented the changing patterns of climatic variables across space and time (Kundu et al., 2015; Nam et al., 2016; Portmann et al., 2009; Qureshi et al., 2014; Río et al., 2011; Stocker et al., 2014).

Although there have been some empirical analyses on general climatic conditions in Vietnam, there are a limited number of studies investigating the spatial and temporal patterns of climatic change (Caesar et al., 2011; Griffiths et al., 2005; Lau and Yang, 1997; Nguyen et al., 2013; Nguyen et al., 2007). Lau and Yang (1997) reported the climatology and annual variability of the Southeast Asian Monsoon using monthly data, with very general information for Vietnam. Griffiths et al. (2005) used the daily maximum and minimum temperature of the Asia-Pacific region to statistically test the trends of changes across countries. For Vietnam, Griffiths et al. (2005) found a significant increase in minimum temperature and a significant decrease in the variability of minimum temperature. This is a notable attempt to analyse the spatial patterns of temperature in Vietnam; however, since only four weather stations were included in the study, its spatial coverage is limited. Nguyen et al. (2007) standardised the monthly sea-surface temperature in the tropical Pacific and the Indian Oceans and precipitation over the central highlands of Vietnam and found a significant relationship between monthly sea-surface temperature and precipitation patterns for different months of the rainy season. Due to the limitation of available data, the study covered a relatively short period of only 21 years, from 1980 to 2000. Recently, Nguyen et al. (2013) contributed to explaining the changes in climatology across regions of Vietnam. In their procedure, they have used the Mann-Kendall trend test, a practice that was applied in the current study.[8] Based on weather data from 60 gauges, the study found a constant increase over time of average temperature and adverse trends of rainfall variability in different sub-regions. Yet, with its focus on the national and regional level, the study leaves a gap for further analysis using a higher level of resolution such as disaggregated local or weather station-level data. In this study, this gap was addressed by using long-term weather station records of meteorological data for the 40-year period of 1975 to 2014 and a higher density of land-based weather stations across regions of Vietnam.

Recent climatic observations suggest that climate in Vietnam is changing rapidly and there is a growing interest to analyze climatic patterns to establish the nature of adverse impacts of climatic variation on climate-exposed production sectors, such as agriculture. This study adds value to the literature investigating changes in climatic conditions in Vietnam in several ways. By integrating statistical and geostatistical techniques, this study provides new evidence of ongoing climate change, both temporally and spatially, and captures the complex distribution of climatic elements. Using records of monthly precipitation and temperature for 1975 to 2014 at 112 meteorological stations across Vietnam, climate data and its spatio-temporal variations and trends were first updated and visually represented by applying geostatistical techniques to generate surface maps of precipitation and temperature patterns in the areas of interest. Then, climate anomalies were extracted from the long-term average of climate, which is defined as a baseline of 30-year averages (1975-2004) of climatological variables. Finally, the output of this step provides a visual representation of the spatial distribution, and also the evolution of climatic variables in recent years compared to climate 'normals'.

As the mapping approach could only supply a 'snapshot' of climate patterns at a given point in time, another question is whether the observed patterns or trends are significant over

[8] The Mann-Kendall trend test is a non-parametric test used to statistically detect a long-term trend in a series of values. Further discussion of this method is provided in the following sections.

time. To address this issue, the Mann-Kendall trend test was applied, carefully controlling for the non-homogeneity problem which may cause biased estimates for the observed meteorological time series (Buishand, 1982; De Paola and Giugni, 2013; Jaiswal et al., 2015; Meshram et al., 2016; Nam et al., 2016; Viola et al., 2014). The non-parametric test confirms the presence of long-run negative or positive trends, which may be observed through mapping, in the homogenous climatic variables.

The study is structured as follows. Section 3.2 provides an overview of the study area, data and workflow used in this study. Section 3.3 specifies the research methods applied, and empirical findings are discussed in Section 3.4. Section 3.5 draws some concluding remarks.

3.2 Study area, data and workflow

3.2.1 Study area

Located in the tropical zone of the Northern Hemisphere, Vietnam is characterised with a tropical monsoon climate influenced by the Southeast Asian Monsoon circulation (Nguyen et al., 2013; UNEP, 2009). As Vietnam extends across 15 degrees of latitude from 8.30 degrees north to 23.22 degrees north, the country's climatology varies significantly between North, Central and South. Thus, the country is characterised by seven climate zones: Northwest (B-I), Northeast (B-II), Northern Delta (B-III), North Central Coast (B-IV), South Central Coast (N-I), Central Highlands (N-II) and Southern Delta (N-III) (Figure 3.1). The Vietnamese territory covers a mainland of about 332,000 square kilometres and a large area of water. The complexity of topography is shown in the digital elevation model in Figure 3.2. Vietnam's geographical features together with the complex topography make the spatial distribution of climate patterns even more diverse. More specifically, precipitation in Vietnam has large variations across time and space (Nguyen et al., 2013). Also, temperature has been rising at an increasing rate in many regions over the recent period (UNEP, 2009).

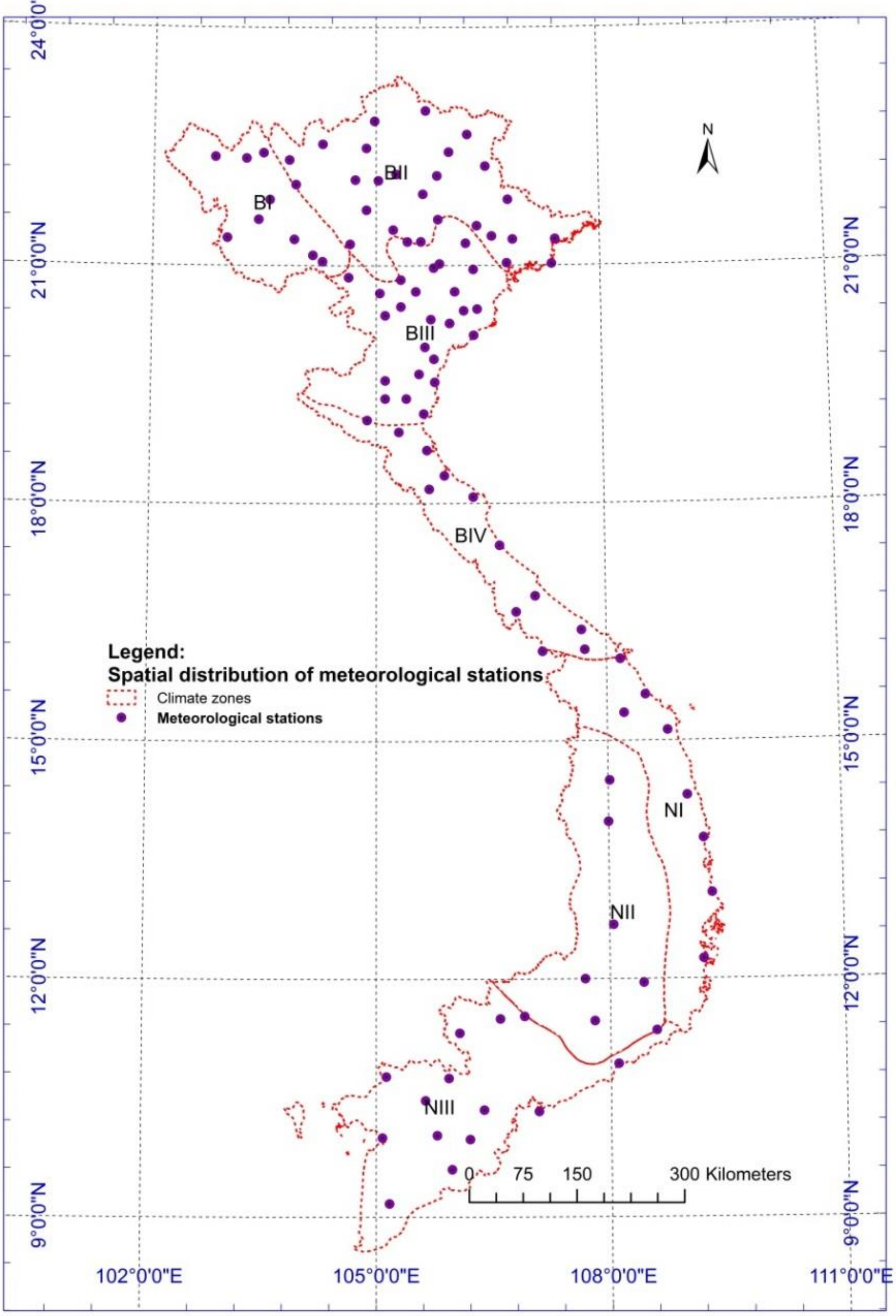


Figure 3.1 Spatial distribution of 112 meteorological stations and climate zones in Vietnam

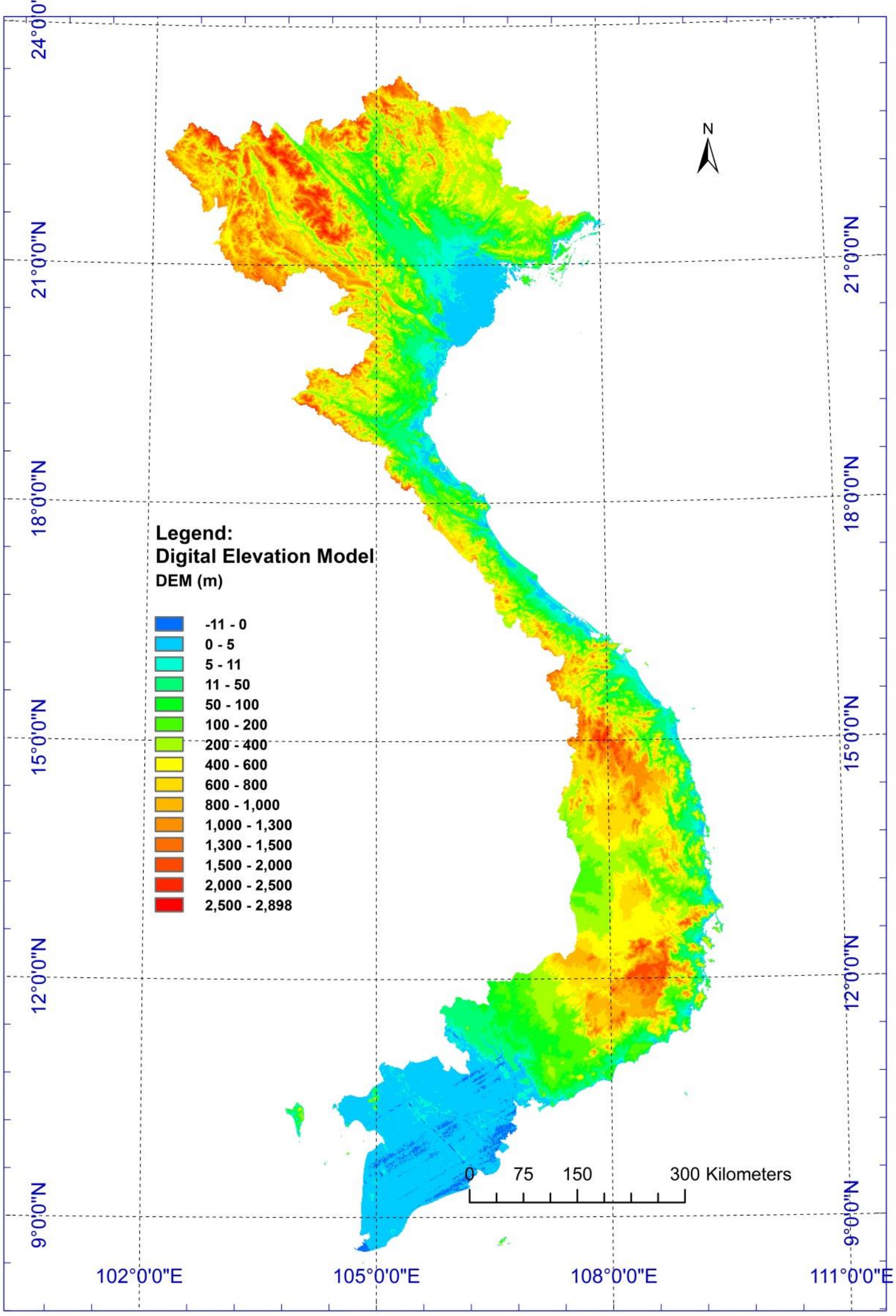


Figure 3.2 Digital elevation model (DEM) of Vietnam

Note: The digital elevation model of Vietnam was extracted from the United States Geological Survey digital elevation model raster database.

3.2.2 Data

A dataset of average monthly temperature and precipitation at 112 meteorological stations across Vietnam for the 40 years from 1975 to 2014 was obtained from the Vietnam National Centre for Hydro-meteorological Forecasting. As rainfall and temperature are the most important elements of climate, we focus on these two variables in this analysis. The 112 land-based weather stations in the study were selected from a total of 250 weather stations nationwide by taking into account data availability, timeframe consistency and the spatial distribution of these stations in order to best represent climatic patterns and to minimise the impacts of missing data.

The availability of observed meteorological data varies significantly across regions, especially for some areas in the North and the South where records were discontinuous due to the war in the 1970's. In addition, record length is not uniform across stations with differences in the beginning and end date of records. The most common timeframe, 1975 to 2014, was chosen for further investigation. Stations where missing values exceeded 5% of total observations were excluded from the analysis (Río et al., 2011). As a result, 112 weather stations widely distributed across different climatic regions of Vietnam were used in the analysis. The locational co-ordinates of the weather stations in the study are shown in Table 3.1, generally presented in an order from north to south.

Our dataset, based on 112 weather stations across various regions has an advantage over many previous studies (such as Nguyen et al. 2007; Nguyen et al. 2013; Thomas et al. 2010) due to its higher station network density. Using a denser network of observations is expected to deliver better spatial coverage and substantially improve accuracy, particularly for interpolation techniques for climatic variables (Jones et al., 2009; Sayemuzzaman, 2014).

Table 3.1 List of 112 climate stations in the study

No.	Station name	Longitude	Latitude	No.	Station name	Longitude	Latitude
1	Muong Te	102.5	22.22	**29**	Chiem Hoa	105.16	22.09
2	Sin Ho	103.14	22.22	**30**	Ham Yen	105.02	22.04
3	Tam Duong	103.29	22.25	**31**	Tuyen Quang	105.13	21.49
4	Than Uyen	103.53	21.57	**32**	Bac Can	105.5	22.09
5	Dien Bien	103	21.22	**33**	Ngan Son	105.59	22.26
6	Lai Chau	103.09	22.04	**34**	Dinh Hoa	105.38	21.55
7	Tuan Giao	103.25	21.35	**35**	Thai Nguyen	105.5	21.36
8	Bac Yen	104.25	21.15	**36**	Phu Ho	105.14	21.27
9	Co Noi	104.09	21.08	**37**	Viet Tri	105.25	21.18
10	Moc Chau	104.41	20.5	**38**	Vinh Yen	105.36	21.19
11	Phu Yen	104.38	21.16	**39**	Bao Lac	105.4	22.57
12	Quynh Nhai	103.34	21.51	**40**	Cao Bang	106.15	11.4
13	Son La	103.54	21.2	**41**	Trung Khanh	106.31	22.5
14	Song Ma	103.44	21.04	**42**	Huu Lung	106.21	21.3
15	Yen Chau	104.18	21.03	**43**	Lang Son	106.46	21.5
16	Chi Ne	105.47	20.29	**44**	That Khe	106.28	22.15
17	Hoa Binh	105.2	20.49	**45**	Bac Giang	106.13	22.18
18	Kim Boi	105.32	20.4	**46**	Luc Ngan	106.33	21.23
19	Lac Son	105.27	20.27	**47**	Son Dong	106.51	21.2
20	Mai Chau	105.03	20.39	**48**	Cua Ong	107.21	21.01
21	Bac Quang	104.52	22.3	**49**	Tien Yen	107.24	21.2
22	Ha Giang	104.58	22.49	**50**	Uong Bi	106.45	21.02
23	Bac Ha	104.17	22.32	**51**	Phu Lien	106.38	20.48
24	Lao Cai	103.58	22.3	**52**	Ha Dong	105.45	20.58
25	Sa Pa	103.49	22.21	**53**	Lang	105.51	21.02
26	Luc Yen	104.43	22.06	**54**	Hai Duong	106.18	20.56
27	MuCangCha	104.03	21.52	**55**	Hung Yen	106.03	20.39
28	Yen Bai	104.52	21.42	**56**	Nam Dinh	106.09	20.24

No.	Station name	Longitude	Latitude	No.	Station name	Longitude	Latitude
57	Van Ly	106.18	20.07	**85**	Quang Nam	108.15	15.20
58	Thai Binh	106.21	20.27	**86**	Quang Ngai	108.48	15.07
59	Nho Quan	105.44	20.20	**87**	Binh Dinh	109.02	14.31
60	Ninh Binh	105.58	20.14	**88**	Binh Dinh	109.13	13.46
61	Hoi Xuan	105.07	20.22	**89**	Phu Yen	109.17	13.05
62	Nhu Xuan	105.34	19.38	**90**	Khanh Hoa	109.12	12.13
63	Thanh Hoa	105.47	19.45	**91**	Ninh Thuan	108.59	11.35
64	Tinh Gia	105.47	19.27	**92**	Binh Thuan	108.06	10.56
65	Yen Dinh	105.40	19.59	**93**	Kon Tum	108.00	14.3
66	Con Cuong	104.53	19.03	**94**	Gia Lai	108.01	13.58
67	Do Luong	105.18	18.54	**95**	Dak Lak	108.03	12.40
68	Quy Chau	105.07	19.34	**96**	Dak Nong	107.41	12.00
69	Quy Hop	105.09	19.19	**97**	Lam Dong	107.49	11.32
70	Quynh Luu	105.38	19.10	**98**	Lam Dong	108.27	11.57
71	Tay Hieu	105.24	19.19	**99**	Binh Phuoc	106.54	11.32
72	Vinh	105.40	18.40	**100**	Binh Phuoc	106.59	11.5
73	Ha Tinh	105.54	18.21	**101**	Tay Ninh	106.07	11.2
74	Huong Khe	105.43	18.11	**102**	Ba Ria-V.Tau	107.05	10.22
75	Ky Anh	106.17	18.05	**103**	Long An	105.56	10.47
76	Ba Don	106.25	17.45	**104**	Tien Giang	106.24	10.21
77	Dong Hoi	106.37	17.29	**105**	Dong Thap	105.38	10.28
78	Dong Ha	107.05	16.51	**106**	Tra Vinh	106.12	9.59
79	Khe Sanh	106.44	16.38	**107**	An Giang	105.08	10.42
80	A Luoi	107.17	16.13	**108**	Can Tho	105.46	10.02
81	Hue	107.35	16.26	**109**	Soc Trang	105.58	9.36
82	Nam Dong	107.43	16.10	**110**	Kien Giang	105.04	10.00
83	Da Nang	108.12	16.02	**111**	Bac Lieu	105.43	9.17
84	Tam Ky	108.28	15.34	**112**	Ca Mau	105.09	9.11

Maps of agricultural land use and cultivated area of rice obtained from the Vietnam General Statistics Office are used to determine the likely effects of climate change on agricultural production in the study area (Figures 3.3 and 3.4). Based on data collected from the 2001 Rural, Agriculture and Fisheries Census, this map shows the spatial distribution of agricultural land at the commune level across the country. Agricultural land is defined as the land area that is used for annual crops (e.g. rice and maize), perennial crops (e.g. rubber and coffee), and pasture grassland.

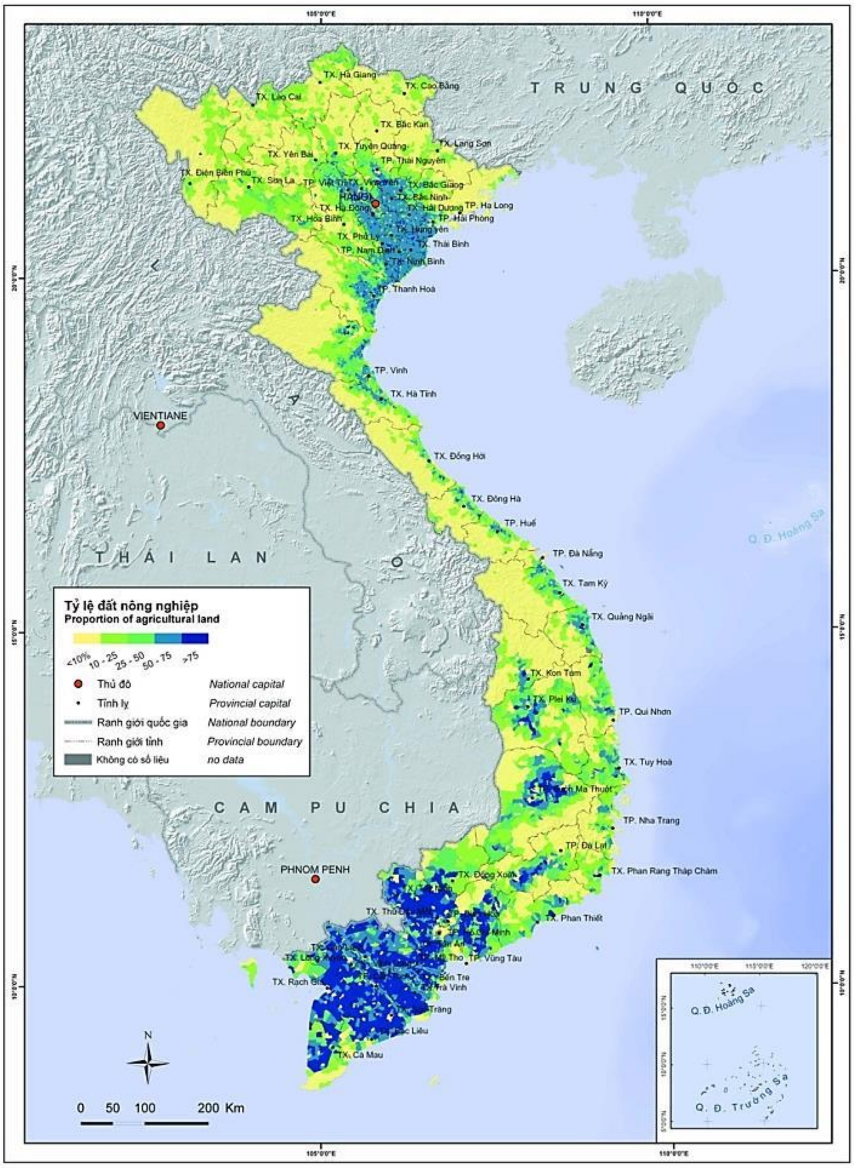


Figure 3.3 Proportion of agricultural land in Vietnam

Source: Vietnam Statistics Office, GSO

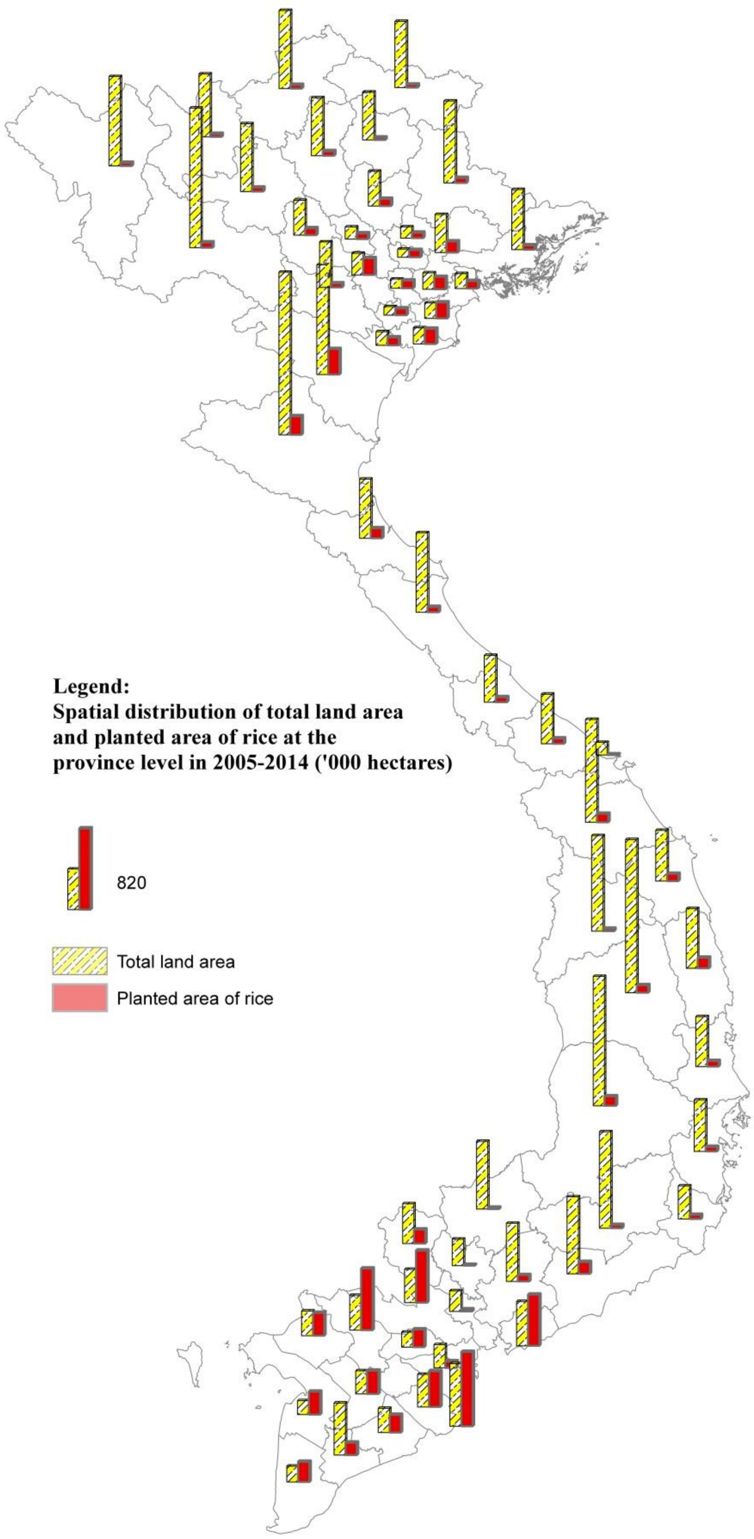


Figure 3.4 The spatial distribution of total land area and planted area of rice over ten years (2005-2014) at the province-level

Source: Author's calculation based on data from General Statistics Office 2014

Figure 3.3 shows that the Red River Delta in the North and the Mekong River Delta in the South have the highest proportion of land used for agricultural production. A relatively high percentage of agricultural land is also identified in many communes along the coast whereas the mountainous areas of the Northwest and Northeast and in the Central Highlands have the lowest percentages of land used for agriculture (Figure 3.3). Figure 3.4 shows the distribution of the cultivated area of rice in Vietnam over the last ten years (2005-2014). In the agricultural sector, crop production is dominated by rice as a major annual crop with an average total planted area of 7.8 million hectares per year over that period (GSO, 2014). It is clear that the Red River Delta in the North and the Mekong River Delta in the South have the largest planted area of rice, accounting for 15.2% and 52.8% of total planted area of rice for the whole country, respectively (Figure 3.4). Some provinces such as Kien Giang, An Giang and Dong Thap in the South and Thanh Hoa, Nghe An and Thai Binh in the North have been identified as the major rice production areas of Vietnam. However, agricultural production, especially rice cultivation, is inherently vulnerable to climate change due to very large acreage under rice with direct exposure to climatic conditions across all regions in Vietnam. Consequently, climatic variability and change are likely to be especially challenging for rice production in Vietnam. Therefore, the effects of climate change on agricultural production were considered with a special focus on rice cultivation. By comparing the spatial distribution of land use and climate patterns, it is possible to identify potential effects of changing climatic conditions on the agricultural sector in Vietnam.

3.2.3 Workflow

Figure 3.5 illustrates the three-stage workflow procedure: data collection, data homogenisation and data analysis. For data collection in Step 1, the dataset was separated into two different periods: 1975-2004 for 30-year averages representing climate normals, and 2005-2014 to indicate current climate. According to the World Meteorological Organization, climate normals are typically defined as the three-decade averages of meteorological parameters including temperature and precipitation (Arguez and Vose, 2011). Since those measurement values of climate normals reflect the long-term meteorological conditions or climatology, they are used to compare a value of a meteorological variable (e.g. temperature or precipitation) to their corresponding reference value (i.e. climate normal value). Those comparisons allow identification of changes in the climatic conditions, long-term trends over years, and shifts in spatial patterns of the climatic variable of interest. In this study, by separating the climate data series into two different periods, climate normals and current climate, it is possible to examine the pattern changes of climate-related variables in the current period compared to its relatively long-term average.

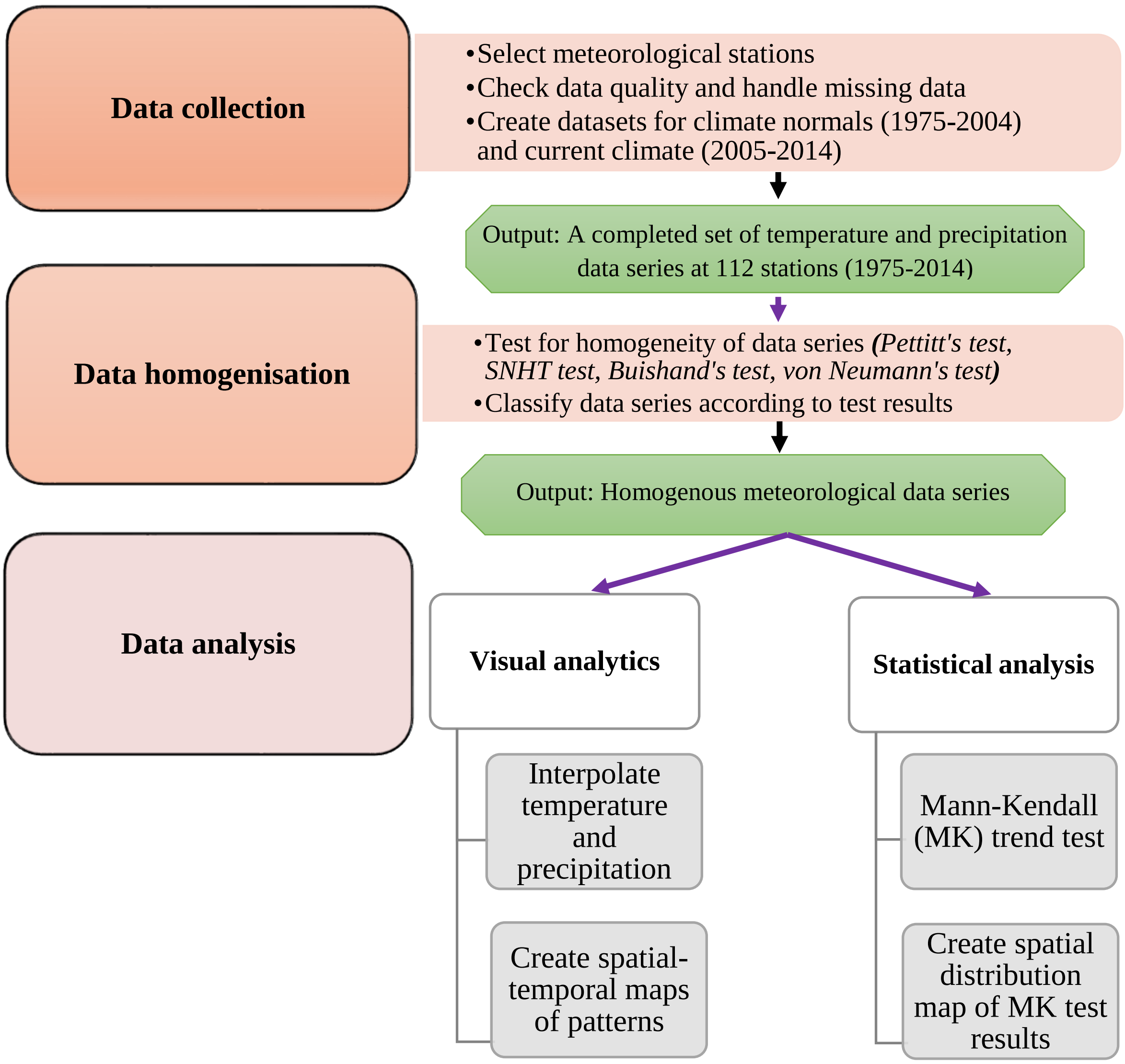


Figure 3.5 Three-stage workflow in data collection, homogenisation and analysis

The process of collecting climatic data at station-level has several constraints such as relocation of the stations and changes in observing practices that may result in discontinuous and unreliable data. Consequently, records of climate-related variables from that process, which are lack accuracy and continuity, may not be able to represent the uniform climatic conditions in the long-term period (Guttman, 1998). Thus, there is a need to assess the homogeneity or uniformity of climate data with respect to non-climatic factors before any analysis. Testing for homogeneity of meteorological time series is a fundamental prerequisite for climate change studies in order to distinguish data series that are affected by non-climate factors such as changes in observation practices, changes in instrumentation and station relocation (Alexandersson and Moberg, 1997; Longobardi and Villani, 2010). Non-homogenous data series implies that climate-related variables may not be representative of temporal climate variability and change. Since homogenous data is a prerequisite for the Mann-Kendall trend test, therefore different homogeneity tests based on long records of precipitation and temperature were applied, including Pettitt's test, standard normal homogeneity test, Buishand's test and Von Neumann's test in Step 2 (Buishand, 1982; Jaiswal et al., 2015; Pettitt, 1979; Wijngaard et al., 2003). These tests were performed in R statistical software using the 'climtrend' package (Sinharay, 2016).

In Step 3, a comprehensive approach integrating statistical testing with geostatistical techniques to examine the changes in temperature and precipitation patterns, identify any possible trends over time, and statistically test the significance of these trends was used. The co-kriging interpolation technique in ArcGIS was used to produce smoothed surface maps of precipitation and temperature patterns and displays variations across space and time.[9] Then, the Mann-Kendall trend test was applied using the R package 'trend' to statistically confirm the presence of long-run negative or positive trends, which might be observed through mapping, in these climatic variables of interest (Pohlert et al., 2016).

[9] Co-kriging is an interpolation technique that uses information on several variables to produce better interpolation maps. This method is discussed in detail in the next section.

3.3 Methodology

To look for evidence of climate change across regions of Vietnam, several geophysical data visualisation and statistical methods were used. Precipitation and temperature series were first tested for homogeneity using a range of statistical tests. After these series were confirmed homogenous, the geostatistical techniques in ArcGIS software in conjunction with a statistical trend test using R software wee used to further explore any change in the patterns of observed climatic variables across space and time.

3.3.1 Data homogenisation

Homogenous data series of climatic variables are required in climate-related studies (Buishand, 1982). Numerous methods for testing for homogeneity have been introduced in the literature (such as Pettitt's test, standard normal homogeneity test, Buishand's test and Von Neumann's test), but combining several methods has proved to be more efficient because each test has its own advantage in detecting any possible break or change point within the data series (Wijngaard et al., 2003). For instance, Pettitt's test and Buishand's test are more capable of detecting break points in the middle of the data series, while the standard normal homogeneity test is more sensitive to any change point at the beginning or end of that series (Hawkins, 1977; Wijngaard et al., 2003). Therefore, four tests were applied to better identify non-homogeneities with the null hypothesis of no break or change point in the data series. Calculation formulas for these tests are in Appendix 3A.

These four tests for homogeneity could lead to different conclusions for an individual data series due to their differences in the power of detecting break points. It is therefore necessary to generalise those conclusions to determine whether or not that data series is homogenous. Following Wijngaard et al. (2003), data series were classified into different classes according to their test results for the null hypothesis of no break or shift within that series. the outcomes of the four tests were grouped into three categories:

Class A: ‘useful’ series if only one or none of the four tests rejects the null hypothesis at 1% significance level.

Class B: ‘doubtful’ series if two tests reject the null hypothesis at 1% significance level.

Class C: ‘suspect’ series if three or four tests reject the null hypothesis at 1% significance level.

Series classified in *Class C* were deemed non-homogenous time series and were not included in the next step due to the high probability of detecting a change point within these series. Thus, Class A and Class B were used in the next step for trend detection. The homogeneity tests and the classification of series are applied separately for temperature and precipitation data series and the results are reported in the following section.

3.3.2 Visual analytics using geostatistical approach

Geostatistical techniques have benefitted enormously from the development of Geographical Information Systems (GIS). In graphical representations of climate data, more user-friendly applications have been used widely by practitioners to accurately and efficiently model spatio-temporal patterns of climatic variables of interest (Johnston et al., 2001; Moral, 2010). As climate data is only observed at certain places, there is a need to predict this information for other locations. Consequently, there is an increasing demand for interpolated surfaces of climate variables using weather station-level data with a wide range of geostatistical methods applied such as inverse distance weighting, kriging or co-kriging and kernel smoothing. Among those, co-kriging shows some advantages while cross-correlations between covariates (such as temperature and elevation) are taken into account to make better interpolation predictions (Cressie, 2015; Moral, 2010; Ninyerola et al., 2000; Pardo-Igúzquiza, 1998; Prudhomme and Reed, 1999).

In this study, temperature and precipitation were selected as the two main elements of climatology for the geostatistical analysis. These variables are examined at annual and monthly scales. For example, average total annual precipitation is calculated by adding the total precipitation over a specified period (such as 1975-2004 for a standard 30-year climatology and 2005-2014 for current climate) and dividing by the total number of years for that corresponding period. Similarly, average monthly precipitation is equal to the sum of monthly rainfall totals divided by the total number of years for the period under study. For temperature, average annual mean temperature is calculated by adding annual temperature for a specified period and dividing by the number of years in that period (30 years for climatology and 10 years for current climate). Average monthly temperature is calculated by summing monthly values and dividing by the total number of years in the specified period. Climate anomaly is defined by the deviation of current climate from the 30-year climatology.

In climate mapping, there is often a strong relationship between elevation and climatic variables such as temperature and precipitation: precipitation generally increases with elevation whereas temperature often decreases as elevation increases (Daly et al., 2008). In our study areas, due to the complexity of topography across weather stations, there may be correlations between meteorological variables and elevation at the same location. The co-kriging interpolation technique is used to map the spatial distribution of rainfall and temperature in connection with topographical features extracted from the digital elevation model.

The theoretical basis and mathematical formulas of co-kriging have been discussed by Cressie (2015), Moral (2010) and Pardo-Igúzquiza (1998). This method predicts the unknown value of a primary variable of interest at a location using information on the measured values of that variable and on an auxiliary variable. The auxiliary variable such as elevation is expected to have some correlation with the primary variable, so it can provide additional information for a better estimation value. The co-kriging technique takes into account the correlation between the primary and auxiliary variables and also the spatial correlation across observed values at various locations.

The Geostatistical Analyst extension of the ArcGIS 10.4 software was applied to produce interpolated surfaces using the ordinary co-kriging method for the variables of interest. Then a set of interpolated map layers of rainfall and temperature for two periods (climate normals for 1975-2004 and current climate for 2005-2014) is generated for further analysis.

Two variables were considered in this case: Z_1 as a primary climatic variable and Z_2 which is derived from the digital elevation model as an auxiliary covariate of elevation at location (s). The ordinary co-kriging assumes the following models (Johnston et al., 2001; Journel and Huijbregts, 1978):[10]

$$Z_{1(s)} = \mu_1 + \varepsilon_{1(s)}$$

$$Z_{2(s)} = \mu_2 + \varepsilon_{2(s)}, \qquad (3.1)$$

where μ_1 and μ_2 are unknown constants; $\varepsilon_{1(s)}$ and $\varepsilon_{2(s)}$ are error terms with possible cross-correlation and autocorrelation.

Our goal is to predict the unknown value Z_1 at location s_0, $Z_{1(s0)}$, based not only on Z_1, but also on the information in the covariate Z_2 because there are often strong correlations between elevation Z_2 and climatic variables Z_1 such as temperature and precipitation. Thus, the primary variable Z_1, autocorrelation for each variable, and cross-correlation between variables are used to yield more robust predictions of $Z_{1(s0)}$. The co-kriging predicted value $\hat{Z}_{1(s0)}$ is a linear combination of all available data points of the two variables of interest (primary and auxiliary):

[10] Additional explanations of the co-kriging technique are in Cressie (2015), Johnston et al. (2001) and Journel and Huijbregts (1978).

$$\hat{Z}_{1(s0)} = \sum_{i=1}^{n} \lambda_{1i} Z_{1i} + \sum_{i=1}^{n} \delta_{2i} Z_{2i}, \qquad (3.2)$$

where λ and δ are the spatial weights across data points in the sample Z_1 and Z_2.

To obtain an unbiased predictor, the deviations between the predicted values and the observed points were minimised:

$$E\left[Z_{1(s0)} - \hat{Z}_{1(s0)}\right]^2 \qquad (3.3)$$

After interpolating, a set of smoothed surface maps of each climatic variable for climate normals and current climate are exported. Unfortunately, the range of predicted values in each interpolated map of precipitation or temperature may vary significantly in different months and periods. For instance, the lowest and highest predicted values of temperature in December during winter are often significantly lower than those in July during summer. That makes the visual comparisons between those months using the maps of output rasters unreasonable due to the difference in the colour ramps automatically applied to each range of predicted values by ArcMap. Thus, there is a need for a standardising process that is able to capture and display all possible predicted values in the interpolated maps. This helps better visualise the interpolation outcomes and makes these graphics visually comparable across space and time.

To address this, certain common criteria was set up for the output rasters, for example, projected coordinate systems (WGS_1984_UTM_Zone_48N), cell size (0.008333 x 0.008333 ~ 1km^2), pixel type (signed 16 bit), and colour ramps.[11] More specifically, to create a colour ramp, a unique colour was manually assigned for an individual group of predicted values, so that the ramp can cover all possible ranges of values of rainfall or temperature in different months or periods. The final interpolated maps are produced using a mosaic dataset technique

[11] Before creating an output for a raster dataset, the pixel type specifies the bit depth of that output. Here, the bit depth of signed 16 bit can contain a range of values around -32768 to 32767 in each pixel. A colour ramp provides a means to apply a range of specified colours to the corresponding range of values from the interpolated surface.

which contains our specified function chains to efficiently display the interpolated surface in connection with the site-specific topographical features.[12]

In geoprocessing raw data for co-kriging and publishing outputs, our workflow contains a number of repeated steps applied to each month or a length of time of meteorological variables. Model Builder tool within ArcGIS provides the interactive means to accurately and efficiently reproduce these geoprocessing procedures. a base model was first constructed using Model Builder tool that was applied to one specific task, such as interpolating annual mean temperature. Then, all necessary modifications were made for the model (such as input and output sources and function parameters) to re-apply that process to another variable, as shown in Appendix 3B. This automating workflow allowed us to avoid mistakes that are likely to be associated with any error-prone geoprocessing procedure.

3.3.3 Statistical analysis

To integrate statistical and GIS techniques, a statistical trend test was applied on climatological variables to confirm the significance of the pattern changes observed through mapping. Long-term upward or downward trends in observed climatic variables were assessed using the non-parametric Mann-Kendall trend test (Kendall, 1962; Mann, 1945). The test is widely applied in the literature to statistically detect a long-term trend in meteorological time series (Viola et al., 2014; Zarenistanak et al., 2014). It is a non-parametric and rank-based test, so no assumptions are required for the underlying distributional properties (Kendall, 1962; Mann, 1945; Meshram et al., 2016). The test is based on a calculation of the Kendall's Tau S statistic value under the null hypothesis of no trend existing in the series of records. Suppose that it exists a pair of observed values x_i, x_j $(i>j)$ series of the meteorological variable of a

[12] A mosaic dataset can be used to combine multiple individual rasters and then display them in an exported map at once.

sequence x_1, x_2... x_n with n observations. An S statistic value is calculated based on pairwise comparisons of each observed value j with all preceding observed data points i as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(x_j - x_i), \qquad (3.4)$$

where
$$sign(x_j - x_i) = \begin{cases} 1, \ if \ (x_j - x_i) > 0 \\ 0, \ if \ (x_j - x_i) = 0 \\ -1, \ if \ (x_j - x_i) < 0 \end{cases} \qquad (3.5)$$

Kendall (1962) assumes that S is approximately normally distributed with expected value $E(S)=0$ and variance $Var(S)$:

$$Var(S) = \frac{1}{n}\left[n(n-1)(2n+5) - \sum_t t(t-1)(2t+5) \right], \qquad (3.6)$$

where t is the extent of any given period. Thus, the standardised Z value could be calculated as follows:

$$Z = \begin{bmatrix} -1, \ if \ S < 0 \\ \dfrac{S+1}{\sqrt{Var(S)}}, \ if \ S > 0 \\ 0, \ if \ S = 0 \end{bmatrix} \qquad (3.7)$$

The test is performed by comparing the absolute value of Z to the critical value of a standard normal distribution to identify the significance level of the trend.

3.4 Results and discussion

3.4.1 Homogeneity tests

The results of homogeneity analysis for meteorological data series are presented in Table 3.2 based on the outcomes of Pettitt's test, standard normal homogeneity test, Buishand's test and Von Neumann's test. These tests determine whether or not the observed time series at each station is homogenous at the 1% significance level. Ignoring the homogeneity property of these series could lead to biased results in data analysis (Vezzoli et al., 2012).

As discussed in Section 3.3, data series were classified into three different classes based on the results of the four homogeneity tests. For precipitation, the majority of data series are *Class A* and *Class B*, i.e. homogenous, whereas *Class C* with 11.6% of the 112 stations is confirmed to be non-homogenous. In contrast, the series of temperature show a relatively large number of stations (33% of the 112 stations) characterised by non-homogeneity. Non-homogenous data series of both precipitation and temperature (*Class C*) that make these variables unrepresentative of temporal climate variability and change are excluded from the procedure of geophysical data visualisation and statistical trend tests in the next step.

Table 3.2 Results of homogeneity tests for meteorological data series

Precipitation series				Temperature series			
Classes	Homogeneity	Number of stations	%	Classes	Homogeneity	Number of stations	%
A	Yes	78	69.6	A	Yes	43	38.5
B	Doubtful	21	18.8	B	Doubtful	32	28.5
C	No	13	11.6	C	No	37	33.0
Total		112	100%	Total		112	100%

3.4.2 Geostatistical analysis

In visual analytics, the procedure as discussed in Section 3.2 was applied using the Geostatistical Analyst extension in ArcGIS combined with a mosaic dataset technique to produce and export the smoothed interpolated surfaces of rainfall and temperature. The outcomes are displayed as three consecutive digital maps of climate normals, current climate, and climate anomalies which is defined as the deviation of current climate from the normal climate.

3.4.2.1 Observed precipitation patterns

Analysis of mean annual precipitation changes

The spatial distribution of average annual rainfall in both current and baseline periods varies considerably across regions (Figure 3.6). Some areas have seen an increase in precipitation while others have experienced a decrease. Generally, locations with high elevation such as the mountainous areas in the Northwest and Central Highlands receive higher rainfall. For climate normals, the highest rainfall is in the Northwest (B-I), North Central Coast (B-IV), Central Highlands (N-II) and the southernmost area of the Southern Delta (N-III). However, recent climatic conditions (2005-2014) have been changing remarkably with a growing drying pattern of precipitation observed in many regions such as the Northern Delta (B-III) and the South Central Coast (N-I) (Figure 3.6-b).

The last map in Figure 3.6 representing rainfall anomalies demonstrates a dramatic heterogeneity in the distribution of precipitation change across regions. Rainfall deficit is likely to spread throughout the country with a number of ‘hotspots’ like the westernmost provinces in the Northwest (B-I), the Red River Delta (B-III), the North Central Coast (B-IV), the northernmost of the Central Highlands (N-II), part of the Mekong River Delta, and some regions in the coastal regions of the southern areas. In contrast, the north-western area of the country shows a significant rainfall surplus with precipitation anomalies as high as 1100 mm. Furthermore, compared to long-term average, annual rainfall during recent years is also increasing considerably in Thua Thien Hue and Quang Nam provinces in the middle of the Central Coast (Figure 3.6-c).

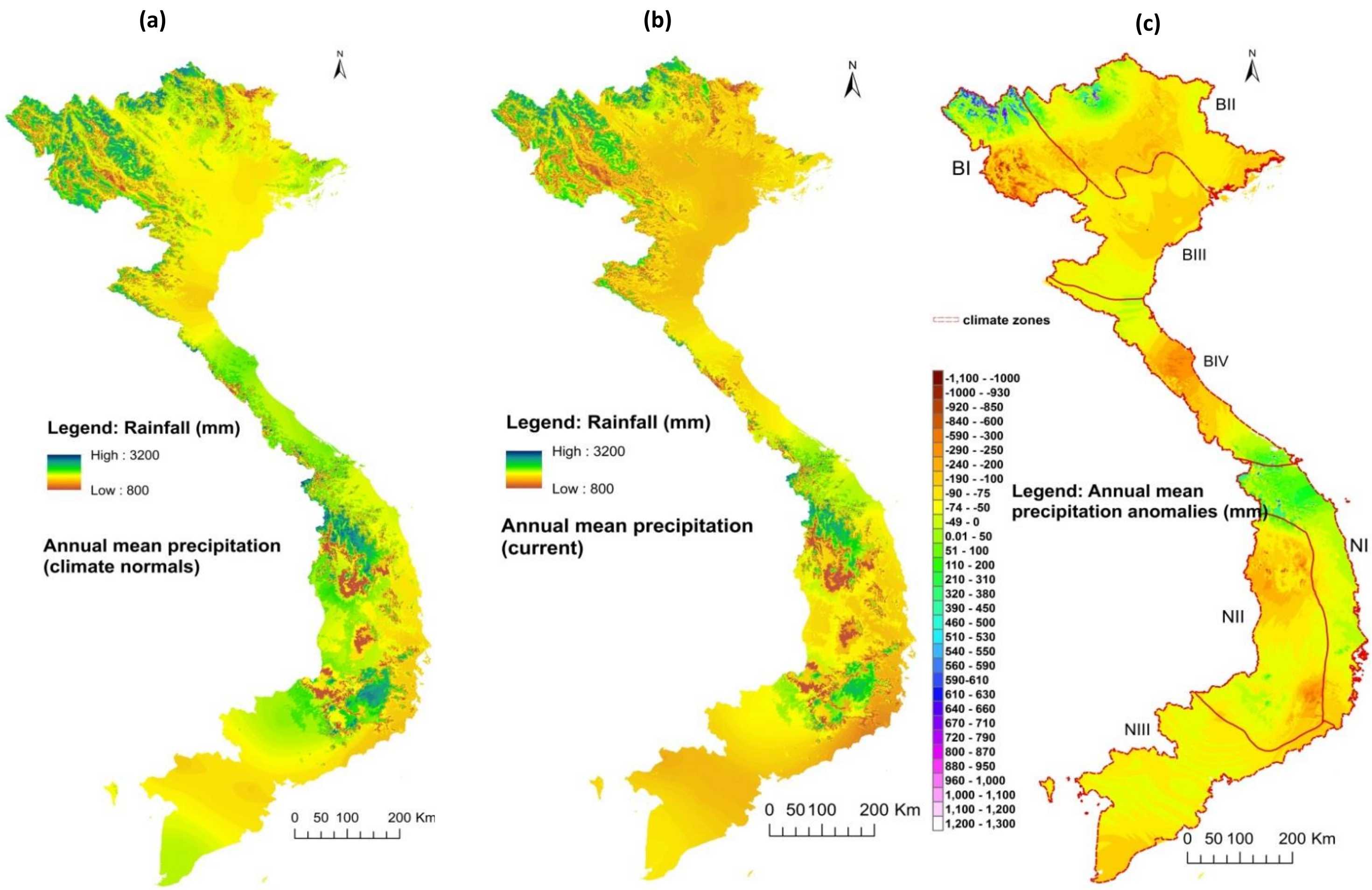


Figure 3.6 Spatial distribution of mean annual precipitation for climate normals *(a)*, current climate *(b)*, and climate anomalies *(c)*

In these ‘hotspot’ areas, very high proportion of land is used for agricultural production, particularly for rice. In the two largest deltas of the Red River and the Mekong River, rice accounts for 68.7% of the total 7.8 million hectares of the rice cultivated in Vietnam (Figures 3.3 and 3.4). More importantly, significant changes in the pattern of rainfall are observed in some provinces with substantial areas of rice (Figure 3.4): Kien Giang (753,600 hectares), An Giang (625,800 hectares) and Ca Mau (127,400 hectares) in the Mekong area, Thanh Hoa (258,600 hectares) and Thai Binh (161,800 hectares) in the lowland areas of the North. Consequently, rainfall pattern changes in those provinces with large rice cultivation areas may affect agriculture activities including rice production. More specifically, there is a strong evidence of the influence of changes in rainfall patterns on crop yields, particularly yield reductions due to water scarcity in irrigated crops like rice (Nelson et al., 2009). Also, altered rainfall patterns are likely to be associated with the increasing intensity of extreme weather events, and pests and plant diseases in rice-growing areas (Rosenzweig et al., 2001).

Overall, visualising the spatio-temporal distribution of precipitation delivers better results in displaying and highlighting the rainfall pattern changes and then identifying their potential impacts on agricultural production. However, since climate-related variables are associated with seasonality, these variables were further explored at monthly intervals to gain greater insight into the underlying distributions of climate processes.

Analysis of total monthly precipitation changes

The changes in the monthly precipitation patterns from region to region and over time are shown in Figure 3.7. The maps show the monthly variations of rainfall in Vietnam are extremely pronounced. For the first four months from January to April (Figure 3.7.1), the rainfall is relatively low and unevenly distributed all over the country. Slightly more rain has been recorded recently in March and April compared to the baseline of the 30-year average from 1975 to 2004.

However, in the four months of the summer season there was a remarkable change in precipitation amount and its pattern (Figure 3.7.2). Rainfall from May to August shows very high rain totals in the Northwest (B-I), the Central Highlands (N-II), and the southernmost regions of the Southern Delta (N-III). Compared to climate normals, current climatic conditions during May to August clearly demonstrate different trends, including a substantial increase in total rainfall in the north-west of the country versus a significant decrease in total rainfall in the Central Highlands (N-II) and also in the rest of the north-western area.

From September to December (Figure 3.7.3), the rainfall patterns move southward with higher precipitation observed in the Central Coast (B-IV and N-I), the Central Highlands (N-II) and the Southern Delta (N-III), while the northern regions of the country are dominated by drier conditions. In particular, the current climate of the Central Coast (B-IV and N-I) and southern areas shows a significant increase in the amount of rain in November and December. Considering climate anomalies from September onwards, there is now very strong evidence of rainfall variability and change from region to region. In Figure 3.7.3, that evidence can be clearly observed and is even more pronounced compared to previous periods by the noticeable rainfall deficit in the northern Central Coast (B-IV and N-I) and, simultaneously, a strongly increasing precipitation in the centre of Vietnam.

Overall, there are remarkably sharp contrasts in the monthly distribution patterns of rainfall variability and change across regions of Vietnam. Clearly, more rainfall has been recorded in the northernmost areas in the first few months of the year and that phenomenon tends to move gradually to the South until the end of the year. At the same time, there is a significant decrease in precipitation in the Northwest (B-I) which also moves along the coast towards the southern areas of the country. These prominent patterns indicate that the complexity in spatio-temporal distribution of those changes has been well-captured using our visual analytics approach. The implication is that Vietnam is likely to face more variations in climatic conditions.

In Vietnam, the growing season for rice varies across regions and can extend from 1 February to 30 December (VAAS, 2010). In the North, the winter-spring rice season starts from early February and continues to the middle of June. Considering rainfall anomalies during this period, more precipitation has been observed in the Northwest (B-I) whereas other areas exhibit notably less precipitation, especially in the month of June. This rainfall pattern change is very likely to have adverse impacts on rice cultivation in this season. For the spring-autumn season (June-November), a similar trend is observed in the early season but not for the last few months of the year of September, October and November.

In contrast, in the Central Coast, it is hard to notice any significant climatic change during the winter-spring season for rice (February-May). However, in the spring-autumn season (June-October/December), the rainfall pattern changes dramatically combining both a decrease in the northern areas and a significant increase in many southernmost areas of the Central Coast. Those notable rainfall anomalies could have large detrimental effects on rice production in those regions. Similarly in the South, both increases and decreases in rainfall are observed across locations, with a very high rainfall deficit in the northernmost area of this region.

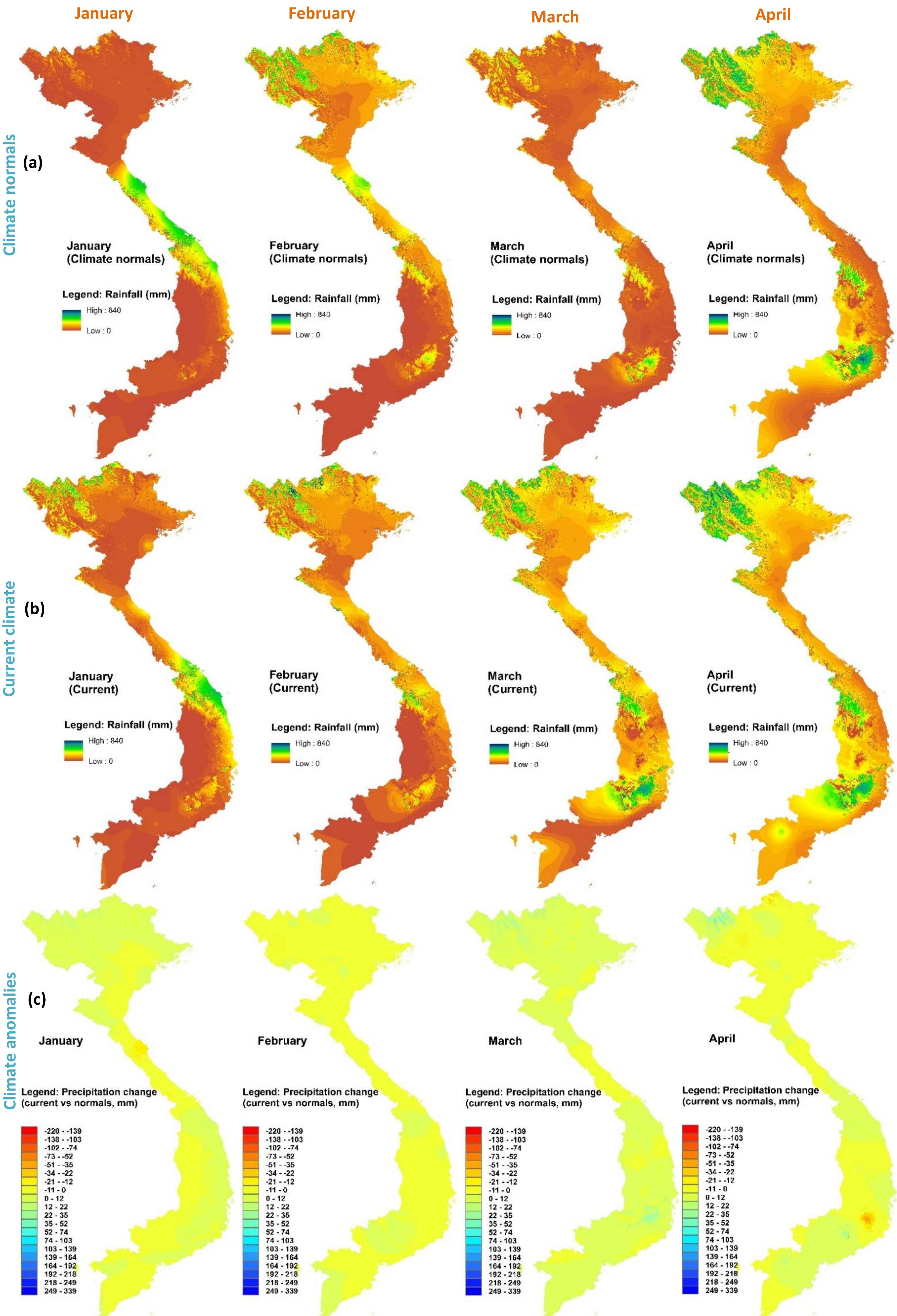


Figure 3.7.1 Spatial distribution of monthly precipitation for January to April for climate normals *(a)*, current climate *(b)*, and climate anomalies *(c)*

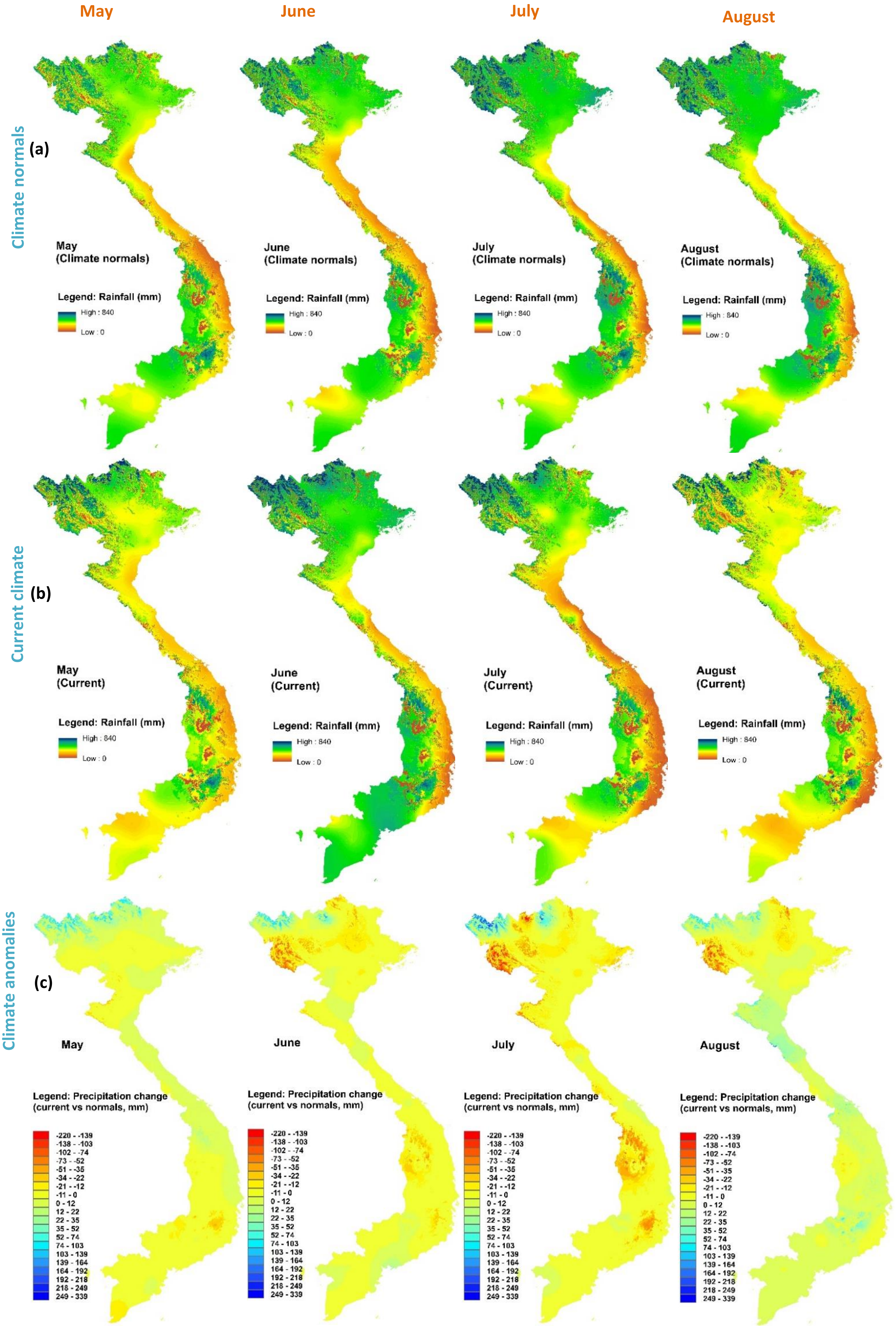


Figure 3.7.2 Spatial distribution of monthly precipitation for May to August for climate normals *(a)*, current climate *(b)*, and climate anomalies *(c)*

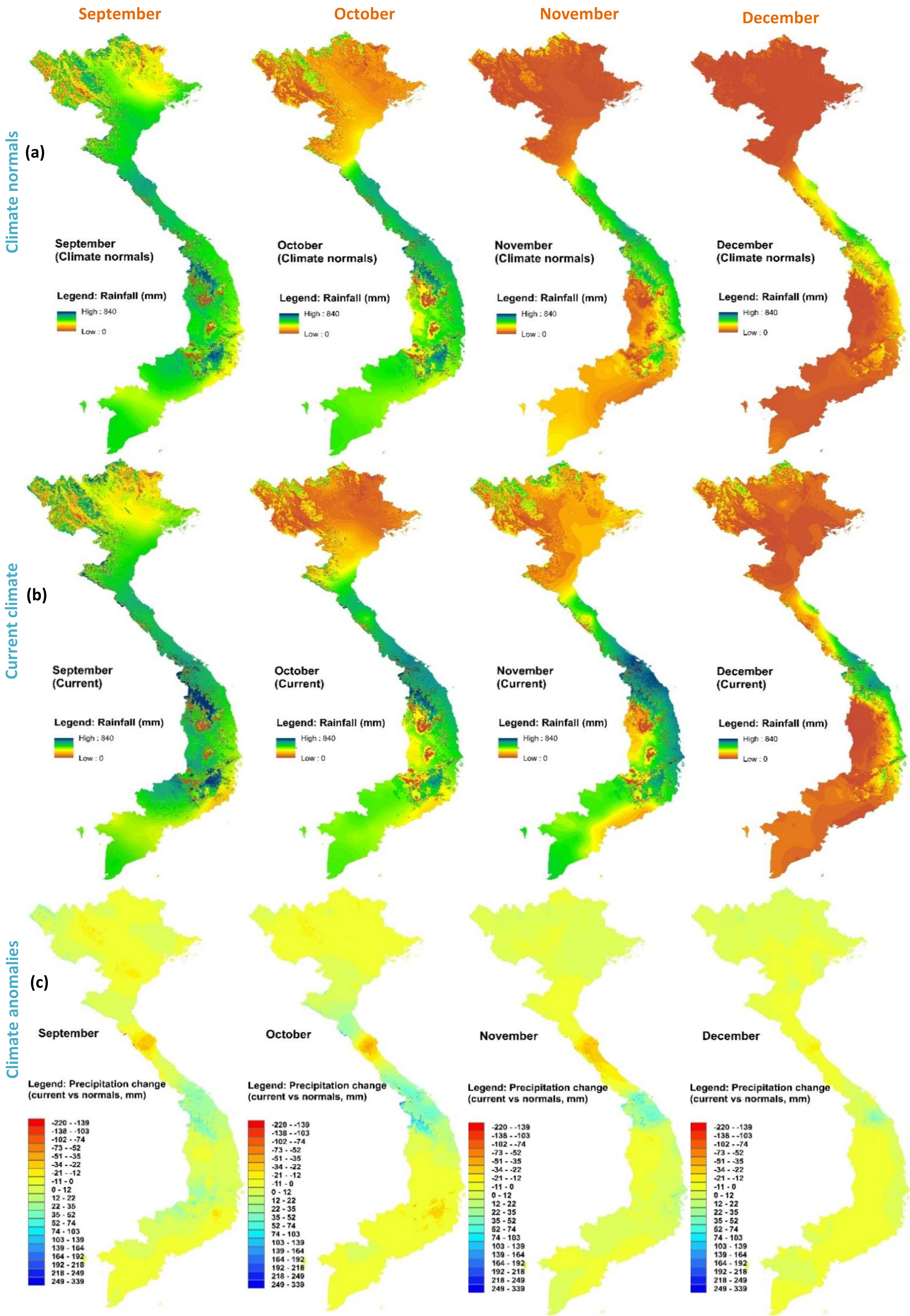


Figure 3.7.3 Spatial distribution of monthly precipitation for September to December for climate normals *(a)*, current climate *(b)*, and climate anomalies *(c)*

3.4.2.2 Observed temperature patterns

Analysis of annual mean temperature

Figure 3.8 shows the spatio-temporal changes of annual average temperature in different regions of Vietnam. Because Vietnam extends across 15 degrees of latitude from 8.30 degrees north to 23.22 degrees north, its temperature pattern varies significantly between North, Central and South with a noticeably higher mean temperature in the southern areas which are closer to the equator. That temperature pattern is very likely to be similar in the two defined periods of the climate normals (1975-2004) and the current climate (2005-2014). During these times, the annual average temperature ranges between 11.95 and 30.34 °C. Lower mean temperatures are observed in the Northwest (B-I) and Central Highlands (N-II), whereas

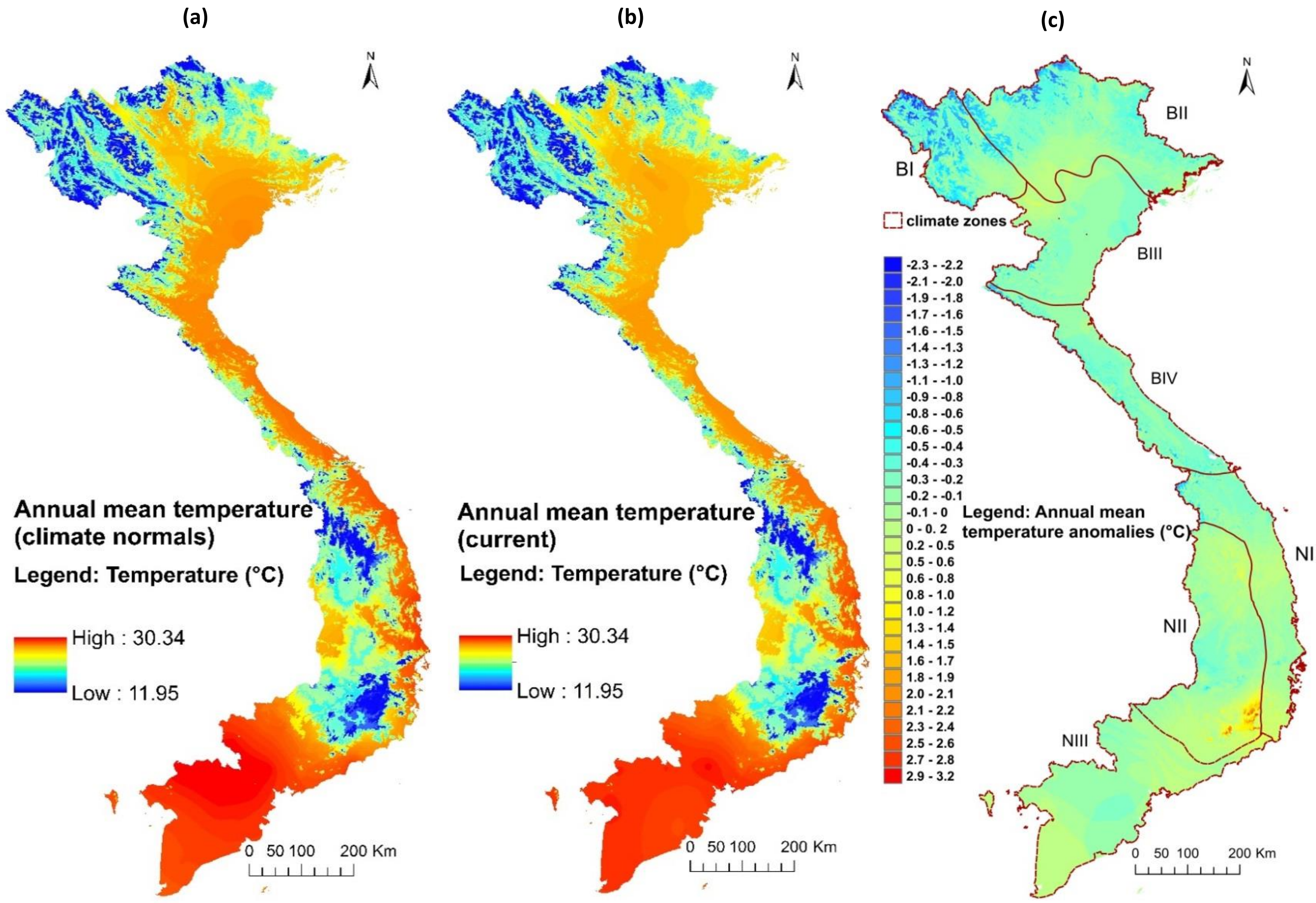


Figure 3.8 Spatial distribution of mean annual temperature for climate normals *(a)*, current climate *(b)*, and climate anomalies *(c)*

in the Southern Delta (N-III) and Central Coast (B-IV and N-I) the average temperature is typically warmer.

Temporal shifts in observed temperature have been found across space while comparing the current climatic conditions with the 30-year average conditions, which is a robust signal of temperature variability and change in Vietnam (Figure 3.8-c). Climate anomalies in temperature show diverse patterns, mixing both increasing and decreasing trends in different locations where some areas may experience more warming or cooling than others. Long-term temperature increase is especially significant in the southernmost areas of the Central Highlands (N-II) where the magnitude of that variation could reach the highest level of 3.2 °C. In contrast, temperature decrease relative to the climate normals has dominated the regions of the Northwest (B-I) with the lowest decrease recorded of -2.3 °C (Figure 3.8-c).

Overall, a pattern of increasing average temperature is observed in the rice-cultivating areas including the Red River and Mekong River deltas (Figures 3.4 and 3.8), which is likely to be especially damaging for rice due to the potential increase of drought intensity. More specifically, some provinces with large areas of rice cultivation such as Kien Giang and Ca Mau in the Mekong delta, Binh Thuan and Quang Ngai in the Central Coast, and Thanh Hoa, Nghe An, Thai Binh and Phu Tho in the northern areas experienced notable increase in temperature. Also, there is growing evidence that warming climate likely increases the severity of plant diseases and water shortages leading to a reduction in productivity (Harvell et al., 2002). Thus, it is expected that the rice sector will be hard hit by the warming pattern. In addition, because only looking at annual mean temperature may miss the monthly changes across the year, the observed temperature series at the monthly scale were therefore further explored. The output is presented in Figure 3.9.

Analysis of monthly mean temperature

Figure 3.9 shows the spatio-temporal distribution of mean temperature and its volatility at the monthly scale across the country. Changes in monthly temperature have been taking place across the whole country compared to the long-term climate normals. Specifically, observations of the warming patterns are the most common over time in many locations from the North to the South of Vietnam such as the Northern Delta (B-III), the South Central Coast (N-I), the Central Highlands (N-II) and the Southern Delta (N-III), except in the northernmost area of the country. The warming patterns in recent years compared with climate normals are observed over different months with an exception in June when a cooler pattern of mean temperature has been seen in the current climatic condition.

Maps of the surface temperature anomalies depict even clearer trends of widespread patterns of increasing average surface temperature across the country, especially in the centre of the Northern Delta (B-III), the South Central Coast (N-I) and part of the Southern Delta (N-III). Those variations in the temperature are the most direct sign that climatic conditions are changing (USEPA, 2016). Furthermore, the highest warming rate has been identified in the southernmost region of the Central Highlands and the Central Coast including Dalat, Ninh Thuan and Binh Thuan provinces. The temperature is over 5.1 °C warmer in the current climate compared to the long-run average (Figure 3.9.2-c).

Overall, compared with the patterns for precipitation, the spatio-temporal changes in temperature show a more uniform tendency characterised by a warming pattern across regions. Visual analytics used in mapping the distribution of temperature contribute significantly to analysing the temperature series and identifying ‘hotspot’ areas.

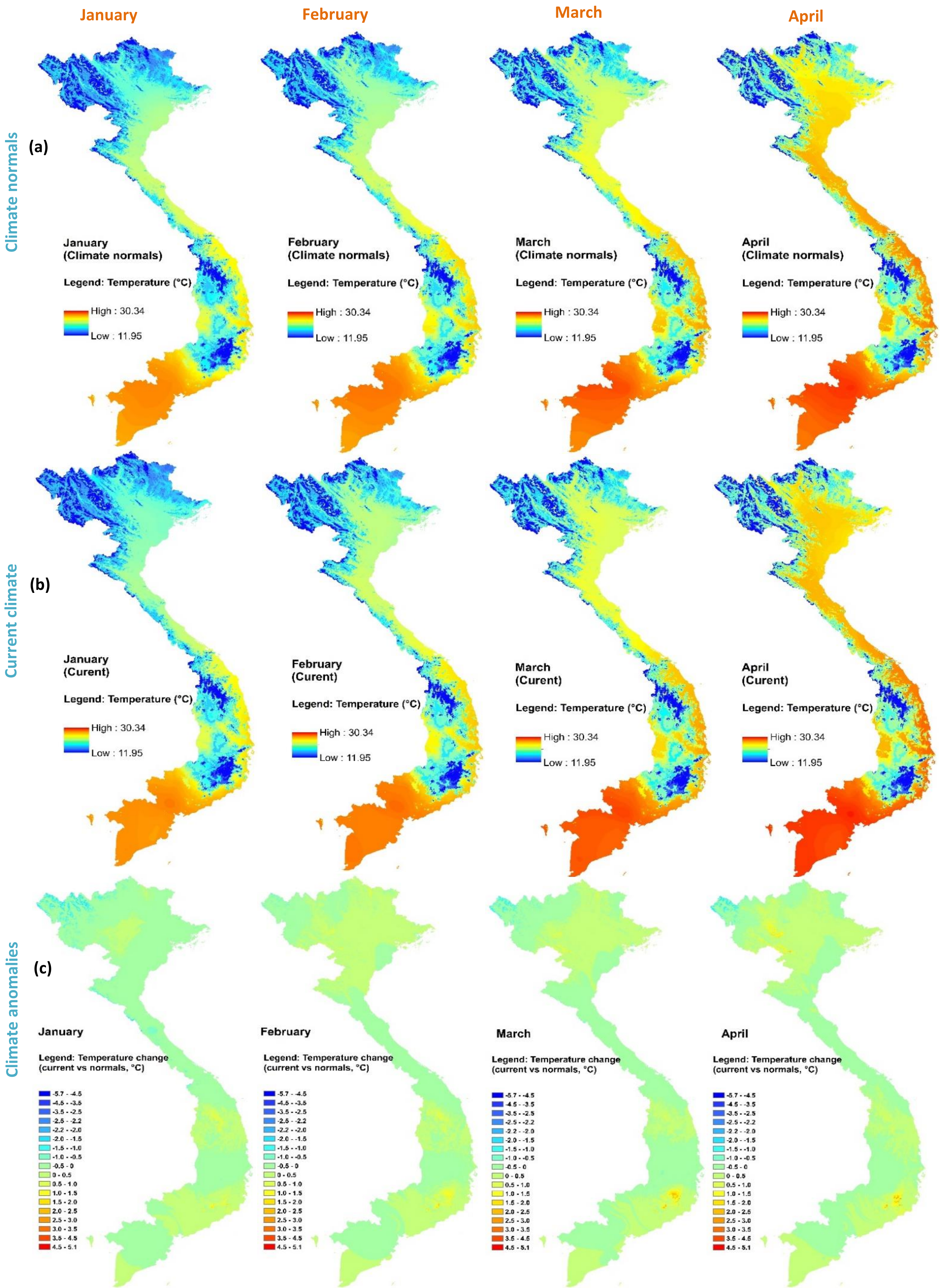


Figure 3.9.1 Spatial distribution of monthly temperature for January to April for climate normals *(a)*, current climate *(b)*, and climate anomalies *(c)*

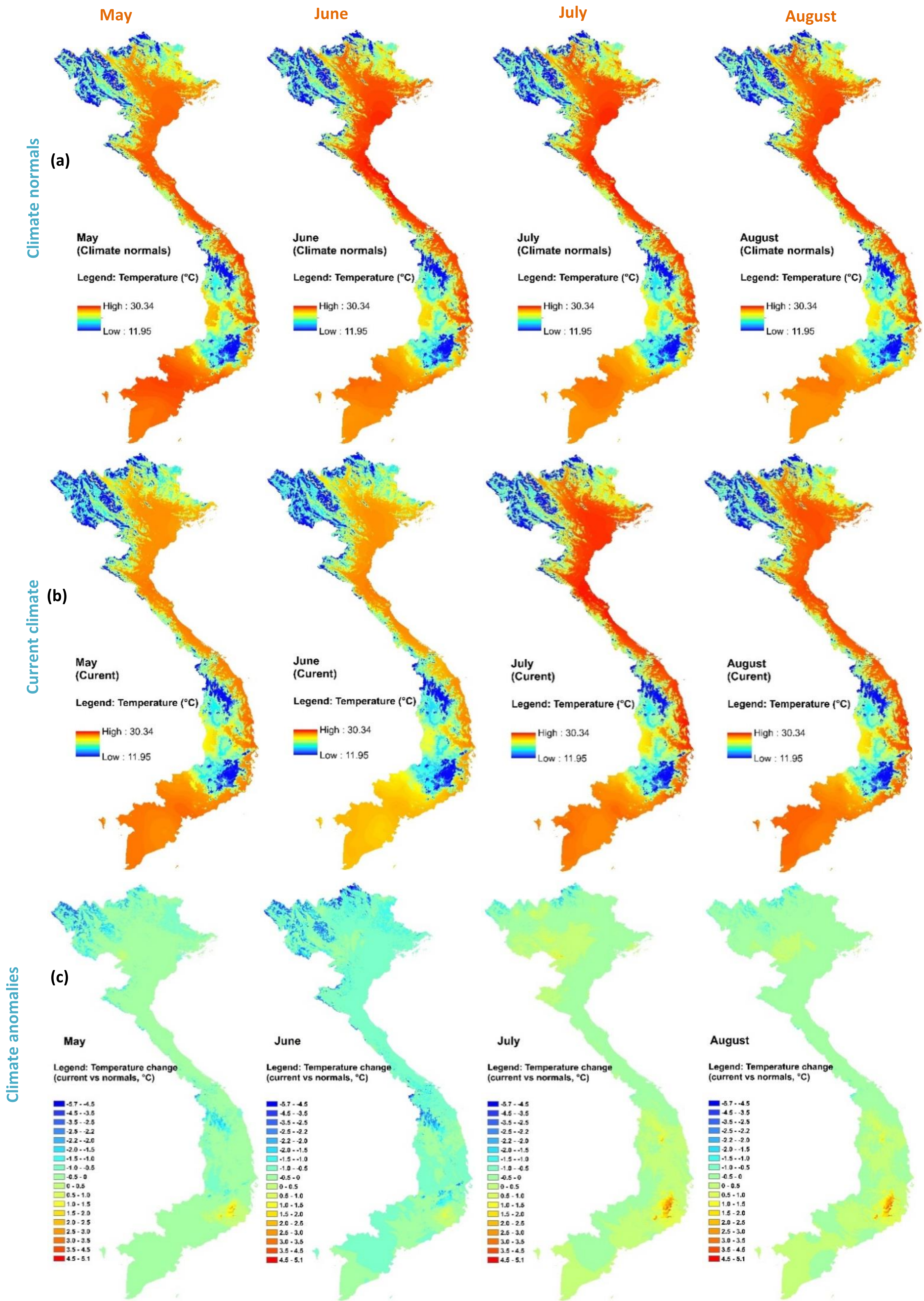


Figure 3.9.2 Spatial distribution of monthly temperature for May to August for climate normals *(a)*, current climate *(b)*, and climate anomalies *(c)*

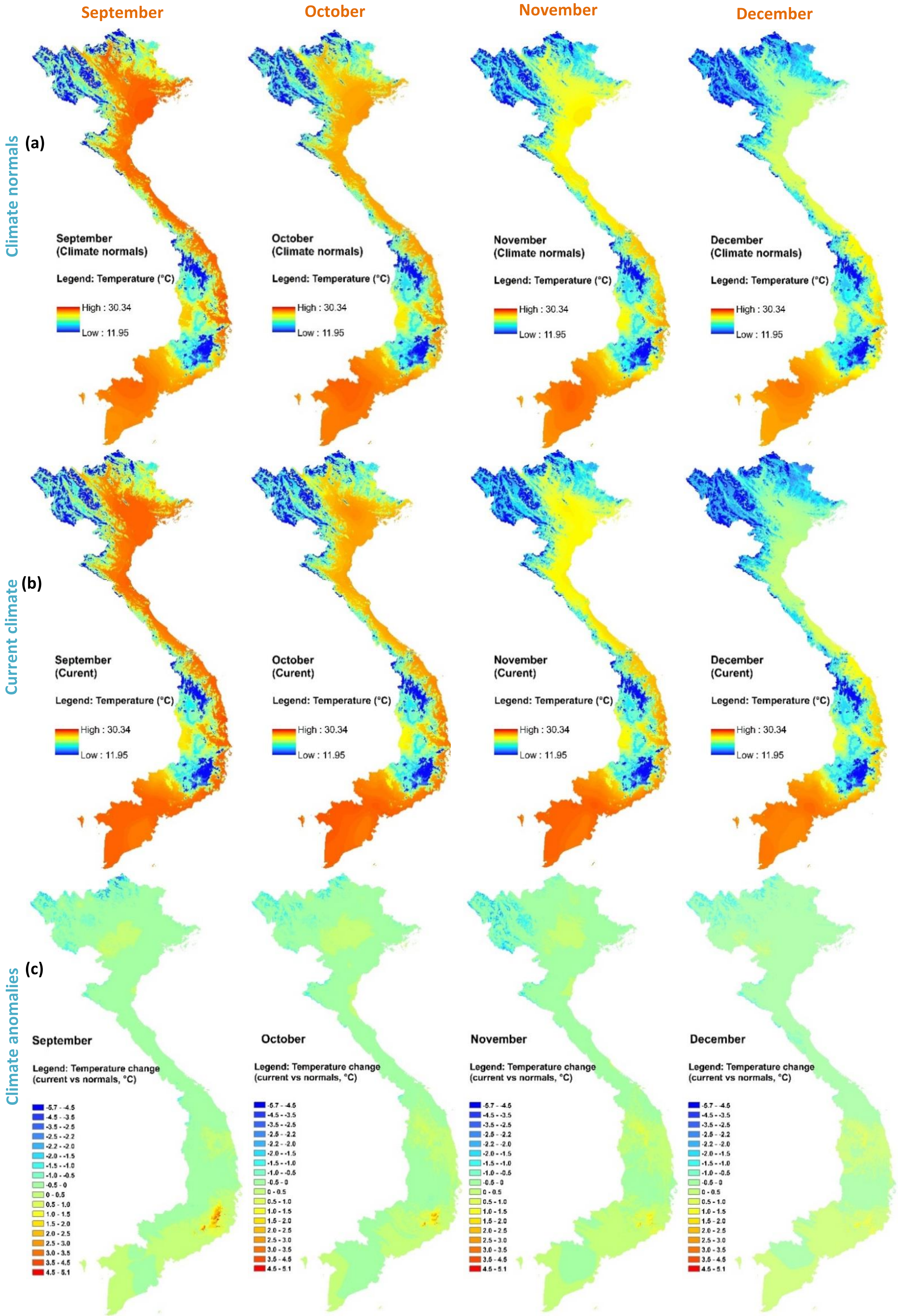


Figure 3.9.3 Spatial distribution of monthly temperature for September to December for climate normals *(a)*, current climate *(b)*, and climate anomalies *(c)*

The spatially uniform increase in temperature during the growing season of rice across the country is likely to have adverse impacts on rice production. In general, the winter-spring rice season now experiences a warmer climate in most regions except the northernmost areas of the country (Figure 3.9.1). The warming pattern is even more intense for the spring-autumn season of rice during the period of June to October/November (Figures 3.9.2 and 3.9.3). Again, the Red River and Mekong River deltas are among the areas with the highest warming rate recorded. Since those two deltas are the primary rice production regions of the country, it is evident that temperature anomalies may have adverse impacts on rice production.

3.4.3 Statistical analysis of trends

The visual analytics using geostatistical techniques efficiently capture the variations from location to location and from year to year in climate-related variables. However, a question still remains whether these observed climate variations represent long-term trends over time and space or are just short-term movements in climatic conditions. Long-term upward or downward trends in observed climatic variables have been assessed using the non-parametric Mann-Kendall trend test with a null hypothesis of no change point existing in the data series at the 10% significance level (Kendall 1962; Mann 1945).

3.4.3.1 Trends in precipitation

Figure 3.10 shows a map of trends in precipitation in the 1975-2014 time intervals. The map presents *Z* statistic values of the Mann-Kendall test representing the sign, magnitude and significance level of the long-term trends. The trend test results was also mapped together with the climate anomalies map and the distribution of agricultural land to assess the results of the visual analytics approach and identify any potential impacts of climate change on the agriculture sector.

The distribution of trend test results for precipitation shows a large and significant variation across the country combining positive significant trends, negative significant trends, and no significant trends in the data series (Figure 3.10). There is statistically significant evidence that out of 99 land-based weather stations, 23 stations show an increase in rainfall over 1975 to 2014 and 19 stations show a decrease. The majority of meteorological stations (57.6%) have insignificant long-term changes in precipitation. While some parts of Vietnam have had changes in the pattern of rainfall, the majority of these changes are statistically insignificant over a long period.

Considering the magnitude of the changes in Figure 3.10, the pattern of increasing precipitation is relatively pronounced in the north-westernmost regions and the centre of the Central Coast (B-IV and N-I) of Vietnam. The magnitude of rainfall pattern change is moderate in the western areas of the Southern Delta (N-III). The decreasing pattern of rainfall is evenly distributed throughout the country with some noticeable rainfall-deficit areas such as part of the Northern Delta (B-III), the northernmost regions of the North Central Coast (B-IV), the Central Highlands (N-II) and the coastal side of the Southern Delta (N-III).

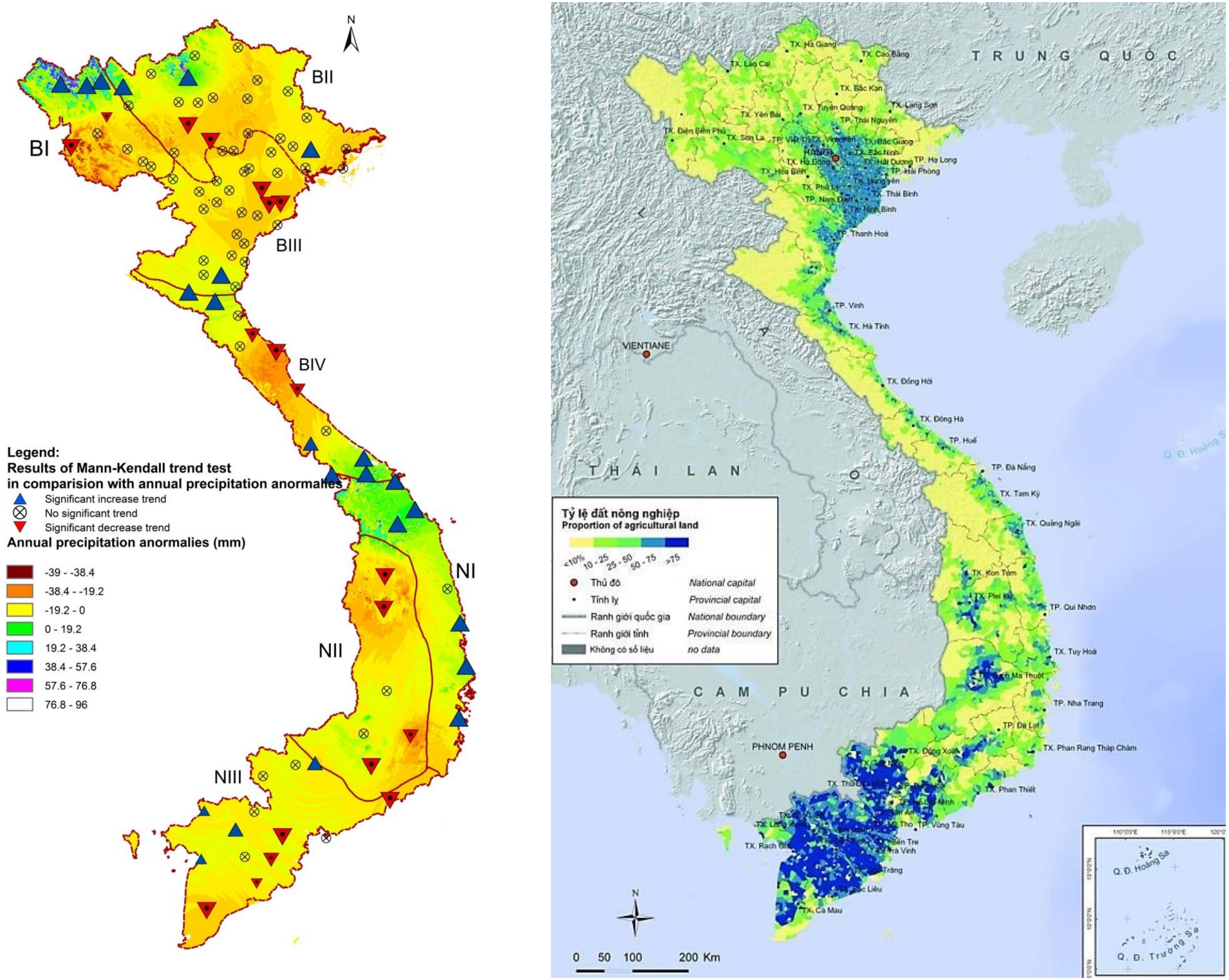


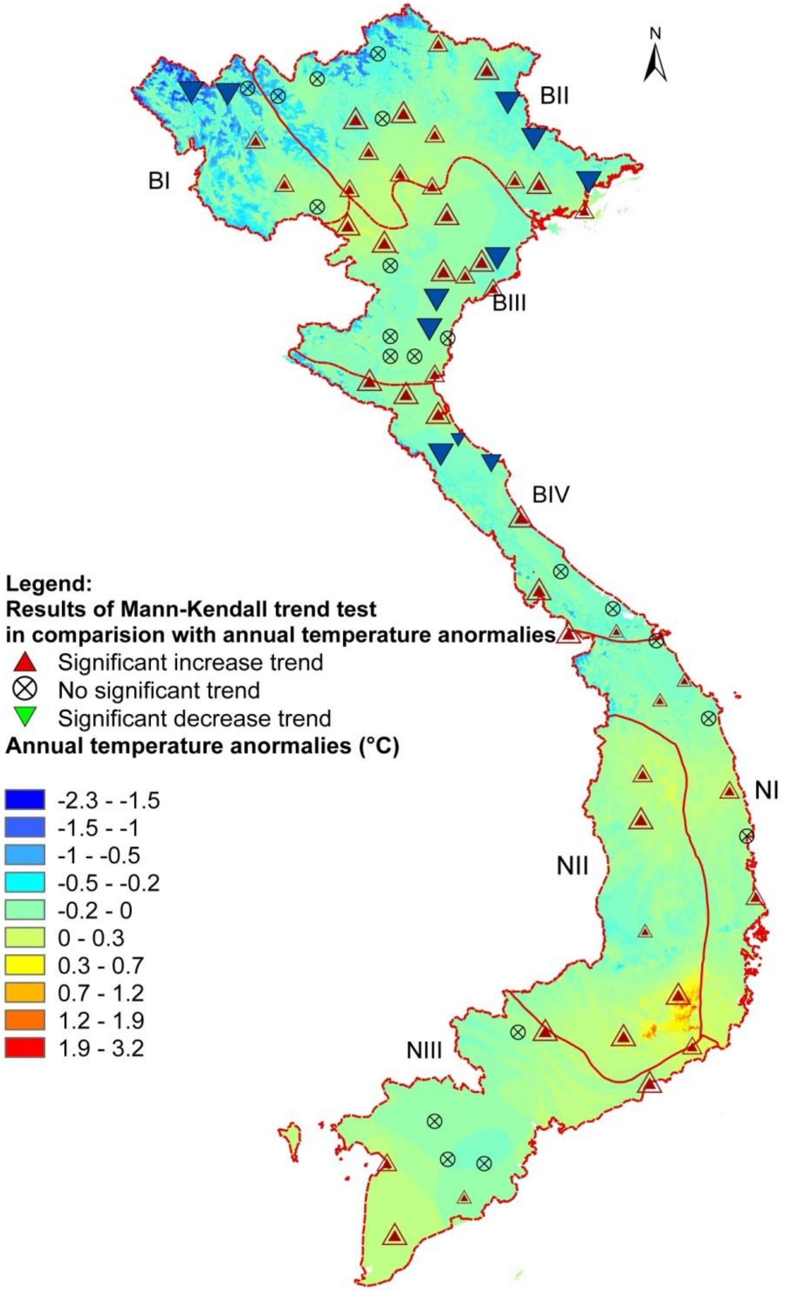
Figure 3.10 Results of Mann-Kendall trend test comparing annual mean precipitation anomalies and the distribution of agricultural land in Vietnam

Comparing results of the statistical analysis in Figure 3.10 and visual analytics in Figure 3.8, there is a very close connection between the pattern of changes obtained using geostatistical techniques and the results of the Mann-Kendall trend test. Specifically, most of those 'hotspot' areas, where significant changes in precipitation patterns have been identified by geostatistical mapping, have also been further confirmed by the statistical significance of the long-term shifts over time and space. For instance, the north-westernmost regions, the centre of the North Central Coast (B-IV), the northern South Central Coast (N-I) and the Central Highlands (N-II) were visually considered as the most prominent areas of precipitation anomalies and, consistent with results of the trend test, those locations also show statistically significant evidence of long-term increasing or decreasing precipitation. We can say that there is a robust evidence that Vietnam's climate is changing, not only in certain short periods but also over long historical records of precipitation.

The long-term significant trend in rainfall pattern is identified in areas where there are very high proportions of agricultural land. Specifically, the main farming area in the North is experiencing a significant decline in rainfall whereas the largest agricultural production area of the country in the South is experiencing both significant increases and decreases in rainfall in various locations. Thus, it is reasonable to expect that changes in the climatic conditions will be very likely to impact agricultural production in those areas.

3.4.3.2 Trends in temperature

The results of the Mann-Kendall trend test for temperature are displayed in Figure 3.11 with the map of climate anomalies. In general, the test results show a uniform distribution of temperature pattern across regions because most parts of the country are likely dominated by a statistically significant warming trend. Over half (58.6%) of the meteorological stations show a statistically significant long-term increase in temperature, while only 14.2% of stations have a decreasing temperature and 26.6% of stations have no significant change (Figure 3.11). All decreasing stations are located in the northern parts of the Central Coast and the North of the country. However, the other stations are widely distributed across large parts of the country.



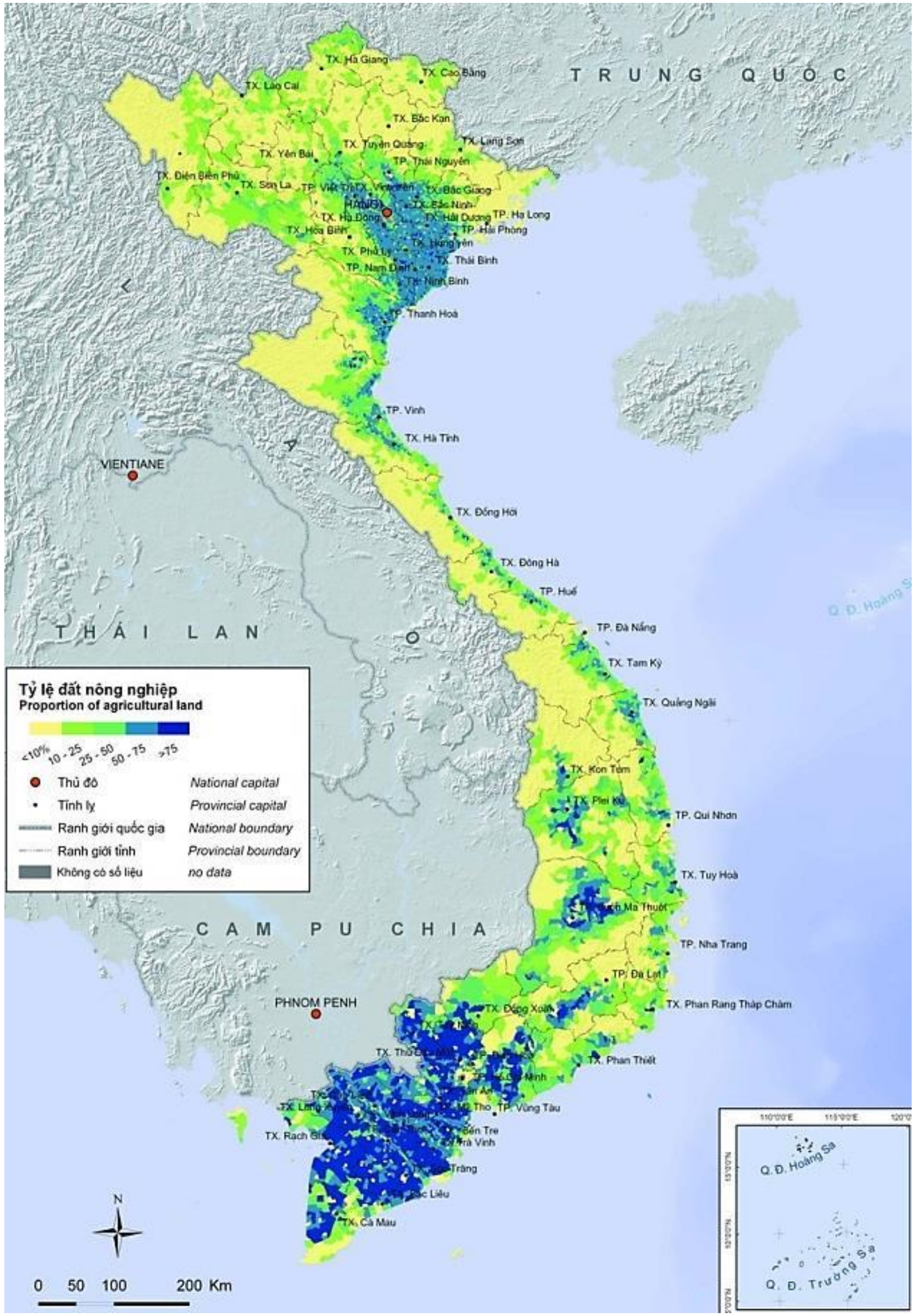


Figure 3.11 Results of Mann-Kendall trend test comparing annual mean temperature anomalies and the distribution of agricultural land in Vietnam

In terms of the magnitude of temperature change, the greatest increase has been identified in the centre of the North, the northernmost and southernmost regions of the Central Coast (B-IV and N-I), and part of the Central Highlands (N-II) and the Southern Delta (N-III). The North of Vietnam has experienced the smallest change because these locations are far away from the equator and also characterised by complex topography (Figures 3.2 and 3.11).

Integrating a statistical approach with the outcome graphics of geostatistical techniques was also applied to the temperature series (Figure 3.11). The outputs of the two approaches are highly correlated from region to region across the country. Thus, most areas with considerably pronounced pattern changes are also associated with statistically significant long-term trends verified by the Mann-Kendall test. However, no statistically significant change in temperature is identified in the northernmost of the country even though a substantial shift in the pattern is observed in the visual analytics. Generally, the long-term trends depicted in the findings of both geostatistical mapping and statistical testing used in this study provide important evidence of spatio-temporal changing climatic conditions throughout Vietnam.

It is clear that most agricultural areas across the country are experiencing a warming pattern in climatic conditions, particularly the two largest rice production areas in the Red River and Mekong River deltas. Many other areas along the coast are also experiencing a long-term increase in temperature which is likely to have impacts on rice production.

3.5 Conclusion

Changes in climate have been observed across the globe, including in Vietnam. These observed shifts in climate patterns could have adverse impacts on natural systems and human activities such as agricultural production. Our study found robust evidence of the spatio-temporal trends of climate-related variables and identified their potential effects on agriculture in Vietnam. Records of monthly precipitation and temperature for a relatively long-term period (1975-2014) over the high density of 112 meteorological stations across the country were used. Combining statistical methods with geostatistical techniques is efficient to graphically represent the distribution of climate patterns, identifying variations and trends over time and testing the statistical significance of those changes.

The findings provide robust evidence of spatio-temporal climate variability and change in Vietnam. The visual analytics indicate that rainfall anomalies exhibit a dramatic heterogeneity across regions, in contrast to the ongoing spatially uniform warming in temperature in most parts of the country. The visual evidence of climate change in Vietnam was further assessed by the Mann-Kendall statistical test. The results confirmed that most of the ‘hotspot’ areas of rainfall and temperature identified by geostatistical mapping have statistically significant long-term changes over time. Thus, the findings confirm that ongoing changes in the climate in many areas throughout the country were not only represented by the variations of climatic elements in certain periods, but also by the long-term trends over many years.

The long-term significant trends in rainfall and temperature patterns were identified in areas with very high proportions of agricultural land, particularly for rice production in the Red River and Mekong River deltas. Changes in the rainfall and temperature patterns are very likely to have some impacts on rice cultivation during the growing season due to the warming across the country and the surplus or deficit of rainfall in certain areas. Thus, it is expected that climate change will have impacts on the agricultural sector, including rice production in many regions of Vietnam. Unfavourable climatic conditions could result in increasing frequency and intensity of flooding, water scarcity and pests and plant diseases, which could lead to lower productivity in rice-growing areas. However, to what extent the changes in climate will affect rice productivity and how farmers will adapt to the changing climate is beyond the scope of this study. It leaves room for further analysis on climate change impacts and adaptation, which will be addressed in the following study.

Our findings contribute significantly to understanding of the underlying climate processes and possible impacts across regions of Vietnam. The evidence-based analysis provides a basis for developing effective climate-related policies to respond to ongoing climate change and help mitigate the adverse impacts of climate change on human social-economic processes, particularly agricultural production in rural areas.

Chapter 4

Farming is adapting: Lessons for adaptation to climate variability and change across regions of Vietnam

Abstract

Farmers have a long record of adapting to changing production environments – including unfavourable climatic patterns – by using various agricultural adaptation practices. This paper employs a cross-sectional time series dataset from nationally representative households in Vietnam to investigate factors behind farmer's choices to adopt soil and water conservation techniques for the purpose of adapting to climatic change. Probabilistic record linkage methods were used to find the best-matched observations from two sets of surveys (VARH and VLSS) to create a 20-year panel dataset. Since farmers' adoption decisions are inherently dynamic, a dynamic random-effects probit model was estimated, controlling for unobserved heterogeneity and state dependence. It is evident that weather shocks and long-run changes in temperature during the rice growing season are significant determinants of farmers' choices to apply adaptation practices given that other factors that may affect producer behaviour are controlled. In addition, the decision to adopt in subsequent periods is strongly influenced by past adoption decision. Results also indicate that farmer's experience, farm size, and access to weather and output price information are associated with households that have decided to apply conservation measures. Overall, this study delivers a better understanding of farmers' decision-making process and its drivers in the face of changing climatic conditions, which is useful for practitioners and policy-makers to facilitate climate-resilient strategies to improve farmers' adaptive capacity under climatic uncertainty.

Keywords: Climatic uncertainty; adaptation; agriculture; longitudinal data; Vietnam

JEL classifications: C25, Q12, Q54

4.1 Introduction

Household livelihoods in developing countries, particularly smallholders in rural areas, depend heavily on agriculture as a predominant source of income. However, agricultural production is inherently vulnerable to weather shocks and long-term shifts associated with climate, and is subject to substantial climate-sensitive resource dependence (Baez et al., 2013; McElwee et al., 2010). Climatic change can manifest through different channels such as increasing temperatures, heavier precipitation or prolonged periods with very little or no precipitation, as well as more frequent and more intense weather-related extreme events (Below et al., 2010; Hisali et al., 2011). Vietnam is among the countries that are likely to be hardest hit by the impacts of climatic variability and change (WB, 2010). Starting from the 1970s, recorded average temperature across Vietnam has increased by 0.26±0.10 ^{0}C per decade, which is twice as much as the rate of global temperature rise for the same period (Nguyen et al., 2013). Also, annual precipitation has shown a declining trend in five out of eight climatic zones in Vietnam over the same period (Nguyen et al., 2013). Climatic uncertainty has also intensified the incidence and magnitude of extreme events such as floods, droughts and typhoons across Vietnam (VNGP, 2011).

IPCC (2007) points out that countries with agriculture counting as a high proportion of the economy, such as Vietnam, are most susceptible to climate change. Climatic variability and change are likely to be especially challenging for rice growing – a key agricultural activity in Vietnam and other developing countries in Southeast Asia − given its direct exposure to variations in temperature and precipitation. As a result, ongoing changes in climatic conditions could impose large detrimental effects on the agricultural sector in many countries, including Vietnam, with implications for food security and household welfare (Di Falco and Veronesi, 2011; Mendelsohn et al., 1994; Qureshi and Whitten, 2014; Thomas et al., 2010a; Yu et al., 2013).

Adaptation is one of the options for reducing the adverse impacts of climate change (Deressa et al., 2009; Mendelsohn and Kurukulasuriya, 2007). Farming households have a long record of adapting to changing production environments, including unfavourable climatic patterns. It could be argued that farming is about constantly adapting to external conditions through the process of behavioural adjustments by individual farm households. Smallholders use complex, interactive, multidimensional and locally-specific adaptation processes, which are driven by various climatic, technological, economic, social and political forces. This results in a wide range of behavioural response strategies for climate change that have been identified in many empirical studies (IPCC, 2007). The most often quoted ones include diversification of crops and income sources, adjustment of various farm management practices, and implementation of soil and water conservation techniques. Among those, conservation of land and water resources is a promising method for adaptation of farming systems to various stresses (Kato et al., 2011; Sietz and Van Dijk, 2015). Some methods, such as terrace farming, soil bunds and conservation tillage, have been suggested as key strategies to reduce the effect of water shortages and worsening soil conditions that come as a result of climate change (Kurukulasuriya and Rosenthal, 2003).

Most previous adaptation research has used cross-sectional datasets to investigate farmer behaviour under climatic variability and change. These micro-level studies focusing on implementation of adaptation practices provide insights into the effects that the characteristics of farms and farmers have on their adaptation decisions. They also investigate the effects of farmers' perceptions about changing climatic conditions and explain what factors govern their decision-making process (Below et al., 2012; Ervin and Ervin, 1982; Maddison, 2007; Roco et al., 2014). However, many of these studies take a snapshot of the data at a given point in time. This implies that cross-sectional data are used to address issues that are inherently dynamic and require cross-section time series data analysis (Besley and Case, 1993; Doss, 2006; Sietz and

Van Dijk, 2015). Consequently, a major obstacle to better understanding the dynamic nature of behavioural change in adopting agricultural practices conducive to adaptation to climate change has been the lack of studies based on long time series cross-section data at the household level (Moser and Barrett, 2006).

This study adds value to the existing literature by investigating factors behind farmers' choices to adopt agricultural practices that aid adaptation to climate change, such as soil and water conservation techniques. The study exploits an extensive longitudinal dataset from the nationally representative sample of households in the Vietnam Living Standard Survey (VLSS) and the Vietnam Access to Resources Household Survey (VARHS) from 1992-2012. A 20-year panel with six waves across different agro-ecological locations in Vietnam allows us to model farmers' choices over a relatively long period. Since decision-making processes on using adaptation practices are inherently dynamic, it is necessary to use longitudinal datasets to overcome the many constraints imposed by analyses based on purely cross-sectional data (i.e. lack of comparisons across time and inability to evaluate the effect of policies). To the best of our knowledge, this study is among very few empirical studies globally that explain the pattern of adopting climate change adaptation practices in agriculture using long panel data sets, and certainly is the first such study for Vietnam.[13]

The dynamic choices that farmers make about adaptation practices were examined, controlling for unobserved household heterogeneity, initial conditions and state dependence. Unobserved heterogeneity refers to those unobservable factors such as farmers' management ability and household wealth, whereas the initial condition problem refers to the simultaneous presence of both lagged dependent variable and unobserved effects in dynamic modelling. Moreover, Heckman (1981) indicates that choice behaviour may exhibit dynamics that could be

[13] Doss (2006) points out that there is a limited number of studies analysing the dynamic patterns of adoption agricultural technologies. Some have been done by Feder et al. (1985), Cameron (1999), Barham et al. (2004).

attributed to two sources: ‘true’ state dependence referring to persistence in choice behaviour due to the effect of the previous choice on the current decision, and ‘spurious’ state dependence, which is caused by unobserved household characteristics affecting the persistence in choice behaviour. It is often noted that previous choices made by farmers on agricultural practices may influence their decision to make those same choices again (Boere et al., 2015; Ervin and Ervin, 1982; Feder et al., 1985; O'Neill and Hanrahan, 2011). This was referred to as state dependence in the present study. Panel data allows us to control for unobserved effects to overcome the ‘spurious’ state dependence problem. Many estimation methods have been proposed in dynamic studies with a view to distinguish between ‘true’ state dependence and unobserved heterogeneity (Heckman, 1981; Orme, 2001; Rabe-Hesketh and Skrondal, 2013; Wooldridge, 2005). Some of those methods were applied in the ensuing empirical work.

Dynamic choices over 20 years and the drivers of adaptation practices made by farmers to cope with the changing climatic conditions were empirically examined. Dynamic econometric modelling methods are applied to a long cross-section time series dataset at the household level, controlling for factors that may influence the decision-making process in order to isolate the effects of climate change on farmers’ choices. Findings from this study could be used to strengthen the adaptive capacity of rural households and farmers and also better inform policy-makers in their agricultural policy-making activities to cope with future changes in the climate.

The remainder of this chapter is organised as follows. Section 4.2 reviews the existing literature. Section 4.3 provides some background on climate change, agricultural production, and adaptation strategies for the changing climate in Vietnam. Section 4.4 presents the conceptual framework, followed by the empirical model and data in Section 4.5. Section 4.6 discusses the results and findings. Conclusions and policy implications are presented in Section 4.7.

4.2 Literature review

There is a long and rich tradition of empirical research that seeks to explain farmers' adoption of particular agricultural innovations (Knowler and Bradshaw, 2007). Feder et al. (1985) provide an extensive survey of the various theoretical and cross-sectional empirical studies on the decisions to adopt agricultural technologies and suggest some key explanatory factors affecting the process of adoption such as farm size, human capital, labour availability, credit constraints, land tenure, and supply constraints. Another important factor influencing the decision-making process pointed out by Adesina and Zinnah (1993) is farmers' perception towards risk and uncertainty. Besides, Feder et al. (1985) also point out that empirical studies have rarely controlled for environmental effects like weather variations because these factors are often difficult to measure and quantify at appropriate spatial and temporal scales.

However, recent research on agricultural adaptation to climate change has paid significant attention to environmental variables, due to the increasing concerns over climate change and its impacts on farming systems. Knowler and Bradshaw (2007) review the findings of 31 recent empirical analyses of farm-level adoption of some soil management and general practices consistent with conservation agriculture to explain how certain variables including rainfall and temperature tend to influence farmers' decisions. In addition, Sietz and Van Dijk (2015) present a meta-analysis of 63 case studies that investigate the adoption of soil and water conservation measures. The meta-analysis reveals a multitude of factors that drive adoption decisions and highlights the adoption of soil and water conservation practices as an emerging way in which farmers adapt to global climate change. Several recent adaptation studies also focus on identifying the determinants of farmer behaviour to respond to climate variability and change, especially in Africa (Marenya and Barrett, 2007; Piya et al., 2013). For example, Maddison (2007) indicates that the process of adaptation to climate change at the farm level is driven by various factors, such as farmer experience and level of education, availability of agricultural extension services and distance to output markets. Di Falco et al. (2011) examine the driving forces behind farm households' decisions to adapt to climate change using a simultaneous equation model. The study found that the primary drivers behind adaptation processes are farmers' access to credit, extension services and information (Di Falco et al., 2011). However, there is practically no previous work on the determinants of farmers' dynamic behaviour on adaptation to climate change in Vietnam. Also, studies using long time series cross-section data to investigate dynamic behaviour are still lacking in the existing literature globally. This leaves a gap in the literature that the current study is aiming to fill.

4.3 Background: Climate change, agricultural production and adaptation strategies in Vietnam

4.3.1 Climate variability and change in Vietnam

Vietnam is one of the countries most vulnerable to climatic variability and change (Adger, 1999). At the national scale, Nguyen et al. (2013) note a trend of increasing average temperature over the last several decades across regions throughout Vietnam. In addition, annual rainfall has declined in five out of eight climatic zones in Vietnam over that period. Further, stretching along over 15 degrees of latitude from 8.30^0N to 23.22^0N, the climatology varies significantly between North, Central and South Vietnam (UNEP, 2009).

Our study sites include six provinces (Ha Tay, Lao Cai, Phu Tho, Nghe An, Khanh Hoa and Long An) across various agro-ecological regions that represent well the spatial distribution of climate patterns in Vietnam. Based on the recorded weather data at these study locations, Figures 4.1 and 4.2 show the long-term trend in temperature and rainfall during the rice growing season over 38 years from 1975 to 2012. More specifically, precipitation and temperature exhibit large variations across space and over time. Growing Degree-days (GDDs) was used to represent long-run temperature conditions during the rice growing season. This variable shows a significant increase since 1975 (Figure 4.1). Cumulative rainfall during the rice growing season which shows a declining trend in many areas was also used (Figure 4.2). Further analyses of climatic conditions at our study sites are provided in Appendix 4C.

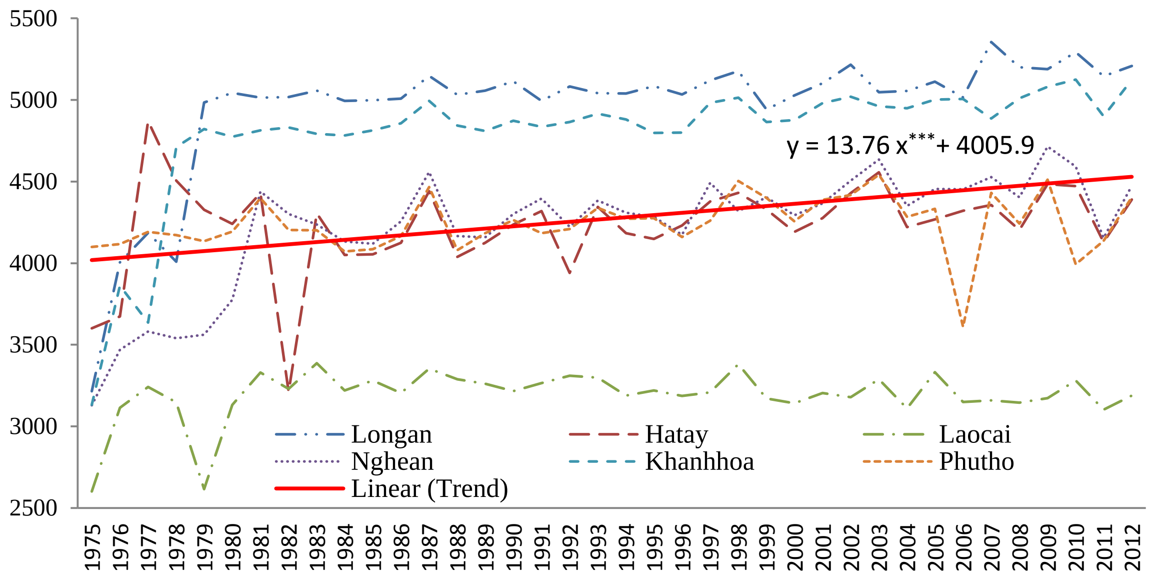


Figure 4.1 Long-term trend in temperature represented by GDDs (^{0}C) during the rice growing season at the study sites (1975-2012)

Source: Author's calculation based on data from the Vietnam National Centre for Hydro-Meteorological Forecasting

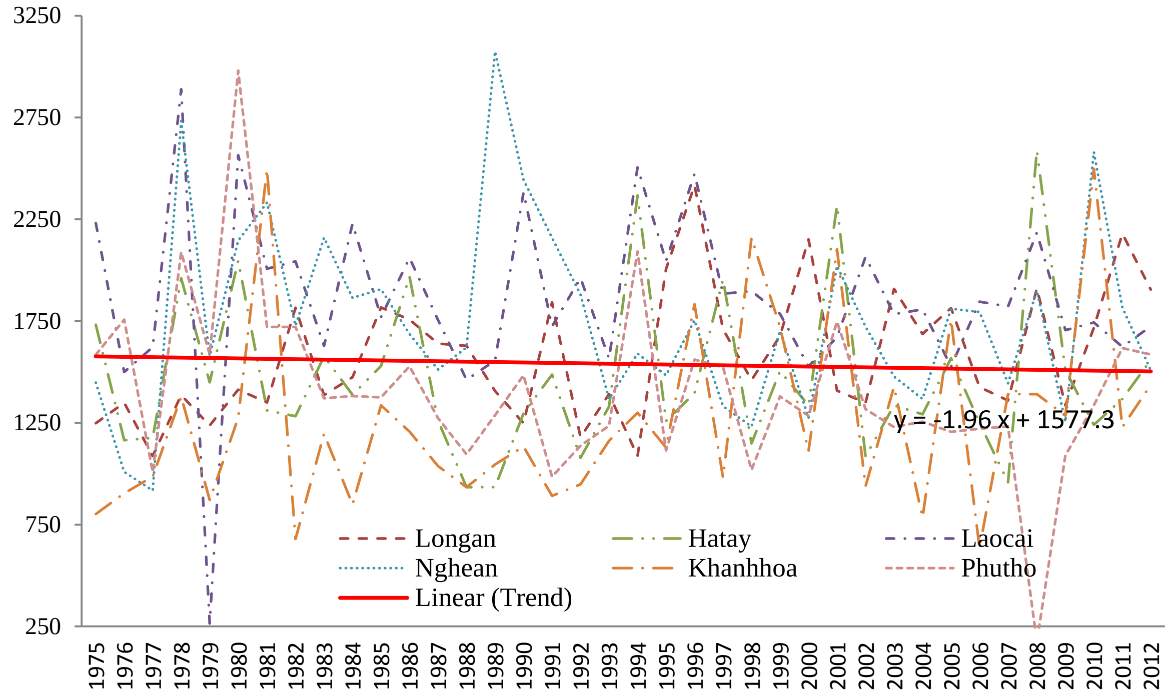


Figure 4.2 Long-term trend in cumulative rainfall (*mm*) during the rice growing season at the study sites (1975-2012)

Source: Author's calculation based on data from the Vietnam National Centre for Hydro-Meteorological Forecasting

Changing climatic conditions have also intensified the incidence and magnitude of extreme events such as floods, droughts and typhoons across Vietnam (Figure 4.3) (VNG, 2007).

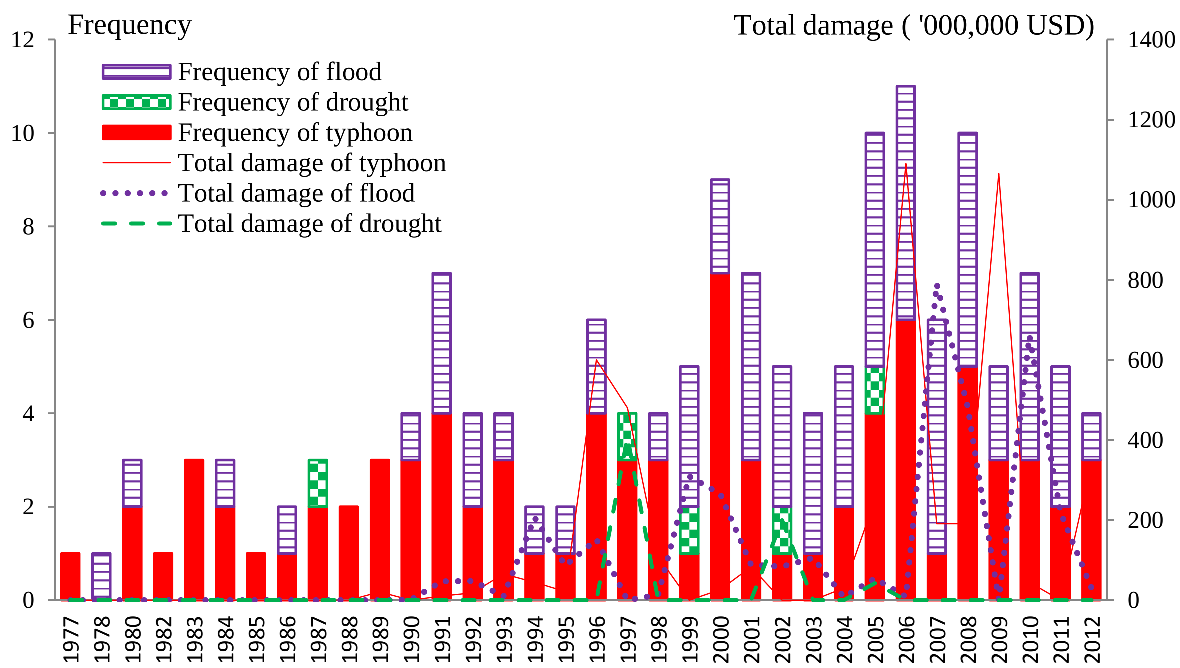


Figure 4.3 Extreme weather events and their damage in Vietnam (1975-2012)

Source: The International Disaster Database, http://www.emdat.be

As drought is the most important extreme event that affects rice farmers, the Standardised Precipitation Index (SPI) (McKee et al., 1993) was applied to identify the variability, magnitude and duration of drought conditions. The advantage of the index is that it can effectively represent the amount of precipitation over time by comparing the observed rainfall with the rainfall climatology at a particular location. The index is scaled from negative values to positive values, with larger negative values indicating that drought is likely to be more severe. Based on our calculation, the index shows that there has been increasing severity and intensity of droughts in many study sites over time (Figures 4.4 and 4.5).[14]

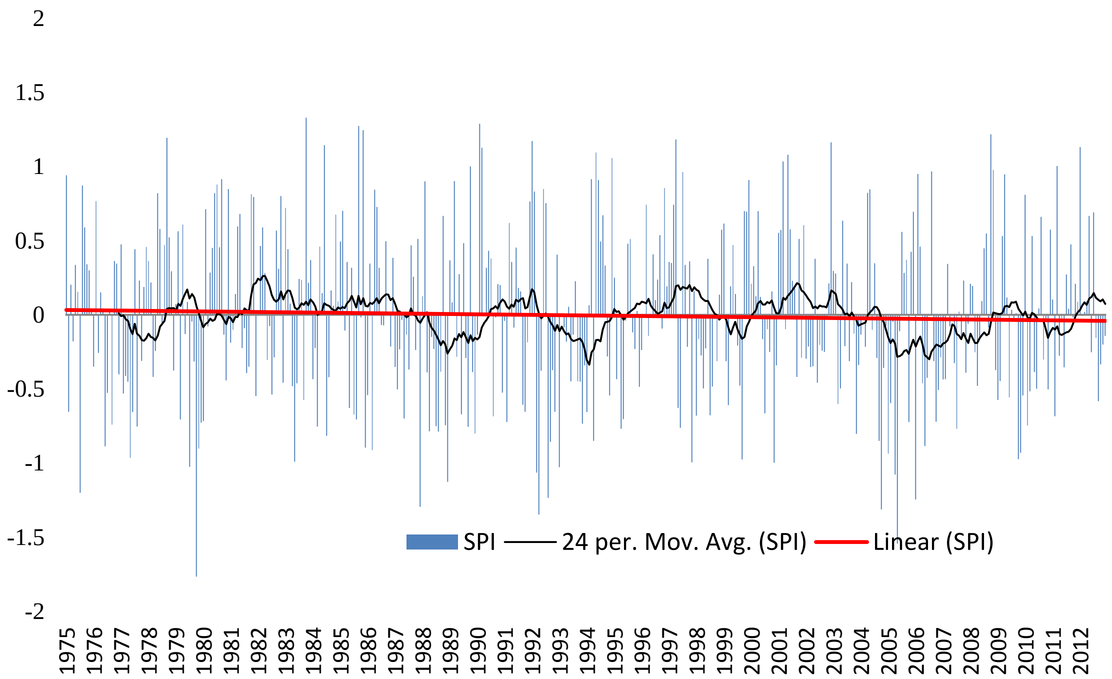


Figure 4.4 The trend of SPI averaged over the study sites (1975-2012)

Source: Author's calculation based on data from the Vietnam National Centre for Hydro-Meteorological Forecasting

The SPI across the six provinces surveyed shows a declining trend, which means that drought is likely to be more severe over time in the study sites (Figure 4.4). As shown in Figure 4.5, the intensity of drought events, approximated by the number of moderate and severe droughts (defined by SPI < -1.00), increases gradually in many areas.

[14] More detail on the SPI across study locations and over time is provided in Appendix 4C.

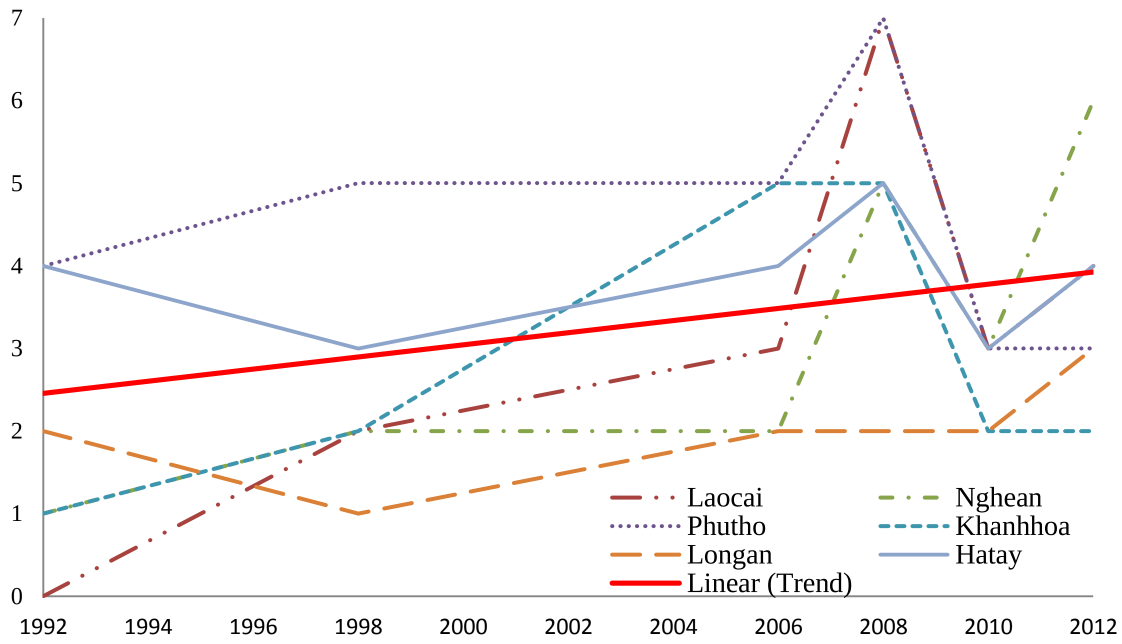


Figure 4.5 The trend of number of moderate and severe droughts at the study sites (1992-2012)

Source: Author's calculation based on data from the Vietnam National Centre for Hydro-Meteorological Forecasting

4.3.2 Agricultural production

Despite the country's rapid economic development, agriculture still plays a key role in the Vietnamese economy, accounting for 22% of the Gross Domestic Product and 54% of the labour force (GSO, 2014). Since 1986, following the *Renovation Policy*, Vietnam has shifted from a centrally planned economy where the State took control of agricultural production to a socialist-orientated market economy where the individual farm is a key decision-making unit (Marsh et al., 2006).[15] This structural transition has allowed farmers flexibility to alter their production systems to follow market signals and better deal with changes in the production environment.

[15] The "*Renovation Policy*" or "*Doi Moi*" in Vietnam was introduced in 1986 with a broad range of policy measures to shift from a centrally planned economy to a market-oriented one. In the agricultural sector, the policy facilitated the growth of the private, household economy and agribusiness.

In the agricultural sector, crop production is still dominated by rice as a major cash crop, using 39.8% of the total agricultural land (GSO, 2014). Rice farmers are typically smallholders and their livelihoods depend heavily on agriculture as the predominant source of income. However, agricultural production, especially rice cultivation, is inherently vulnerable to climate change due to very large acreage under rice across all regions in Vietnam, so that diversification is difficult. In addition, the technique of growing rice as a typical broad acre crop renders it directly exposed to climatic conditions.

4.3.3 Adapting to changing environmental conditions

Changing climatic conditions in Vietnam are likely to be especially damaging for rice cultivation, given its exposure to shifts in temperature and precipitation. Vietnamese farmers are applying a broad range of strategies that allow them to adapt to changing production conditions. The most common adaptation practices include diversification of crops and income sources, adjustment of various farm management practices, and adoption of soil and water conservation techniques when it comes to climate change.

In reality, as climatic change occurs gradually, farm adjustments to that phenomenon are largely unnoticed, the so-called autonomous adaptation (Feenstra et al., 1998; Smit and Skinner, 2002; Smit and Wandel, 2006). However, as discussed earlier, the climatic conditions in our study areas have changed considerably in terms of increased average temperature and an increase in the rate and magnitude of droughts. As a result, it is expected that some specific adaptation practices would have been adopted to mitigate the adverse impact of climate risks (Feenstra et al., 1998). In the study areas, farmers have been observed using rock bunds, soil bunds, terraces and grass lines as conservation measures.[16] Visual descriptions of these methods are detailed in

[16] These soil and water conservation techniques were also introduced by FAO in published technical manuals. These manuals briefly present the theoretical background and benefits of these techniques and also discuss their application at the farm level.

Appendix 4A. Applying these soil and water conservation practices is a key adaptation method to maintain soil moisture, alleviate the growing water-shortages and worsening soil conditions, and mitigate the negative impacts of higher temperatures and lower rainfall (Kurukulasuriya and Rosenthal, 2003). Rock and soil bunds are typically built to control surface runoff and harvest rainwater to mitigate the impact of soil erosion and increase soil moisture. Other techniques, such as building grass lines and terraces, have also been widely applied in these areas. These adaptation practices often require substantial inputs such as building materials and labour.

4.4 Conceptual framework

To examine the dynamic patterns of Vietnamese farmers' decision-making process, a dynamic discrete choice model of adaptation practices, controlling for unobserved heterogeneity and state dependence was constructed. Unobserved heterogeneity refers to those unobservable factors such as farmers' management ability, household wealth and attitude towards adoption of conservation techniques. These factors may influence the decision-making process of an individual farmer. Panel data analysis allows us to control adequately for time-invariant unobserved heterogeneity. In this study, a farmer's decision to use soil and water conservation techniques as adaptation practices is modelled as a binary choice: adoption ($y = 1$) or non-adoption ($y = 0$).

Discrete choice models are based on the random utility framework (Greene, 2003; McFadden, 1980). This framework has been used frequently in technology adoption in general, and in studies on adoption of conservation practices as a part of the response to more profound impacts of climate-related changes in particular (Lambert et al., 2007; Sietz and Van Dijk, 2015).

The model is based on the notion that the i^{th} farmer faces a pair of choices: adoption (*j*) or non-adoption (*k*); and the utility associated with the two choices follows the underlying random utility function:

$$U_{ij} = v(\mathbf{X}_{ij}, \boldsymbol{\beta}_j) + \varepsilon_{ij} \qquad (4.1)$$

$$U_{ik} = v(\mathbf{X}_{ik}, \boldsymbol{\beta}_k) + \varepsilon_{ik} \qquad \textit{for } i = 1, \ldots, N, \qquad (4.2)$$

where $v(\mathbf{X}_i, \boldsymbol{\beta})$ is a deterministic term, which is dependent on the explanatory variables X_i, and an unknown vector of parameters β to be estimated, and ε_i is a random error term. The random utility model hypothesises that a farmer will decide to adopt an adaptation practice if the use of that measure provides greater utility than not adopting it. If the farmer is observed to make choice *j*, then it can be assumed that the farmer perceives that choice as having higher utility than the alternative choice. An indicator function can be used with a value of 1 if $U_{ij} > U_{ik}$ and value of 0 if $U_{ij} \leq U_{ik}$ (Greene, 2003), denoted by:

$$Y_i = \begin{cases} 1 \; if \;\; U_{ij} > U_{ik} \\ 0 \;\; if \;\; U_{ij} \leq U_{ik} \end{cases} \qquad (4.3)$$

Then, the probability that *j* will be chosen satisfies:

$$\begin{aligned} \Pr[Y = 1] &= Pr[U_{ij} > \; U_{ik}] \\ &= \; Pr[(v(\mathbf{X}_{ij}, \boldsymbol{\beta}_j) + \varepsilon_{ij}) \; - \; (v(\mathbf{X}_{ik}, \boldsymbol{\beta}_k) + \varepsilon_{ik}) \; > \; 0] \\ &= \; Pr[X'\beta \; + \; \varepsilon > \; 0], \qquad (4.4) \end{aligned}$$

where the term $X'\beta$ collects all the observable information about the difference between the two utility functions, and ε denotes the difference between the two random errors (i.e. the unobserved factors).

In the probit model, ε_i is assumed to have a standard normal distribution and requires being independently and normally distributed. Estimation of the binary probit model is usually based on the method of maximum likelihood where each observation is treated as a single draw ($Y_1 = y_1$, $Y_2 = y_2 \ldots$, $Y_n = y_n$) from a Bernoulli distribution (Greene, 2003). Then, the likelihood function to be used in the estimation of the parameters is expressed as:

$$Pr\left(Y_1 = y_1,\ Y_2 = y_2 \ldots,\ Y_n = y_n \mid X\right) = \prod_{yi=0}[1 - F(X'_i\,\beta)]\prod_{yi=1} F(X'_i\,\beta) \qquad (4.5)$$

4.5 Empirical model and data

4.5.1 Empirical model

Following the approach of Wooldridge (2005), and Skrondal and Rabe-Hesketh (2014), we specify a dynamic random-effects probit model, as follows:

$$Pr(y_{it} = 1 \mid y_{it-1}, x_{it}, z_{it}, \varepsilon_{it}) = \beta x_{it} + \gamma z_{it} + \rho y_{it-1} + \mu_i + \varepsilon_{it} \qquad (4.6)$$

$$t = 1,2,\ldots..6; \quad i = 1,2,\ldots.N,$$

where y_{it-1}: lagged choice variable y_{it}; ρ is the state dependence parameter; x_{it}: a vector of explanatory variables including climatic variables such as SPI45, drought, and temperature; z_{it}: a vector of control variables such as farm-level specific characteristics and socio-economic drivers; and μ_i: an unobserved individual-specific effect, which captures the unobserved heterogeneity. To take into account the unobserved effects, the composite error term was decomposed into the individual-specific time-invariant μ_i term, and $\varepsilon_{it} \sim N(0, \sigma_u^2)$.

Equation (4.6) can be alternatively written as a latent response formulation:

$$y^*_{it} = \beta x_{it} + \gamma z_{it} + \rho y_{it-1} + \mu_i + \varepsilon_{it} \qquad (4.7)$$

where, ε_{it} is assumed to be independently and identically distributed over time and the observed binary choice of adoption or not of climate adaptation techniques y_{it} is:

$$y_{it} = \begin{cases} 1 & if \quad y*_{it} > 0 \\ 0 & if \quad y*_{it} \leq 0 \end{cases} \qquad (4.8)$$

It is often noted that the initial choice to adopt agricultural practices may influence farmer's subsequent decision, which is referred to as state dependence.

A standard approach to handling longitudinal dependence is to use a model where binary responses y_{it} are regressed on lagged responses y_{it-1} (Skrondal and Rabe-Hesketh, 2014). However, in the presence of unobserved heterogeneity, estimation is inconsistent due to an issue known as the 'initial condition problem' (Heckman, 1981). The root of that problem lies in the potential correlation between the initial dependent variable y_{i0} (the first observation for the dependent variable) and the unobserved effects μ_i in the estimated model. If the initial condition problem is ignored, uncorrected heterogeneity not only leads to an overstatement of the state dependence effect, but could also lead to an understatement of the impact of other factors influencing the decision-making process (Heckman, 1981; Moser and Barrett, 2006; Nolan, 2010).

It could be assumed that unobserved heterogeneity μ_i is independent of the explanatory variables; but that assumption would be perhaps too strong since some correlation may exist between observable and unobservable characteristics of a household. For instance, a farmer's unobservable ability in farm management or risk preference may correlate with a farmer's observable age and education level. Mundlak (1978) proposes an approach to relax this assumption by allowing for correlated random effects, and this method has been further developed by Wooldridge (2005) and Skrondal and Rabe-Hesketh (2014). Wooldridge's estimator shows a computational advantage in comparison with other estimators developed by Heckman (1981) and Orme (2001). However, Skrondal and Rabe-Hesketh (2014) suggest that the initial values of all explanatory variables should be added to the model to avoid estimation bias, especially for a panel with a limited number of survey rounds, as in our case. Further, any misspecification in a dynamic random-effects probit model will result in biased parameters that potentially overstate or understate the effect of regressors (Heckman, 1981; Panos, 2008). Therefore, to allow for correlated effects, state dependence and initial conditions, the conditional approach of Skrondal and Rabe-Hesketh (2014) was applied to parameterise the individual/household effects μ_i by way of the following auxiliary regression:

$$\mu_i = \alpha_{y0} y_{i0} + \alpha_{x0} x_{i0} + \alpha_{z0} z_{i0} + \alpha_{\bar{x}} \bar{x}_i + \alpha_{\bar{z}} \bar{z}_i + u_i \qquad (4.9)$$

where y_{i0} is the initial condition (i.e. the first observation for the dependent variable); $\bar{x}_i$, $\bar{z}_i$: vector of within-individual/household means for the time-varying independent variables x_{it} and z_{it}; x_{i0}, z_{i0}: the initial conditions of x_{it} and z_{it}.

Thus, following Skrondal and Rabe-Hesketh (2014), Equation 4.7 can be specified as a latent variable model to be estimated as:

$$y^*_{it} = \beta x_{it} + \gamma z_{it} + \rho y_{it-1} + \alpha_{y0} y_{i0} + \alpha_{x0} x_{i0} + \alpha_{z0} z_{i0} + \alpha_{\bar{x}} \bar{x}_i + \alpha_{\bar{z}} \bar{z}_i + u_i + \varepsilon_{it} \qquad (4.10)$$

This is a dynamic random-effects model, controlling for unobserved heterogeneity, state dependence and correlated initial conditions. The estimated results of the three specifications of the empirical model were presented: a pooled model, Wooldridge's estimator (2005) and Skrondal and Rabe-Hesketh (2014) estimator. The primary distinction between the Wooldridge (2005) and Skrondal and Rabe-Hesketh (2014) estimators is that Skrondal and Rabe-Hesketh add initial conditions of all explanatory variables to the model and use a contiguous sequence of data on the dependent variable, whereas Wooldridge does not. Starting with the pooled model, and moving to the Wooldridge (2005) and Skrondal and Rabe-Hesketh (2014) estimators, each of those estimators has a more complex specification than the previous. This raises caution about the predictive power and the estimation consistency across models and estimators. Therefore, while Skrondal and Rabe-Hesketh's (2014) approach was used in estimation, a pooled model specification (Equation 4.11) and the Wooldridge (2005) (Equation 4.12) were also reported specification for comparison purposes.

$$y_{it} = \beta x_{it} + \gamma z_{it} + \rho y_{it-1} + \varepsilon_{it} \qquad (4.11)$$

$$y_{it} = \beta x_{it} + \gamma z_{it} + \rho y_{it-1} + \alpha_{y0} y_{i0} + \alpha_{\bar{x}} \bar{x}_i + \alpha_{\bar{z}} \bar{z}_i + u_i + \varepsilon_{it} \qquad (4.12)$$

4.5.2 Data

Household data

The study uses the same dataset that was used in Chapter 2, which is a rich longitudinal dataset from a nationally representative sample of households from six provinces (Ha Tay, Lao Cai, Phu Tho, Nghe An, Khanh Hoa and Long An) across various agro-ecological regions of Vietnam. That panel dataset was created by combining data from two separate national representative surveys, the Vietnam Living Standard Survey (VLSS 1992-1993, 1997-1998) and the Vietnam Access to Resources Household Survey (VARHS 2006, 2008, 2010, 2012). The procedure to create the panel dataset used in this study can be found in Section 2.4.1 in Chapter 2.

Weather and climate data

As a common practice in studies of adaptation to climate change, Baez et al. (2013) suggest that it is necessary to recognise two distinct phenomena associated with changing climatic conditions: 'shocks' and 'shifts'. Shocks are referred to as weather variability and intensity and severity of extreme events such as floods, droughts and typhoons while shifts in climate are represented by gradual changes in rainfall and temperature patterns over long time periods (Baez et al., 2013). In this study, the impacts of both 'shocks' and 'shifts' on farmers' adaptation behaviour were taken into account with a particular focus on drought conditions since drought directly affects the ability to maintain soil moisture. In this study, climatic shocks refer to the number of moderate and severe droughts that each household experienced in the last two years prior to the time of the survey, and the magnitude of the SPI. Changes in temperature were represented by Growing Degree-Days (GDDs) during the rice growing season of the corresponding survey year.

The dataset of daily rainfall and temperature over 38 years (1975-2012) at 22 weather stations from the Vietnam National Centre for Hydro-Meteorological Forecasting was used to construct climate variables. These variables were constructed based on data from the weather station nearest to the surveyed household. Given the wide spatial distribution of surveyed farm households across different agro-ecological zones, and the relatively long time series of observed weather data over the study period, it is possible to capture both cross-sectional and temporal variations of climate-related variables in this study (Figures 4.1, 4.2, 4.4 and 4.5). The conventional approach to include climate variables is to simply take a monthly or annual average of temperature or rainfall over the study period. However, agronomic studies have shown that the growth and development of plants are firmly related to the accumulation of heat and precipitation within certain thresholds during their growing season (Deschenes and Greenstone, 2007). In addition, the development of plants does not occur if the temperature at a given time is below a minimum threshold value (i.e. 8^0C for rice). Deschenes and Greenstone (2007) also argue that this method is better for evaluating the impact of climatic change and variability in the agricultural sector. Consequently, this approach was applied to generate climatic variables regarding the absorbent threshold that is suitable for plants to grow, which is 8^0C – 30^0C for rice (Steduto et al., 2009).

For climatic variables, GDDs represent the cumulative heat to which the rice crop was exposed within the upper and lower absorbent threshold during the entire growing season (McMaster and Wilhelm, 1997). Using daily data on temperature for the relevant survey year from the weather station closest to the surveyed farm, daily GDDs for rice were calculated during the growing season, which varies from 1 February to 30 December across various regions in Vietnam.[17] The cumulative GDDs are the sum of all daily GDDs that have occurred from the start to the end date of the rice growing season.

For climatic shock variables, Thomas et al. (2010) recommend that an effective way to determine whether a household has been affected by extreme weather is to ask them directly because respondents know exactly what natural disasters have happened in their area. However, a drawback of the approach is that households are unable to differentiate precisely the level of intensity and severity of each extreme event. To overcome that limitation, the Standardised Precipitation Index (SPI) developed by McKee et al. (1993) which can capture the variability, magnitude and duration of droughts was applied.[18] The index was designed to quantify the precipitation deficit for multiple timescales using long-run observed precipitation data (Svoboda et al., 2012). Positive values of SPI indicate greater than median rainfall, and negative values indicate less than median precipitation, or deficit, during the relevant period. Based on observed data of the weather stations located near farming households, a household-specific variable labelled SPI45 was created to capture the value of SPI in April and May of the previous year. This was justified based on the growth stages of rice, where reproductive and ripening stages take place during these months, and the rice crop is most sensitive to weather conditions, especially droughts during that period (Sridevi and Chellamuthu, 2015). A variable labelled 'drought' was also created to capture the intensity of the drought event using the number of moderate and severe droughts (defined by SPI < -1.00) experienced by households in the last two years of the corresponding survey round.

Furthermore, climate normals were defined as 30-year averages of temperature. In this study, climate normals of temperature are calculated using the long-run average of GDDs

[17] The formula used to calculate GDDs is provided in Appendix 4B.
[18] The SPI was calculated using the SPI software by the National Drought Mitigation Centre. More information is provided in Appendix 4B.

(AGDDs) between 1975 and a year before the relevant survey year. Rainfall-related variables were excluded from regression analysis due to the possibility of potential simultaneity between these covariates and the SPI, which is calculated using rainfall data.

4.6 Results and discussion

4.6.1 Results of descriptive analysis

Farmers' decision to apply soil and water conservation techniques (i.e. rock bunds, soil bunds, grass lines and terraces) as a climate change adaptation measure is modelled as a dichotomous outcome. In this study, farmers were classified as adopters if they applied any of the conservation techniques mentioned earlier. The dynamics of the aggregate adoption decision for the period 1992 to 2012 are presented in Figure 4.6.

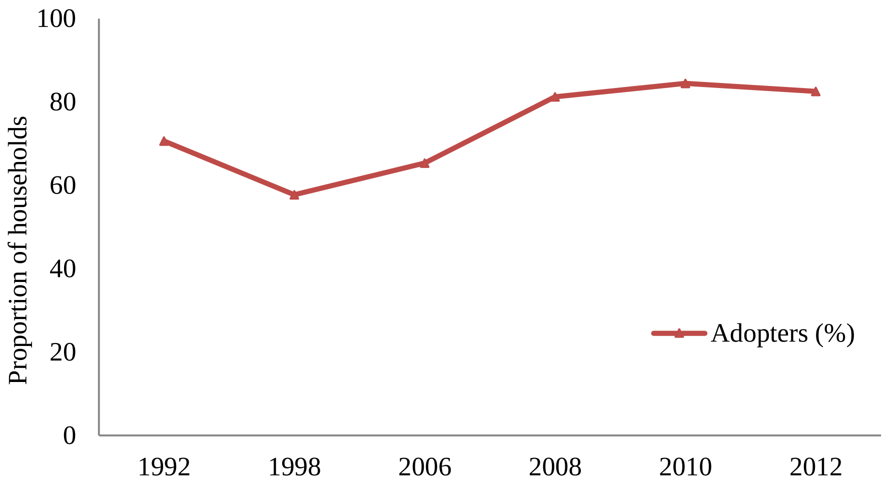


Figure 4.6 Percentage of households that adopted some of the soil and water conservation techniques (1992-2012)

As the main objective of this study is to investigate factors behind farmers' choice to adopt agricultural practices that aid adaptation to climate change, the potential effect of climatic change on production decisions was addressed by incorporating various variables representing weather and climate risks. To do so, weather shocks, climate variability and climatic change were simultaneously differentiated. In this context, weather shock is defined as SPI < -1.00 based on data from the weather station closest to the surveyed farm, which refers to the number of moderate and severe droughts that each household experienced in the last two years. Climate variability is captured by the value of SPI in April and May of the previous year, during the reproductive and ripening stages of rice. These household-specific climatic variables are calculated using data from weather stations located near the farming households. The application of conservation techniques directly links to drought conditions in the way of conserving moisture, facilitating nitrogen-fixation and increasing the soil-carbon content, leading to mitigation of the adverse impacts of climatic change (Khonje et al., 2015; Manda et al., 2016). Consequently, it is expected that if farmers observe increased climatic variability and climatic change over the years, they would be more likely to adopt soil and water conservation techniques.

In addition, other factors that may influence the decision-making process of individual farmers were controlled for. Several covariates were selected for household and farm characteristics (e.g. household head experience, farm size, access to information) and information on input and output markets. The selection is based on a literature review of previous technology adoption in agriculture (Doss, 2006; Sietz and Van Dijk, 2015).

Household and farm characteristics were first controlled for by using variables that best describe the features of the farms. The experience of the household head is believed to be positively associated with technology adoption. Evidence from various sources indicates that there is a positive relationship between the number of years of experience in agriculture and the adoption of improved agricultural technologies. Moreover, Deressa et al. (2009) and Piya et al.

(2013) confirm that access to weather information and information about new techniques could facilitate the adaptation process to climatic variations and change. Information such as new agricultural practices, short-term forecasts and seasonal forecasts may be available to farmers through radio, television and extension agents. It is regularly hypothesised that access to credit eases the cash constraints of smallholders and allows them to invest more in farm production and management (Knowler and Bradshaw, 2007). In addition to household characteristics, studies on adoption of conservation measures also pay attention to the biophysical features of the farm. As farm size is found to influence adaptation positively or negatively (Maddison, 2007; Piya et al., 2013), the overall impact of farm size on adoption is inconclusive (Knowler and Bradshaw, 2007).

We also control for commune-level input and output market information through labour and farm-gate average price variables. A set of year-specific dummy variables is also included in the model to capture inter-temporal changes, spatial heterogeneity and policy variability, which are unobservable in the data.

Table 4.1 presents the descriptive statistics for the variables used in the study. The dataset covers a broad range of variables that may affect the decision-making process of farmers. Explanatory variables include all factors representing extreme events, climate variability and change. The descriptive analysis shows a slight difference in the means of all variables of interest between adopters and non-adopters, and it is even more noticeable when considering the descriptive statistics across years provided in Appendix 4D. Table 4.1 shows that adopters have greater farm size, produce more output, and have longer experience in farming; they also more often access weather information, and on average receive a higher farm-gate price compared to non-adopters.

Table 4.1 Description of outcome, explanatory and control variables

Variable	Description	Level of observation	Full sample Mean	Full sample Std. Dev.	Adopters Mean	Adopters Std. Dev.	Non-adopters Mean	Non-adopters Std. Dev.
Outcome variable								
Soil and water conservation	Household applied soil and water conservation techniques (yes=1)	Households and years	0.72	0.45	1.0		0.0	
Explanatory variables								
Extreme events, climate variability and change								
SPI45 $_{(t-1)}$	Value of SPI in April and May of the previous year	Households and years	-0.41	0.77	-0.57	0.76	-0.38	0.67
Drought	Number of moderate and severe drought in the last 2 years	Households and years	1.00	1.76	1.01	3.2	0.88	2.38
GDDs	Growing degree-days: Cumulative warmth during the growing season of rice (^{0}C)	Households and years	4415.7	425.7	4364.7	412.8	4448.3	442.6
AGDDs	Average of GDDs between 1975 and a year before relevant census year (^{0}C)	Households and years	4056.5	500.3	4018.3	464.1	4076.3	551.6
Control variables								
Soil and water conservation $_{(t-1)}$	Lag outcome variable	Households and years	0.43	0.49	1.0		0.0	
Household and farm characteristics								
Household size	Number of family members	Households and years	4.67	0.49	4.72	1.71	4.56	1.74
Credit	Access to credit	Households and years	0.59	0.49	0.61	0.48	0.58	0.49
Experience	Experience of household head in rice cultivation (years)	Households and years	13.27	5.83	13.62	5.79	12.06	6.6
Farm size	Farmland operated by household (m^2)	Households and years	4053.3	8400.6	4255.9	9421.3	4089.9	7210.7
Information	Access to information on weather and climate change (yes=1)	Households and years	0.44	0.5	0.52	0.5	0.44	0.5
Input and output information								
Labour wages $_{(t-1)}$	Average regional labour wages in previous season (1000VND/day)*	Regions and years	62.92	49.79	62.53	55.04	42.66	41.93
Farm-gate price $_{(t-1)}$	Average regional retail price of rice in previous season (1000VND/kg)*	Regions and years	3.29	3.52	3.32	3.94	2.15	1.49

*Note: *VND, Vietnamese Dong (approximately 16.015 VND/$U.S. averaged over 1992 to 2012)*

In dynamic modelling, it is crucial to properly handle missing data of the response variable in any particular round of the survey during the study period. Since descriptive statistics ignore missing observations of the decision-making outcome, the nature of the data was described by investigating the patterns of the missing data on the dependent variable of interest, which is farmers' decisions to adopt conservation technologies.

Table 4.2 Patterns of missing data for adoption decision of conservation practices in household data

Frequency	%	Cumulative	Pattern
108	34.18	34.18	111111
86	27.22	61.39	111..1
52	16.46	77.85	111.11
23	7.28	85.13	111...
23	7.28	92.41	1111.1
7	2.22	94.62	1111..
6	1.90	96.52	11111.
4	1.27	97.78	111.1.
2	0.63	98.42	1..111
5	1.58	100	(others)
316		100	xxxxxx

Notes: 1 denotes non-missing and dot (.) denotes missing

In Table 4.2, '1' denotes non-missing and a dot (.) denotes the missing value of the response variable in any of the six waves of the surveys. For example, a pattern '111111' indicates that 34.18% of the 316 observations in the 'linked' dataset have full responses on the adoption decision for all six waves of the surveys (see Section 2.4.1 in Chapter 2 for details to create the 'linked' dataset). Similarly, '111..1' indicates that there are missing data on the response variable in the fourth and fifth waves of the surveys. As suggested by Skrondal and Rabe-Hesketh (2014), in the dynamic modelling of farmers' choice with concerns about initial conditions, it is critical to focus on observations that have at least two consecutive non-missing values across surveyed periods. These observations will contribute to the analysis of the dynamic random-effects probit model if the status of the previous adoption decision is required. The missing patterns also help decide the values of the initial conditions imposed on outcome variables. Skrondal and Rabe-Hesketh (2014) suggest that observations that are preceded and succeeded by missing data should not be used.

4.6.2 Estimation of the dynamic adoption model

To investigate factors behind smallholders' decision-making process for adoption of soil and water conservation technologies, and specifically in the effects of climate related factors, a dynamic model of discrete choice of adopting conservation practices, controlling for unobserved heterogeneity and state dependence was estimated.[19] Table 4.3 below presents the estimation results from a dynamic random-effects probit model for the probability of adoption using the Skrondal and Rabe-Hesketh (2014) estimator. The independent variables contain all variables listed in Table 4.1 plus year fixed effects. To address the initial condition problem as suggested by Wooldridge (2005) and Skrondal and Rabe-Hesketh (2014), means of time-varying variables and variables representing the initial conditions over time were included. For comparison purpose, the pooled probit estimates are also reported in the same table which allows us to assess the explanatory power of the dynamic random-effects model.

[19] All models were estimated by Stata 14.0 with xtprobit, meprobit, and margins functions. The number of integration points for meprobit function is sensitive for achieving convergence. The more integration points, the more accurate the approximation to the log likelihood is. After several trials, we ended up with 133 integration points, which produced a robust estimation.
We also re-estimated these models using GLLAMM, a user-written program developed by Rabe-Hesketh, which provided identical results.

Table 4.3 The decision to adopt soil and water conservation techniques: a dynamic random-effects probit model

	Pooled probit model	Dynamic probit model
Explanatory variables		
SPI45 $_{(t-1)}$	0.11632	0.11303*
	(0.0682)	(0.0495)
Drought	0.03042	.05143*
	(0.0237)	(0.0211)
GDDs	-0.00046*	-0.00038
	(0.0002)	(0.0003)
AGDDs	0.00005	0.00440***
	(0.0001)	(0.0010)
Control variables		
Conservation techniques $_{(t-1)}$	0.16887	0.14199**
	(0.0895)	(0.0579)
Household size	0.00237	-0.00602
	(0.0263)	(0.0195)
Credit	-0.05573	-0.12623
	(0.0904)	(0.1010)
Information	0.27660**	0.38017***
	(0.1018)	(0.1067)
Experience	0.02047**	0.02212**
	(0.0074)	(0.0111)
Farm size	0.00000	0.00002*
	(0.0000)	(0.0000)
Labour wages $_{(t-1)}$	0.00096	-0.00146
	(0.0024)	(0.0052)
Farm-gate price $_{(t-1)}$	0.06862	0.14014**
	(0.0430)	(0.0437)
Constant	1.70047*	2.91725***
	(0.6639)	(0.8219)
Year dummy	Yes	Yes
Contiguous sequence	Yes	Yes
Initial condition	No	Yes
Within-household means	No	Yes
Log likelihood	-594.529	-616.965

*Notes: 1. Standard errors are presented in parentheses 2. *, **, *** Significant at 10%, 5%, 1% level*

For the estimated parameters, the signs of the coefficients are particularly informative. A positive (negative) sign means that any increase in the independent variable is associated with an increase (decline) in the probability of adoption of soil and water conservation technologies.

In the presence of unobserved heterogeneity, estimation is inconsistent due to an issue known as the "initial condition problem" owning to the simultaneous presence of both the lagged dependent variable and unobserved effects (Heckman, 1981). This can violate the strict exogeneity assumption, which can result in an overstatement of the state dependence effect and at the same time an understatement of the impact of other factors influencing the decision-making process (Heckman, 1981; Moser and Barrett, 2006; Nolan, 2010). In this study, it is found that the estimated results are consistent with many previous empirical studies because comparing the two specified models, the pooled probit estimates overestimate the impact of the previous adoption decision and underestimate the effects of the other independent variables (Arulampalam and Stewart, 2009; Heckman, 1981; Moser and Barrett, 2006; Stewart, 2007). The result is reinforced when marginal effects of the models were analysed in the next step. The dynamic model allowing unobserved effects also presents a substantial advantage regarding the explanatory power with the greater statistical significance of independent covariates.

There is statistically significant evidence of the effect of climatic variability and change on farmers' behaviour. More specifically, the decision to adopt adaptation measures is strongly affected by weather shocks (e.g. severity and intensity of drought), and long-run changes in temperature during the rice growing season; and their effects are found to be statistically significant. Farms experiencing more extreme droughts in the last two years and a lower SPI show a greater propensity to adopt these conservation technologies. In Vietnam, natural disasters such as droughts, floods and tropical cyclones often cause considerable damage to the agricultural production system, including soil and water conservation structures (Chau et al., 2013; Phong et al., 2010). Thomas et al. (2010) and Yu et al. (2013), using a similar dataset as ours, also point out that droughts lead to a decrease in farm productivity. As a consequence, experiencing these climate-related shocks encourages farmers to invest in conservation practices to protect their farmland and increase farm productivity. Hence, our results show that frequency of droughts and a low SPI likely encourage farmers to adopt soil and water conservation practices due to their benefits of protecting water sources, soil moisture and general soil improvement given that climate change has already been observed in these areas. The result is consistent with our expectations, and with results from other empirical studies (Adger, 1999; Ding et al., 2009; Zilberman et al., 2011).

In addition, since the study takes into account both the temporal trend in climatic change, i.e. the increasing average GDDs over 30 years, and the cross-sectional variation of household exposure to the changing climate at different study sites, we find that households with greater exposure to long-term warming and increasing number of extreme events tend to be associated with higher likelihood of adopting soil and water conservation techniques. Because there is a noticeable increase in annual temperature and greater variations in rainfall over time in many parts of Vietnam, applying these measures alleviates water shortages and soil degradation, and mitigates the adverse effects of the changing climate.

For the control variables, we can say that there is state dependence in farmers' decision to adopt soil and water conservation techniques over time. Farmers who applied conservation practices at time *t-1* show considerable tendency to reapply those practices at time *t*. Households' initial choice positively influences their current adoption decision.

It is also evident that farm characteristics, such as farm size, household head's experience and access to meteorological information are also associated with households that have decided to apply soil and water conservation. Access to weather information such as rainfall and temperature forecasts has a positive and significant effect on the likelihood of implementing these conservation techniques, which can be explained by the enhancements of farmers' capacity and preparedness to cope with changing production conditions through ongoing updates of weather information (Sietz and Van Dijk, 2015; Tambo and Abdoulaye, 2012). As expected, the probability of adoption increases significantly with farmers' experience in agricultural production, which reflects the important role of the household head as a decision-maker in the application of these techniques. Our findings are in line with many previous studies (Bryan et al., 2009; Kassie et al., 2013; Marenya and Barrett, 2007).

However, household size and access to credit have no statistically significant effect on current adoption of soil and water conservation technologies. Due to the importance of institutional support in promoting adaptation strategies, especially for the case of small-scale producers with budget constraints, access to credit should facilitate the decision to apply conservation techniques. Moreover, although family members manually implement most of these practices on their farms, there is no evidence of any relationship between larger household size and the application of various adaptation strategies.

In addition, input and output market information through regional labour and farm-gate average prices were controlled for. The estimated results indicate that farm-gate price of rice contributes to the decision to adopt conservation technologies, which reflects farmers' expectation of higher output price when they observe an increase in the farm-gate price of rice in the previous year. In this case, they are willing to respond to that increase by investing more in their farmland to boost the output. The important role of input and output market prices in farmers' decision-making process of technology adoption has been well-recognised in the literature (Adesina and Zinnah, 1993; Below et al., 2012; Feder et al., 1985; Shiferaw et al., 2013). By accounting for the effects of farm and household characteristics, access to credit and meteorological information, and information on input and output prices, it is possible to isolate the effects of climate change and also find statistical evidence of those effects on farmers' behaviour in using adaptation practices to cope with the changing climatic conditions.

In general, the dynamic specification, controlling for state dependence, unobserved heterogeneity and initial conditions, results in significant improvements in the explanatory power of the dynamic model in comparison to the pooled model. It is evident that the dynamic model provides a better understanding of farmers' decision-making process and its drivers. It helps inform practitioners and policy-makers in their policy-making activities to facilitate climate-resilient strategies to improve smallholders' adaptive capacity under ongoing climatic uncertainty.

4.6.3 Robustness checks

To assess the robustness of the dynamic model and the Skrondal and Rabe-Hesketh estimator, the following was performed:

(1) Separate and estimate two different sets of data: one set with all available data on the dependent variable, and another set with only the data where there is a contiguous sequence on the dependent variable. The latter includes observations with at least two consecutive non-missing responses on adoption decision for all six waves of survey rounds. These observations will contribute to our dynamic probit model because the status of the previous adoption decision is required. Skrondal and Rabe-Hesketh (2014) suggest using only observations with at least two consecutive non-missing values of the dependent variable to achieve higher estimation consistency.

(2) For each set defined in (1), re-estimate the pooled probit model and Skrondal and Rabe-Hesketh estimator; add and estimate a new estimator (Wooldridge's estimator) for comparison purposes.

(3) Estimate and report average marginal effects (AME) making it comparable across all models. In the probit model, the sign of the coefficients expresses the direction of the effects of the independent variables on the predicted probability. However, the magnitudes of those coefficients are not directly comparable across models (Wooldridge, 2010). Wooldridge (2010) suggests that estimating AME is sufficient for overcoming this limitation and it may also increase the estimation efficiency across models. The AME measures the expected change in the predicted probability of the dependent variable with respect to a unit change in the independent covariates. The estimation results of the AME are reported in Table 4.4.

Moving from the pooled probit model to the Wooldridge (2005) and to the Skrondal and Rabe-Hesketh (2014) estimators, consistent results were confirmed compared to the estimated coefficients reported in Table 4.3. More specifically, the dynamic specifications (models 2, 3, 5 and 6 in Table 4.4) considerably increase the explanatory power of the models. Controlling for unobserved heterogeneity and initial conditions in the dynamic models reduces the magnitude of the effect of state dependence and generally increases the magnitude of the impacts of independent variables on the probability of adoption. Comparing the two sampling approaches in Table 4.4 (models 1, 2 and 3 to models 4, 5 and 6), it is also obvious that the approach suggested by Skrondal and Rabe-Hesketh (2014) of only using the dependent variable with a contiguous sequence has some advantages in terms of explanatory power and magnitude of the marginal effects.

Table 4.4 Average marginal effects

	All available data of y			Only y with contiguous sequence		
Variables	Pooled probit (1)	Wooldridge estimator (2)	Skrondal & Rabe-Hesketh estimator (3)	Pooled probit (4)	Wooldridge estimator (5)	Skrondal & Rabe-Hesketh estimator (6)
Explanatory variables						
SPI45$_{(t-1)}$	.03990	.04220**	.04157**	.03712	.03425*	.03493**
	(.0209)	(.0139)	(.0147)	(.0221)	(.0165)	(.0151)
Drought	.00978	.01648**	.01528*	.00970	.01578*	.01399**
	(.0072)	(.0056)	(.0062)	(.0075)	(.0062)	(.0065)
GDDs	-.00014*	-.00010	-.00009	-.00014*	-.00013	-.00011
	(.00005)	(.0001)	(.0001)	(.00005)	(.0001)	(.0001)
AGDDs	.00001	.00106**	.00104**	.00001	.00136***	.00135***
	(.00003)	(.0003)	(.0003)	(.00004)	(.0003)	(.0003)
Control variables						
Conservation	.05033	.04936***	.04085***	.05318	.05006**	.04752***
techniques $_{(t-1)}$	(.0274)	(.0114)	(.0107)	(.0284)	(.0143)	(.0186)
Household size	-.00139	-.00763	-.00961	.00075	-.00016	-.00186
	(.0080)	(.0069)	(.0087)	(.0084)	(.0068)	(.0060)
Credit	-.01678	-.02670	-.02818	-.01779	-.03367	-.03901
	(.0282)	(.0384)	(.0398)	(.0288)	(.0298)	(.0312)
Experience	.00638**	.00795*	.00792*	.00653**	.00710*	.00683**
	(.0022)	(.0036)	(.0037)	(.0023)	(.0037)	(.0035)
Farm size	6.1e-07	4.2e-06	3.7e-06*	1.0e-06	5.2e-06	5.0e-06**
	(1.3e-6)	(2.9e-6)	(1.9e-6)	(1.3e-6)	(3.0e-6)	(2.1e-6)
Information	.07050*	.08550**	.08854**	.08829**	.11342***	.11750***
	(.0303)	(.0264)	(.0290)	(.0322)	(.0309)	(.0329)
Labour wages $_{(t-1)}$	.00047	-.00034	-.00033	.00030	-.00059	-.00045
	(.0005)	(.0007)	(.0006)	(.0007)	(.0016)	(.0015)
Farm-gate price $_{(t-1)}$	.02140	.03320*	.03519*	.02190	.04013***	.04331***
	(.0127)	(.0118)	(.0169)	(.0136)	(.0078)	(.0136)

Notes: 1. Standard errors are presented in parentheses *2. *, **, *** Significant at 10%, 5%, 1% level*

In the probit model, various kinds of misspecification such as heteroskedastic errors and omitted variables would lead to biased or inconsistent estimators (Yatchew and Griliches, 1985). In this study, it is suspected that correlations among variables and heteroskedastic disturbances may be present due to the significant variations in farm and farmer characteristics and also in their production capacities and farming strategies across different regions and over time. Therefore, several model diagnostics were conducted, including statistical tests for multicollinearity, heteroskedasticity and autocorrelation to avoid invalid conclusions.

To detect multicollinearity, two well-known indicators were used: Tolerance (i.e. correlations between variables) and Variance Inflation Factor – VIF (i.e. the level of estimated coefficient is being inflated by multicollinearity).[20] Our estimated results confirm a low level of multicollinearity in the models as the largest value of VIF is 5.33 (equivalent to a value of tolerance of 0.187) from variables of year fixed effects. After testing for heteroskedasticity, the results of the Breusch-Pagan test reject the underlying assumption of homoscedasticity in the estimation models.[21] Thus, robust standard errors were applied when regression models are estimated.

The potential inter-temporal correlation in the sample is also concerned. Therefore, a test for autocorrelation using Wooldridge's serial correlation test (Drukker, 2003; Wooldridge, 2015) was applied.[22] The test result does not reject the null hypothesis of no serial correlation at 1% significance level in our models. Consequently, it could be concluded that serially correlated error terms do not exist in our models.

[20] The indicators are calculated using Stata user-written program 'collin' from Philip B. Ender, UCLA Department of Education.
[21] We here apply Stata user-written program 'regcheck' from Mehmet Mehmetoglu, Norwegian University of Science and Technology.
[22] The Stata user-written program 'xtserial' of David M. Drukker, Stata Corporation, is used to test for autocorrelation in the data.

4.7 Concluding remarks and policy implications

The study is motivated by the ongoing changes in climatic conditions that impose detrimental effects on the agricultural sector, and on small-scale farmers' livelihood in many countries, including Vietnam. Our study assesses and compares factors associated with the decisions of rice farmers to adapt to climate change by implementing various soil and water conservation technologies.

The study employs a rich longitudinal dataset from a nationally representative sample of households in the Vietnam Living Standard Survey (VLSS) and the Vietnam Access to Resources Household Survey (VARHS) from 1992 to 2012. This 20-year panel data allows us to take advantage of the longitudinal dataset for dynamically modelling farmers' responses to climate variability and change. Since farmers' decisions to adapt to climate change are inherently dynamic, a dynamic random-effects probit model, controlling for unobserved heterogeneity and state dependence was estimated.

The results of the analysis reveal that there is statistically significant evidence of the effects of climate change on farmers' decision-making process. The decision to implement soil and water conservation practices is strongly influenced by weather shocks, drought intensity and long-run changes in temperature during the rice growing season. Thus, it is evident that Vietnamese farmers are constantly adapting to environmental changes to mitigate adverse impacts and increase their resilience to ongoing changes in the climate.

There is evidence of persistence in farmers' choice to implement soil and water conservation techniques over time. In addition, access to information on farm-gate price of rice and the weather forecast is associated with households that have decided to apply conservation techniques. Consequently, it is necessary to highlight the important role of providing meteorological and market information, and extension services on farm production and management to promote adaptation to ongoing climatic changes. Since small-scale farmers in

Vietnam face numerous constraints, it is likely to require more public investment in dissemination of climate-related and market information to farmers, as well as climate-resilient practices. In addition, farmers' experience and farm size also foster the application of these adaptation strategies in a changing production environment.

The dynamic model provides a better understanding of farmers' decision-making process and its drivers which is critical for practitioners and policy-makers to facilitate climate-resilient strategies to improve small-scale farmers' adaptive capacity under climatic uncertainty. However, there are important avenues for further research on the potential impact of adoption of conservation practices on rural households' welfare. Filling this gap could significantly increase our understanding of what factors drive farmers' decision to adopt and how this contributes to improving their overall well-being.

Chapter 5

Conclusion

5.1 Introduction

The primary goal of this research was to assess factors associated with agricultural technology changes in Vietnam and to model the decisions of rice farmers to apply adaptation strategies in response to changing production conditions, including pronounced evidence of climatic variability and change. The study focused on rice-cultivating households because agricultural production in Vietnam is still dominated by rice as a major cash crop, using 39.8% of the total agricultural land (GSO, 2014). Also, agricultural production, particularly rice cultivation, has been experiencing significant technological change over time, and is also inherently vulnerable to climate-related risks associated with variations in the production environment.

Three separate empirical studies were conducted. The first study examined the pattern and drivers behind agricultural technology changes by farming households. This study investigated agricultural technology change and its determinants at the farming household level using an extensive 20-year panel dataset of nationally representative surveys of Vietnam. Probabilistic record linkage methods were used to find the best-matched observations from the two original surveys (VARH and VLSS) in order to create a long panel dataset. Such a 20-year panel with six waves across different agro-ecological locations allowed us to examine agricultural technology changes at the farm level over a relatively long period. The two-stage estimation strategy provided an efficient way to determine how and to what extent the changes in agricultural practices (i.e. new seed varieties, chemical fertilisers, pesticides, and machinery) have been affected by various covariates, allowing for potential correlation among different technologies used by rice farmers.

The second study identified empirical evidence of climate change across Vietnam, as well as the potential effects on agricultural production. In this study, statistical methods with geostatistical techniques were combined to graphically represent the distribution of climate patterns, identifying variations and trends over time, and testing the statistical significance of those changes. Then, we compared the observed climate change with the spatial pattern of agricultural land use across Vietnam to identify the likely impacts of climate change on agricultural production. By using records of monthly precipitation and temperature for a relatively long-term period (1975 to 2014) over a high density of 112 meteorological stations across the country, robust visual and statistical evidence of climatic change throughout Vietnam were provided.

The third study then examined how farmers have altered their farming practices over time in response to the observed changes in climatic conditions. Since farmers' decisions to take up adaptation practices are inherently dynamic, a dynamic random-effects probit model, controlling for unobserved heterogeneity and state dependence was estimated. Using a relatively long panel dataset across different agro-ecological locations in Vietnam, it is possible to model farmers' choices over a relatively long period.

These studies gave a better understanding of the factors driving, and the constraints deterring, agricultural production over time in Vietnam to enhance smallholder farmers' adaptive capacity to cope with changing production conditions.

5.2 Key findings and policy implications

5.2.1 Agricultural technology change

The first study addressed two research questions: How has agricultural technology changed in the last 20 years in Vietnam? What factors have contributed to those technology changes over time?

Key conclusions that could be drawn from this study are:

(i) There have been significant changes in the pattern and determinants of agricultural practices applied by farmers across Vietnam, with notable contributions from improved seed varieties and the rapid spread of agricultural mechanisation.

(ii) The price of hired agricultural labour as an input and the price of rice, as well as macro-level socio-economic conditions such as the growing urban population and the increasing agricultural wages, were found to be the main factors driving both the decision to use agricultural practices and the intensity of their use across various agro-ecological regions of Vietnam.

(iii) However, the findings also showed a weak and uncertain spillover effect from some government policies aimed at improving access to credit and extension services on agricultural technology changes in the study area.

Policy implications

(i) It is regularly hypothesised that access to credit eases the cash constraints of smallholders and allows them to invest more in farm production and management. Lack of such access may prevent farmers from applying agricultural practices, in particular for practices that require high initial investment. In this study, the negative coefficients for access to credit are implausible although their effects on the level of technology use are not statistically significant. Thus, improving the efficiency of the credit market and the accessibility of smallholders to that market could be promising for the goal of promoting new agricultural technologies to improve farmers' wellbeing.

(ii) In addition, when considering the application of a set of technology components within an individual household as interrelated decisions, the multiple-equation models, such as Seemingly Unrelated Regression (SUR) are widely used in the literature (Smale et al., 1995). That is because the decisions to use several agricultural technologies are likely to be jointly made by an individual farming household. In that case, the SUR specification is relevant when it is able to capture the potential cross-correlation among different decisions which have been made by rice producers. In this study, using the SUR approach, there is evidence of cross-correlation between the decisions to use agricultural technologies through the very high statistical significance level of their co-variances. This confirmed our hypothesis of the simultaneous relationships among the use of agricultural practices within an individual farm. Thus, follow-up policy interventions need to account for the interrelationships in an individual smallholder's decision-making process to apply agricultural advances.

5.2.2 Empirical evidence of climate change

The second study addressed the following research questions: What is the empirical evidence of climate change across regions of Vietnam? What are the potential effects of those changes on the agricultural sector, particularly for rice production?

Key findings

(i) The analysis found evidence that climatic conditions are changing at different rates across regions of Vietnam. The study provided robust evidence, both geospatially and statistically, of the significant variations in the distribution patterns of rainfall and temperature. The visual analytics showed remarkable changes in the spatio-temporal distribution patterns of rainfall and temperature. The Mann-Kendall trend test confirmed the statistically significant long-term trends of over 40-year in most of the ‘hotspot’ areas identified by geostatistical mapping.

(ii) The significant changes in the long-term trends of climate variables were in areas with a very high proportion of agricultural land, particularly land used for rice production in the Red River and Mekong River deltas. This raises a growing concern over the adverse impacts of climatic risks particularly on agricultural production.

Policy implications

(i) Visual analytics used in mapping the distributions of precipitation and temperature can contribute significantly to analysing the precipitation and temperature series and identifying ‘hotspot’ areas across Vietnam. Rainfall anomalies demonstrated a dramatic heterogeneity in the distribution of precipitation change across regions. The spatio-temporal changes in temperature, however, showed a more uniform tendency characterised by a warming pattern across regions. Also, most areas with considerably pronounced precipitation and temperature pattern changes were also associated with statistically significant long-term trends verified by the Mann-Kendall test. These prominent patterns indicate that Vietnam is likely to face more variations in climatic conditions. The knowledge of spatio-temporal climate variability and change should be disseminated and transferred to stakeholders such as policy-makers, researchers, farmers and communities so the evidence can guide the decision-making process and implementation of effective adaptation responses to cope with a changing climate.

(ii) Findings from this study point out that significant changes in the pattern of rainfall were observed in some provinces with substantial areas of rice. It is also clear that most agricultural areas across the country are experiencing a warming pattern in climatic conditions, particularly the two largest rice production areas in the Red River and Mekong River deltas. More importantly, there is strong evidence of the influence of changes in temperature and rainfall patterns on crop yields, particularly yield reductions due to water scarcity in irrigated crops like rice (Nelson et al., 2009). Also, altered temperature and rainfall patterns are likely to be associated with increasing pests and plant diseases in rice-growing areas (Rosenzweig et al., 2001). Since adverse trends in rainfall and temperature patterns were identified in areas with a very high proportion of agricultural land, particularly for rice production, future policy interventions should also target those areas to mitigate the impacts of climate change and improve farmers' resilience to the changing climate.

5.2.3 Farmers' adaptation to climate change

The third study addressed the research questions: To what extent have farmers used soil and water conserving technologies as adaptation practices in response to changing climate conditions? What are the main drivers influencing farmers' decision-making process of applying certain adaptation practices to cope with climate change?

Key findings

(i) Farmers in the study areas have been constantly adapting to the changing climate by applying various agricultural adaptation practices. Weather shocks and long-run changes in temperature during the rice growing season are significant determinants of a rice farmer's choice to apply adaptation practices given that other factors that may affect farmers' behaviour are controlled.

(ii) In addition, there is evidence of persistence in farmers' adaptation behaviour over time because their decision to adopt conservation practices in subsequent periods is strongly influenced by their past adoption decision. Also, the dynamic specification, controlling for state dependence, unobserved heterogeneity and initial conditions, resulted in significant improvements in the explanatory power of the dynamic model in comparison to the pooled model. It is evident that the dynamic model provides a better understanding of farmers' decision-making process and its drivers.

Policy implications

(i) The application of conservation techniques directly links to drought conditions by conserving moisture, facilitating nitrogen-fixation, and increasing the soil-carbon content, leading to mitigation of the adverse impacts of climatic change (Khonje et al., 2015; Manda et al., 2016). Consequently, we expect that if farmers observe increased climatic variability and climatic change over the years, they would be more likely to adopt soil and water conservation techniques. As expected, findings from this study indicate that Vietnamese farming households have been adapting to changing climatic conditions, specifically the long-term warming and the increasing number of extreme events, by applying soil and water conservation practices. Thus, farmers' adoption of those conservation practices is highly correlated with climate variability and change. Therefore, it is necessary to facilitate climate-resilient strategies such as the use of soil and water conservation measures to improve farmers' adaptive capacity to cope with climatic uncertainty and mitigate its negative impacts.

(iii) Findings also reveal that access to information on farm-gate price of rice and the weather forecast is associated with households that have decided to apply conservation techniques. Consequently, it is necessary to highlight the important role of providing meteorological and market information to promote adaptation practices to cope with ongoing climatic changes.

5.3 Limitations and further research

Although this research provides important insights into farming in changing production conditions in Vietnam, several limitations were identified which generate suggestions for further research. The primary target of the study was rice growing households in rural Vietnam where rice is still the dominant crop. However, the income generating activities of these households are diverse, and they do not solely produce rice crops. Thus, a more comprehensive approach that also takes into account the roles and effects of other economic activities on rural households' decision-making processes would be necessary to fully understand their behavioural responses in a changing production environment.

Further, there may exist heterogeneity in the distribution of returns to using agricultural practices across the sample of farmer households in this study. It is very likely that factors associated with households with low returns are different from those with high returns. Thus, future work that separates observations along the distribution of returns across the sample of rice growers may provide more intuitive information, especially policy implications for different groups of farmers such as by location or region and at different quintiles in the distribution of productivity or income.

There are also important avenues for further research on the extent that changes in climate will affect rice productivity and the potential impact of adoption of adaptation practices on rural households' welfare. Filling this gap could significantly increase our understanding of how those changes are affecting farmers' overall wellbeing.

Finally, empirical studies on climate change adaptation explicitly benefit from projections of future climatic variability and change. These projections in combination with baseline information could be used to build and model future scenarios, which can predict the likely impact of changing climate on human activities and also assess the effectiveness of a range of adaptation strategies on climate change mitigation.

Vietnamese farmers have been operating their farms under a continuously transforming policy environment over recent decades, specifically since the *Renovation Policy* in the mid-1980s. Such policy transitions have created more favourable conditions for the development of the agricultural sector to meet the growing demand for food, both domestically and internationally. However, new challenges are emerging, climate change in particular, and their impacts on agricultural production have been increasingly pronounced. In an era with new and emerging challenges, further policy action is required to help the agricultural sector adapt to ongoing changes in the production environment.

REFERENCES

Adesina, A.A., and Zinnah, M.M., 1993. Technology characteristics, farmers' perceptions and adoption decisions: A Tobit model application in Sierra Leone. *Agricultural Economics* 9, 297-311.

Adger, N., 1999. Social vulnerability to climate change and extremes in Coastal Vietnam. *World Development* 27, 249-269.

Alene, A. D., Manyong, V. M., Omanya, G., Mignouna, H. D., Bokanga, M., and Odhiambo, G. 2008. Smallholder market participation under transactions costs: Maize supply and fertilizer demand in Kenya. *Food Policy* 33(4), 318-328.

Alexandersson, H., and Moberg, A., 1997. Homogenization of Swedish temperature data. Part I: Homogeneity test for linear trends. *International Journal of Climatology* 17, 25-34.

Arguez, A., and Vose, R.S., 2011. The definition of the standard WMO climate normal: The key to deriving alternative climate normals. *Bulletin of the American Meteorological Society* 92, 699-704.

Arulampalam, W., and Stewart, M.B., 2009. Simplified implementation of the Heckman estimator of the dynamic probit model and a comparison with alternative estimators. *Oxford Bulletin of Economics and Statistics* 71, 659-681.

Baez, J., Kronick, D., and Mason, A., 2013. *Rural households in a changing climate.* Policy Research Working Paper. World Bank.

Baldwin, E., Johnson, K., Berthoud, H., and Dublin, S., 2015. Linking mothers and infants within electronic health records: a comparison of deterministic and probabilistic algorithms. *Pharmacoepidemiology and Drug Safety* 24, 45-51.

Banerjee, A.V., 2000. *Prospects and strategies for land reform*. Annual World Bank Conference on Development Economics. World Bank, 253-284.

Barham, B.L., Foltz, J.D., Jackson-Smith, D., and Moon, S., 2004. The dynamics of agricultural biotechnology adoption: lessons from series rBST use in Wisconsin, 1994–2001. *American Journal of Agricultural Economics* 86, 61-72.

Bellemare, M.F., and Barrett, C.B., 2006. An ordered Tobit model of market participation: Evidence from Kenya and Ethiopia. *American Journal of Agricultural Economics* 88, 324-337.

Below, T., Artner, A., Siebert, R., and Sieber, S., 2010. *Micro-level practices to adapt to climate change for African small-scale farmers: A review of selected literature*, IFPRI Discussion Paper, Environment and Production Technology Division, International Food Policy Research Institute, Washington, DC.

Below, T.B., Mutabazi, K.D., Kirschke, D., Franke, C., Sieber, S., Siebert, R., and Tscherning, K., 2012. Can farmers' adaptation to climate change be explained by socio-economic household-level variables? *Global Environmental Change* 22, 223-235.

Beltran, J.C., White, B., Burton, M., Doole, G.J., and Pannell, D.J., 2013. Determinants of herbicide use in rice production in the Philippines. *Agricultural Economics* 44, 45-55.

Besley, T., and Case, A., 1993. Modeling technology adoption in developing countries. *American Economic Review* 83, 396-402.

Bezu, S., Kassie, G.T., Shiferaw, B., and Ricker-Gilbert, J., 2014. Impact of improved maize adoption on welfare of farm households in Malawi: A panel data analysis. *World Development* 59, 120-131.

Blasnik, M., 2010. RECLINK: Stata module to probabilistically match records. Statistical Software Components. Boston College Department of Economics.

Boere, E., Peerlings, J., Reinhard, S., and Heijman, W., 2015. The dynamics of dairy land use change with respect to the milk quota regime. *European Review of Agricultural Economics* 42, 651-674.

Bryan, E., Deressa, T.T., Gbetibouo, G.A., and Ringler, C., 2009. Adaptation to climate change in Ethiopia and South Africa: options and constraints. *Environmental Science & Policy* 12, 413-426.

Buishand, T.A., 1982. Some methods for testing the homogeneity of rainfall records. *Journal of Hydrology* 58, 11-27.

Burke, W.J., Myers, R.J., and Jayne, T.S., 2015. A triple-hurdle model of production and market participation in Kenya's dairy market. *American Journal of Agricultural Economics* 97, 1227-1246.

Byrne, P.J., Capps, O., and Saha, A., 1996. Analysis of Food-Away-from-Home expenditure patterns for U.S. households, 1982-1989. *American Journal of Agricultural Economic*s 78, 614-627.

Caesar, J., Alexander, L.V., Trewin, B., Tse-ring, K., Sorany, L., Vuniyayawa, V., Keosavang, N., Shimana, A., Htay, M.M., Karmacharya, J., Jayasinghearachchi, D.A., Sakkamart, J., Soares, E., Hung, L.T., Thuong, L.T., Hue, C.T., Dung, N.T.T., Hung, P.V., Cuong, H.D., Cuong, N.M., and Sirabaha, S., 2011. Changes in temperature and precipitation extremes over the Indo-Pacific region from 1971 to 2005. *International Journal of Climatology* 31, 791-801.

Chau, V.N., Holland, J., Cassells, S., and Tuohy, M., 2013. Using GIS to map impacts upon agriculture from extreme floods in Vietnam. *Applied Geography* 41, 65-74.

Chavas, J.-P., 2001. Structural change in agricultural production: Economics, technology and policy, *Handbook of Agricultural Economic*s. Elsevier, 263-285.

Christen, P., 2012. *Data matching: concepts and techniques for record linkage, entity resolution, and duplicate detection*. Springer Science & Business Media.

Conway, D., van Garderen, E.A., Deryng, D., Dorling, S., Krueger, T., Landman, W., Lankford, B., Lebek, K., Osborn, T., Ringler, C., Thurlow, J., Zhu, T., and Dalin, C., 2015. Climate and southern Africa's water-energy-food nexus. *Nature Climate Change* 5, 837-846.

Cragg, J.G., 1971. Some statistical models for limited dependent variables with application to the demand for durable goods. *Econometrica* 39, 829-844.

Cressie, N., 2015. *Statistics for spatial data*. John Wiley & Sons.

Critchley, W., 1991. A manual for the design and construction of water harvesting scheme for plant production. FAO. AGL/MISC/17/91. Available from http://www.fao. org/dowep/u3160e/4316e04.htm.

Crozier, C., and Corps, P., 1986. *Soil conservation techniques for hillside farms: a guide for Peace Corps volunteers*. Peace Corps Information Collection and Exchange.

D'Souza, G., Cyphers, D., and Phipps, T., 1993. Factors affecting the adoption of sustainable agricultural practices. *Agricultural and Resource Economics Review* 22, 159-165.

Daly, C., Halbleib, M., Smith, J.I., Gibson, W.P., Doggett, M.K., Taylor, G.H., Curtis, J., and Pasteris, P.P., 2008. Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *International Journal of Climatology* 28, 2031-2064.

De Paola, F., and Giugni, M., 2013. Coupled spatial distribution of rainfall and temperature in USA. *Procedia Environmental Sciences* 19, 178-187.

Deressa, T.T., Hassan, R.M., Ringler, C., Alemu, T., and Yesuf, M., 2009. Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global Environmental Change* 19, 248-255.

Deschenes, O., and Greenstone, M., 2007. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American Economic Review* 97, 354-385.

Di Falco, S., and Veronesi, M., 2011. On adaptation to climate change and food security: a micro-perspective from Ethiopia. *American Journal of Agricultural Economics* 1, 1-18.

Di Falco, S., Veronesi, M., and Yesuf, M., 2011. Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics* 93, 829-846.

Diagne, A., and Demont, M., 2007. Taking a new look at empirical models of adoption: average treatment effect estimation of adoption rates and their determinants. *Agricultural Economics* 37, 201-210.

Ding, Y., Schoengold, K., and Tadesse, T., 2009. The impact of weather extremes on agricultural production methods: Does drought increase adoption of conservation tillage practices? *Journal of Agricultural and Resource Economics*, 395-411.

Doss, C.R., 2006. Analyzing technology adoption using microstudies: limitations, challenges, and opportunities for improvement. *Agricultural Economics* 34, 207-219.

Drukker, D.M., 2003. Testing for serial correlation in linear panel-data models. *Stata Journal* 3, 168-177.

Dusetzina, S.B., Tyree, S., Meyer, A., Meyer, A., Green, L., and Carpenter, W., 2014. *Linking data for health services research: a framework and instructional guide.* Agency for Healthcare Research and Quality (US), Rockville (MD).

Ervin, C.A., and Ervin, D.E., 1982. Factors affecting the use of soil conservation practices: hypotheses, evidence, and policy implications. *Land Economics* 58, 277-292.

Feder, G., Just, R., and Zilberman, D., 1985. Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change* 33(2), 255-298.

Feenstra, J.F., Burton, I., Smith, J.B., and Tol, R.S., 1998. *Handbook on methods for climate change impact assessment and adaptation strategies.* The United Nations Environment Programme (UNEP).

Fellegi, I.P., and Sunter, A.B., 1969. A theory for record linkage. *Journal of the American Statistical Association* 64, 1183-1210.

General Statistics Office (GSO), 2014. Statistical Yearbook of Vietnam. Statistical Publishing House, Hanoi.

General Statistics Office (GSO), 2001. The Rural, Agriculture and Fisheries Census 2001. Department of Agriculture, Forestry and Fishery Statistics, Vietnam General Statistics Office.

Gill, L., 2001. *Methods for automatic record matching and linkage and their use in national statistics*. Office for National Statistics.

Gomatam, S., Carter, R., Ariet, M., and Mitchell, G., 2002. An empirical comparison of record linkage procedures. *Statistics in Medicine* 21, 1485-1496.

Greene, W.H., 2003. *Econometric analysis*. Prentice Hall.

Griffiths, G.M., Chambers, L.E., Haylock, M.R., Manton, M.J., Nicholls, N., Baek, H.J., Choi, Y., Della-Marta, P.M., Gosai, A., Iga, N., Lata, R., Laurent, V., Maitrepierre, L., Nakamigawa, H., Ouprasitwong, N., Solofa, D., Tahani, L., Thuy, D.T., Tibig, L., Trewin, B., Vediapan, K., and Zhai, P., 2005. Change in mean temperature as a predictor of extreme temperature change in the Asia–Pacific region. *International Journal of Climatology* 25, 1301-1330.

Grundy, E., and Jitlal, M., 2007. Socio-demographic variations in moves to institutional care 1991–2001: a record linkage study from England and Wales. *Age and Ageing* 36, 424-430.

Gu, L., Baxter, R., Vickers, D., and Rainsford, C., 2003. *Record linkage: Current practice and future directions*. CSIRO Mathematical and Information Sciences Technical Report 3, 83.

Guiver, T., 2011. Sampling-based clerical review methods in probabilistic linking. *Methodology Research Paper*, 55-304.

Guttman, N.B., 1998. *Homogeneity, data adjustments and climatic normals*. National Climatic Data Center, Asheville, United State.

Hawkins, D.M., 1977. Testing a sequence of observations for a shift in location. *Journal of the American Statistical Association* 72, 180-186.

Hayami, Y., and Ruttan, V.W., 1970. Agricultural productivity differences among countries. *American Economic Review* 60, 895-911.

Heckman, J.J., 1977. *Sample selection bias as a specification error (with an application to the estimation of labor supply functions)*. National Bureau of Economic Research Cambridge, Mass., USA.

Heckman, J.J., 1981. Heterogeneity and state dependence: studies in labor markets. *University of Chicago Press*, 91-140.

Hisali, E., Birungi, P., and Buyinza, F., 2011. Adaptation to climate change in Uganda: evidence from micro level data. *Global Environmental Change* 21, 1245-1261.

IPCC, 2007. *Climate change 2007: impacts, adaptation and vulnerability.* Intergovernmental Panel on Climate Change, Cambridge University Press.

Jaiswal, R.K., Lohani, A.K., and Tiwari, H.L., 2015. Statistical analysis for change detection and trend assessment in climatological parameters. *Environmental Processes* 2, 729-749.

Jenkins, S.P., Lynn, P., Jäckle, A., and Sala, E., 2008. The feasibility of linking household survey and administrative record data: New evidence for Britain. *International Journal of Social Research Methodology* 11, 29-43.

Johnston, B. F., & Mellor, J. W., 1961. The role of agriculture in economic development. *American Economic Review* 51(4), 566-593.

Johnston, K., Ver Hoef, J.M., Krivoruchko, K., and Lucas, N., 2001. *Using ArcGIS geostatistical analyst*. Esri Redlands.

Jones, D.A., Wang, W., and Fawcett, R., 2009. High-quality spatial climate data-sets for Australia. *Australian Meteorological and Oceanographic Journal* 58, 233.

Josephson, A.L., Ricker-Gilbert, J., and Florax, R.J.G.M., 2014. How does population density influence agricultural intensification and productivity? Evidence from Ethiopia. *Food Policy* 48, 142-152.

Journel, A.G., and Huijbregts, C.J., 1978. *Mining geostatistics.* Academic Press.

Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., and Mekuria, M., 2013. Adoption of interrelated sustainable agricultural practices in smallholder systems: Evidence from rural Tanzania. *Technological Forecasting and Social Change* 80, 525-540.

Kato, E., Ringler, C., Yesuf, M., and Bryan, E., 2011. Soil and water conservation technologies: a buffer against production risk in the face of climate change? Insights from the Nile basin in Ethiopia. *Agricultural Economics* 42, 593-604.

Kendall, M.G., 1962. *Rank correlation methods*. Oxford University Press.

Khonje, M., Manda, J., Alene, A.D., and Kassie, M., 2015. Analysis of adoption and impacts of improved maize varieties in Eastern Zambia. *World Development* 66, 695-706.

Knowler, D., and Bradshaw, B., 2007. Farmers' adoption of conservation agriculture: A review and synthesis of recent research. *Food Policy* 32, 25-48.

Kremer, M., 1993. Population growth and technological change: one million BC to 1990. *The Quarterly Journal of Economics* 108, 681-716.

Kundu, S., Khare, D., Mondal, A., Mishra, and P.K., 2015. Analysis of spatial and temporal variation in rainfall trend of Madhya Pradesh, India (1901–2011). *Environmental Earth Sciences* 73, 8197-8216.

Kurukulasuriya, P., and Rosenthal, S., 2003. *Climate change and agriculture: A review of impacts and adaptations World Bank climate change series paper no. 91*. Paper prepared and published for the Rural Development Group and Environment Department of the World Bank, 106.

Lambert, D.M., Sullivan, P., Claassen, R., and Foreman, L., 2007. Profiles of US farm households adopting conservation-compatible practices. *Land Use Policy* 24, 72-88.

Lau, K.M., and Yang, S., 1997. Climatology and interannual variability of the Southeast Asian summer monsoon. *Advances in Atmospheric Sciences* 14, 141-162.

Lee, D.R., 2005. Agricultural sustainability and technology adoption: Issues and policies for developing countries. *American Journal of Agricultural Economics* 87, 1325-1334.

Longobardi, A., and Villani, P., 2010. Trend analysis of annual and seasonal rainfall time series in the Mediterranean area. *International Journal of Climatology* 30, 1538-1546.

Maddison, D., 2007. *The perception of and adaptation to climate change in Africa*. World Bank Publications.

Manda, J., Alene, A.D., Gardebroek, C., Kassie, M., and Tembo, G., 2016. Adoption and impacts of sustainable agricultural practices on maize yields and incomes: Evidence from rural Zambia. *Journal of Agricultural Economics* 67, 130-153.

Mann, H.B., 1945. Nonparametric tests against trend. *Econometrica* 13, 245-259.

Marenya, P.P., and Barrett, C.B., 2007. Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in western Kenya. *Food Policy* 32, 515-536.

Marsh, S.P., MacAulay, T.G., and Hung, P., 2006. Agricultural development and land policy in Vietnam : An overview and theoretical perspective. In S. P. Marsh, T. G. MacAulay, and P. V. Hung (Eds.), Agricultural Development and Land Policy in Vietnam. Canberra, Australia: Australian Centre for International Agricultural Research.

Mason, N.M., and Smale, M., 2013. Impacts of subsidized hybrid seed on indicators of economic well-being among smallholder maize growers in Zambia. *Agricultural Economics* 44, 659-670.

McElwee, P., Tuyen, N.P., Be, N.V., Duat, L.Q., Phuong, D.T., Dung, N.T., and Adutt, G., 2010. *The Social Dimensions of Adaptation to Climate Change in Vietnam*, Discussion Paper. The World Bank, Washington, DC.

McFadden, D., 1980. Econometric models for probabilistic choice among products. *The Journal of Business* 53, S13-S29.

McIntosh, C., Sarris, A., and Papadopoulos, F., 2013. Productivity, credit, risk, and the demand for weather index insurance in smallholder agriculture in Ethiopia. *Agricultural Economics* 44, 399-417.

McKee, T.B., Doesken, N.J., and Kleist, J., 1993. *The relationship of drought frequency and duration to time scales*, Proceedings of the 8th Conference on Applied Climatology. American Meteorological Society Boston, MA, USA, 179-183.

McMaster, G.S., and Wilhelm, W.W., 1997. Growing degree-days: one equation, two interpretations. *Agricultural and Forest Meteorology* 87, 291-300.

Megersa, B., Markemann, A., Angassa, A., Ogutu, J.O., Piepho, H.-P., and Zaráte, A.V., 2014. Impacts of climate change and variability on cattle production in southern Ethiopia: Perceptions and empirical evidence. *Agricultural Systems* 130, 23-34.

Mendelsohn, R., and Kurukulasuriya, P., 2007. *Crop Selection: Adapting to Climage Change in Africa*. Policy Research Working Papers. The World Bank, Washington, DC.

Mendelsohn, R., Nordhaus, W.D., and Shaw, D., 1994. The impact of global warming on agriculture: a Ricardian analysis. *American Economic Review*, 753-771.

Meshram, S.G., Singh, V.P., and Meshram, C., 2016. Long-term trend and variability of precipitation in Chhattisgarh State, India. *Theoretical and Applied Climatology*, 1-16.

Moral, F.J., 2010. Comparison of different geostatistical approaches to map climate variables: application to precipitation. *International Journal of Climatology* 30, 620-631.

Moser, C.M., and Barrett, C.B., 2006. The complex dynamics of smallholder technology adoption: the case of SRI in Madagascar. *Agricultural Economics* 35, 373-388.

Mundlak, Y., 1978. On the pooling of time series and cross section data. *Econometrica: Journal of the Econometric Society*, 69-85.

Nam, W.-H., Hong, E.-M., and Baigorria, G.A., 2016. How climate change has affected the spatio-temporal patterns of precipitation and temperature at various time scales in North Korea. *International Journal of Climatology* 36, 722-734.

Nelson, G.C., Rosegrant, M.W., Koo, J., Robertson, R., Sulser, T., Zhu, T., Ringler, C., Msangi, S., Palazzo, A., and Batka, M., 2009. Climate change: Impact on agriculture and costs of adaptation. International Food Policy Research Institute, Washington, DC.

Nguyen, D.Q., Renwick, J., and McGregor, J., 2013. Variations of surface temperature and rainfall in Vietnam from 1971 to 2010. *International Journal of Climatology*, 1-16.

Nguyen, T.D., Uvo, C., and Rosbjerg, D., 2007. Relationship between the tropical Pacific and Indian Ocean sea-surface temperature and monthly precipitation over the central highlands, Vietnam. *International Journal of Climatology* 27, 1439-1454.

Ninyerola, M., Pons, X., and Roure, J.M., 2000. A methodological approach of climatological modelling of air temperature and precipitation through GIS techniques. *International Journal of Climatology* 20, 1823-1841.

Nolan, A., 2010. A dynamic analysis of household car ownership. *Transportation Research Part A: Policy and Practice* 44, 446-455.

O'Neill, S., and Hanrahan, K., 2011. Decoupling of agricultural support payments: the impact on land market participation decisions. *European Review of Agricultural Economics* 39 (4), 639–659.

OECD, 2015. *Agricultural Policies in Viet Nam,* in: OECD. (Ed.), OECD Food and Agricultural Reviews. OECD Publishing.

Ong, T.C., Mannino, M.V., Schilling, L.M., and Kahn, M.G., 2014. Improving record linkage performance in the presence of missing linkage data. *Journal of Biomedical Informatics* 52, 43-54.

Orme, C.D., 2001. Two-step inference in dynamic non-linear panel data models. *Unpublished paper, University of Manchester.* Available at http://personalpages.manchester.ac.uk/staff/chris.orme/documents/Research%20Papers/initcondlast.pdf.

Panos, S., 2008. *State dependence in work-related training participation among British employees: A comparison of different random effects probit estimators*. MPRA Paper.

Pardo-Igúzquiza, E., 1998. Comparison of geostatistical methods for estimating the areal average climatological rainfall mean using data on precipitation and topography. *International Journal of Climatology* 18, 1031-1047.

Pesaran, M., 2006. Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure. *Econometrica*, 74(4), 967-1012.

Pettitt, A.N., 1979. A non-parametric approach to the change-point problem. *Journal of the Royal Statistical Society. Series C (Applied Statistics)* 28, 126-135.

Phong, T., Tuan, T.H., The, B.D., and Tinh, B.D., 2010. *Adaptation behaviors of communities and households to extreme climate events in Quang Nam province, Viet Nam: towards* *a set of possible adaptation measures*, Research Report. The Economy and Environment Program for Southeast Asia (EEPSEA).

Pingale, S.M., Khare, D., Jat, M.K., and Adamowski, J., 2014. Spatial and temporal trends of mean and extreme rainfall and temperature for the 33 urban centers of the arid and semi-arid state of Rajasthan, India. *Atmospheric Research* 138, 73-90.

Piya, L., Maharjan, K.L., and Joshi, N.P., 2013. Determinants of adaptation practices to climate change by Chepang households in the rural Mid-Hills of Nepal. *Regional Environmental Change*, 1-11.

Place, F., and Dewees, P., 1999. Policies and incentives for the adoption of improved fallows. *Agroforestry Systems* 47, 323-343.

Pohlert, T., 2016. Package 'trend'. Available at http://cran.r-project.org/web/packages/trend/.

Portmann, R.W., Solomon, S., and Hegerl, G.C., 2009. Spatial and seasonal patterns in climate change, temperatures, and precipitation across the United States. *Proceedings of the National Academy of Sciences* 106, 7324-7329.

Prudhomme, C., and Reed, D.W., 1999. Mapping extreme rainfall in a mountainous region using geostatistical techniques: a case study in Scotland. *International Journal of Climatology* 19, 1337-1356.

Qureshi, M. E., Whitten, S. M., and Franklin, B., 2014. Impacts of climate change on the irrigation sector in the southern Murray-Darling Basin, Australia. *Water Resources and Economics,* 40-49.

Qureshi, M. E., and Whitten, S. M. (2014). Regional impact of climate variability and adaptation options in the southern Murray-Darling Basin, Australia. *Water Resources and Economics, 112- 123.*

Rabe-Hesketh, S., and Skrondal, A., 2013. Avoiding biased versions of Wooldridge's simple solution to the initial conditions problem. *Economics Letters* 120, 346-349.

Rahm, M.R., and Huffman, W.E., 1984. The adoption of reduced tillage: the role of human capital and other variables. *American Journal of Agricultural Economics* 66, 405-413.

Ransom, J., Paudyal, K., and Adhikari, K., 2003. Adoption of improved maize varieties in the hills of Nepal. *Agricultural Economics* 29, 299-305.

Recha, J., Kapukha, M., Wekesa, A., Shames, S., and Heiner, K., 2014. *Sustainable agriculture land management practices for climate change mitigation: A training guide for smallholder farmers.* Washington, DC. EcoAgriculture Partners.

Ricker-Gilbert, J., Jayne, T.S., and Chirwa, E., 2011. Subsidies and crowding out: A double-hurdle model of fertilizer demand in Malawi. *American Journal of Agricultural Economics* 93, 26-42.

Río, S.d., Herrero, L., Fraile, R., and Penas, A., 2011. Spatial distribution of recent rainfall trends in Spain (1961–2006). *International Journal of Climatology* 31, 656-667.

Roco, L., Engler, A., Bravo-Ureta, B., and Jara-Rojas, R., 2014. Farm level adaptation decisions to face climatic change and variability: Evidence from Central Chile. *Environmental Science & Policy* 44, 86-96.

Rosenzweig, C., Iglesias, A., Yang, X., Epstein, P.R., and Chivian, E., 2001. Climate change and extreme weather events; implications for food production, plant diseases, and pests. *Global Change and Human Health* 2, 90-104.

Sayemuzzaman, M., 2014. *Spatio-temporal trends of climate variability in North Carolina*. ProQuest Dissertations And Theses, North Carolina Agricultural and Technical State University,; Publication Number: AAT 3639240; ISBN: 9781321235326.

Schultz, T.W., 1964. *Transforming traditional agriculture.* University of Chicago Press.

Shiferaw, B., Kassie, M., Jaleta, M., and Yirga, C., 2013. Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy* 44, 272-284.

Sietz, D., and Van Dijk, H., 2015. Land-based adaptation to global change: What drives soil and water conservation in western Africa? *Global Environmental Change* 33, 131-141.

Sinharay, S., 2016. Some remarks on applications of tests for detecting a change point to psychometric problems. *Psychometrika*, 1-13.

Skrondal, A., and Rabe-Hesketh, S., 2014. Handling initial conditions and endogenous covariates in dynamic/transition models for binary data with unobserved heterogeneity. *Journal of the Royal Statistical Society: Series C (Applied Statistics)* 63, 211-237.

Smale, M., Heisey, P.W., and Leathers, H.D., 1995. Maize of the ancestors and modern varieties: The microeconomics of high-yielding variety adoption in Malawi. *Economic Development and Cultural Change* 43, 351-368.

Smit, B., and Skinner, M.W., 2002. Adaptation options in agriculture to climate change: a typology. *Mitigation and Adaptation Strategies for Global Change* 7, 85-114.

Smit, B., and Wandel, J., 2006. Adaptation, adaptive capacity and vulnerability. *Global Environmental Change* 16, 282-292.

Soong, J. (2006). Soil fertility and changes in fertilizer use for intensive rice cultivation in the Red River Delta and Mekong Delta of Vietnam. *ISP Collection*, 340.

Sridevi, V., and Chellamuthu, V., 2015. Impact of weather on rice–A review. *International Journal of Applied Research* 1(9), 825-831.

Steduto, P., Hsiao, T.C., Raes, D., and Fereres, E., 2009. AquaCrop—The FAO crop model to simulate yield response to water: I. Concepts and underlying principles. *Agronomy Journal* 101, 426-437.

Stewart, M.B., 2007. The interrelated dynamics of unemployment and low-wage employment. *Journal of Applied Econometrics* 22, 511-531.

Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley, P.M., 2014. *Climate change 2013: The physical science basis*. Cambridge University Press Cambridge, UK, and New York.

Sunding, D., and Zilberman, D., 2001. *The agricultural innovation process: Research and technology adoption in a changing agricultural sector*, Handbook of Agricultural Economics. Elsevier, 207-261.

Suri, T., 2011. Selection and comparative advantage in technology adoption. *Econometrica* 79, 159-209.

Svoboda, M., Hayes, M., and Wood, D., 2012. *Standardized precipitation index user guide*. World Meteorological Organization Geneva, Switzerland.

Tambo, J.A., and Abdoulaye, T., 2012. Climate change and agricultural technology adoption: the case of drought tolerant maize in rural Nigeria. *Mitigation and Adaptation Strategies for Global Change* 17, 277-292.

The Food and Agriculture Organization Corporate Statistical Database (FAOSTAT). Available at www.fao.org/faostat/en/.

The International Disaster Database. Available at http://www.emdat.be.

Thomas, T., Christiaensen, L., Do, Q.T., and Trung, L.D., 2010. *Natural disasters and household welfare: evidence from Vietnam*. World Bank Policy Research Working Paper Series, The World Bank, Washington, DC.

Timmer, C.P., 1988. *The agricultural transformation*. Handbook of Development Economics 1, 276-331.

Tobin, J., 1958. Estimation of relationships for limited dependent variables. *Econometrica* 26, 24-36.

UNEP, 2009. *Vietnam Assessment Report on Climate Change. Institute of Strategy and Policy on Natural Resources and Environment*, Van hoa - Thong tin Publishing House, Hanoi.

United States Environmental Protection Agency (USEPA), 2016. Climate change indicators in the United States, Fourth edition. Available at www.epa.gov/climate-indicators.EPA 430-R-16-004.

United States Geological Survey (USGS). Digital Elevation Model. Available at data.geocomm.com/dem/.

Ut, T.T., and Kajisa, K., 2006. The impact of Green Revolution on rice production in Vietnam. *The Developing Economies* 44, 167-189.

VAAS, 2010. *Rice Production in Vietnam.* Vietnam Academy of Agricutural Sciences.

Vezzoli, R., Pecora, S., Zenoni, E., and Tonelli, F., 2012. *Data analysis to detect inhomogeneity, change points, trends in observations: An application to Po River discharge extremes*. CMCC Research Paper.

Viola, F., Liuzzo, L., Noto, L.V., Lo Conti, F., and La Loggia, G., 2014. Spatial distribution of temperature trends in Sicily. *International Journal of Climatology* 34, 1-17.

VNG, 2007. *National Strategy for Natural Disaster Prevention, Response, and Mitigation to 2020*. Vietnam Government, Hanoi.

VNGP, 2011. *The National Strategy on Climate Change*. Vietnam Government Portal.

Wasi, N., and Flaaen, A., 2015. Record linkage using Stata: Preprocessing, linking, and reviewing utilities. *Stata Journal* 15, 672-697.

World Bank, 2010. Vietnam: *Economics of Adaptation to Climate Change*. The World Bank, Washington, DC.

Wijngaard, J.B., Klein Tank, A.M.G., and Können, G.P., 2003. Homogeneity of 20th century European daily temperature and precipitation series. *International Journal of Climatology* 23, 679-692.

Winkler, W.E., 2006. *Overview of record linkage and current research directions*, Bureau of the Census. Citeseer.

Wooldridge, J.M., 2005. Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics* 20, 39-54.

Wooldridge, J.M., 2010. *Econometric analysis of cross section and panel data*. MIT press.

Wooldridge, J.M., 2015. *Introductory econometrics: A modern approach*. Nelson Education.

Xu, Z., Burke, W.J., Jayne, T.S., and Govereh, J., 2009. Do input subsidy programs “crowd in” or “crowd out” commercial market development? Modeling fertilizer demand in a two-channel marketing system. *Agricultural Economics* 40, 79-94.

Yatchew, A., and Griliches, Z., 1985. Specification error in probit models. *The Review of Economics and Statistics* 67, 134-139.

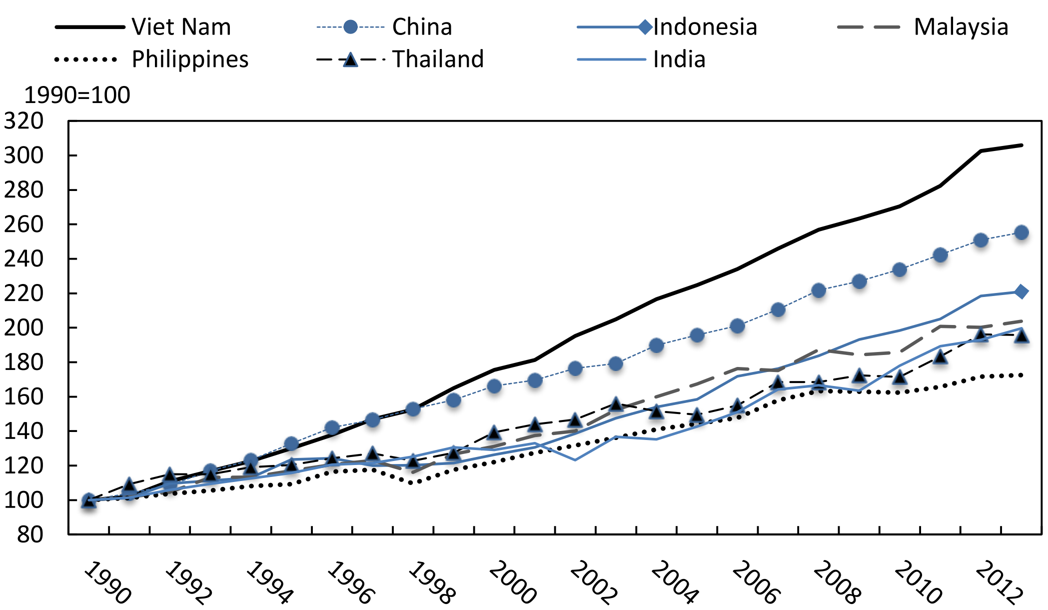
Yu, B., Zhu, T., Breisinger, C., and Hai, N.M., 2013. *How are farmers adapting to climate change in Vietnam?*, IFPRI Discussion Paper, International Food Policy Research Institute, Washington, DC.

Zarenistanak, M., Dhorde, A.G., and Kripalani, R.H., 2014. Trend analysis and change point detection of annual and seasonal precipitation and temperature series over southwest Iran. *Journal of Earth System Science* 123, 281-295.

Zilberman, D., Dinar, A., MacDougall, N., Khanna, M., Brown, C., and Castillo, F., 2011. Individual and institutional responses to the drought: the case of California agriculture. *Journal of Contemporary Water Research and Education* 121, 3.

APPENDICES

Appendix 2A: Growth in gross agricultural output in selected Asian countries, 1990-2013



Note: The FAO indices of agricultural production show the relative level of the aggregate volume of agricultural production for each year in comparison with the base period. In this figure, indices based on the 2004-06 period have been recalculated taking indices for 1990 as 100.
Source: Food and Agriculture Organization Corporate Statistical Database – FAOSTAT; OECD, 2015.

Appendix 2B: The estimated results of year dummy and within-household means variables for two-stage procedure

Decision to apply	(1) Seed choice (b/se)	(2) Fertiliser choice (b/se)	(3) Pesticide choice (b/se)	(4) Machinery choice (b/se)
tenureumn	0.69157	1.99418***	-1.87297***	-0.59523
	(0.4959)	(0.4558)	(0.5263)	(0.5806)
wageumn	1.07360	-1.10173	0.24987	3.01581
	(1.6735)	(1.8479)	(1.6556)	(2.1764)
urbanumn	-0.45398	0.82973	0.19345	-1.20266
	(0.6405)	(0.7041)	(0.6341)	(0.8348)
hsizeumn	0.00711	-0.05954	-0.06445	-0.02934
	(0.0519)	(0.0773)	(0.0524)	(0.0718)
farmsizeumn	-0.00004***	-0.00003**	0.00004**	0.00002
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
laborwumn	0.00476	0.00309	-0.00715*	-0.01800***
	(0.0031)	(0.0037)	(0.0031)	(0.0042)
gatepriceumn	-0.07327	0.01714	-0.06987	-0.02946
	(0.0453)	(0.0627)	(0.0465)	(0.0696)
extensionumn	0.39418	0.45620	0.19733	0.95453**
	(0.2181)	(0.2524)	(0.2384)	(0.2965)
creditumn	-0.28709	0.31029	0.06266	-0.20744
	(0.2147)	(0.2433)	(0.2104)	(0.2552)
year1	-0.10054	0.22762	0.16629	0.29209
	(0.1640)	(0.1905)	(0.1829)	(0.2078)
year3	-0.22721	-0.11833	-0.31301*	-0.32923
	(0.1333)	(0.1662)	(0.1396)	(0.2199)
year2	0.03236	0.30289*	0.25973	-0.14081
	(0.1386)	(0.1329)	(0.1478)	(0.1658)
year5	-1.15475***	-0.53010**	-0.31100	0.10489
	(0.2260)	(0.2010)	(0.3369)	(0.2813)
year6	0.42232**	0.13750	-0.11193	-0.21369
	(0.1361)	(0.1435)	(0.1569)	(0.1777)

Intensity of application	Seed used	Fertilisers used	Pesticides used	Machinery used
Tenureumn*	0.03490	-1.55586	-0.59314	0.32342
	(0.3037)	(1.1556)	(0.3479)	(0.9194)
wageumn	-1.37509*	-4.40534***	-2.73145***	-0.37833
	(0.6049)	(1.0112)	(0.7676)	(0.7386)
urbanumn	0.16263	2.99784	2.34544**	-0.91564
	(0.3634)	(2.9147)	(0.8954)	(2.4292)
hsizeumn	3.84682*	0.00007**	0.00005***	-0.00002*
	(1.5853)	(0.0000)	(0.0000)	(0.0000)
farmsizeumn	0.00001	-0.11270	-0.18136***	-0.12595
	(0.0000)	(0.1015)	(0.0485)	(0.0936)
laborwumn	0.01168	-0.00353	-0.00240	0.02466***
	(0.0412)	(0.0050)	(0.0021)	(0.0064)
gatepriceumn	-0.00298	0.23735**	0.04671	0.07994
	(0.0023)	(0.0789)	(0.0597)	(0.0625)
extensionnumn	-0.02922	-0.63551	-0.26590*	-0.55992
	(0.0317)	(0.3970)	(0.1341)	(0.3238)
creditumn	0.35315*	-0.51840	0.01904	0.06292
	(0.1661)	(0.4414)	(0.1374)	(0.3252)
year1	0.02159	0.63745*	0.35720**	0.42674*
	(0.2078)	(0.2650)	(0.1193)	(0.2128)
year3	0.29228	-0.52849*	-0.40311***	-0.40877*
	(0.1665)	(0.2486)	(0.1139)	(0.2058)
year2	-0.32107**	0.16540	0.19170	-0.81771**
	(0.1093)	(0.3324)	(0.1427)	(0.2757)
year5	-0.49320***	-0.08284	-0.13606	-1.81570***
	(0.1266)	(0.4638)	(0.1884)	(0.3384)
year6	-0.53210*	-0.62981*	-0.29318**	-0.06680
	(0.2286)	(0.2651)	(0.0938)	(0.1762)

*Note: * (_umn) denote within-household means of variables for Correlated Random Effect (CRE)*

Appendix 2C: Testing underlying assumptions in the estimation models

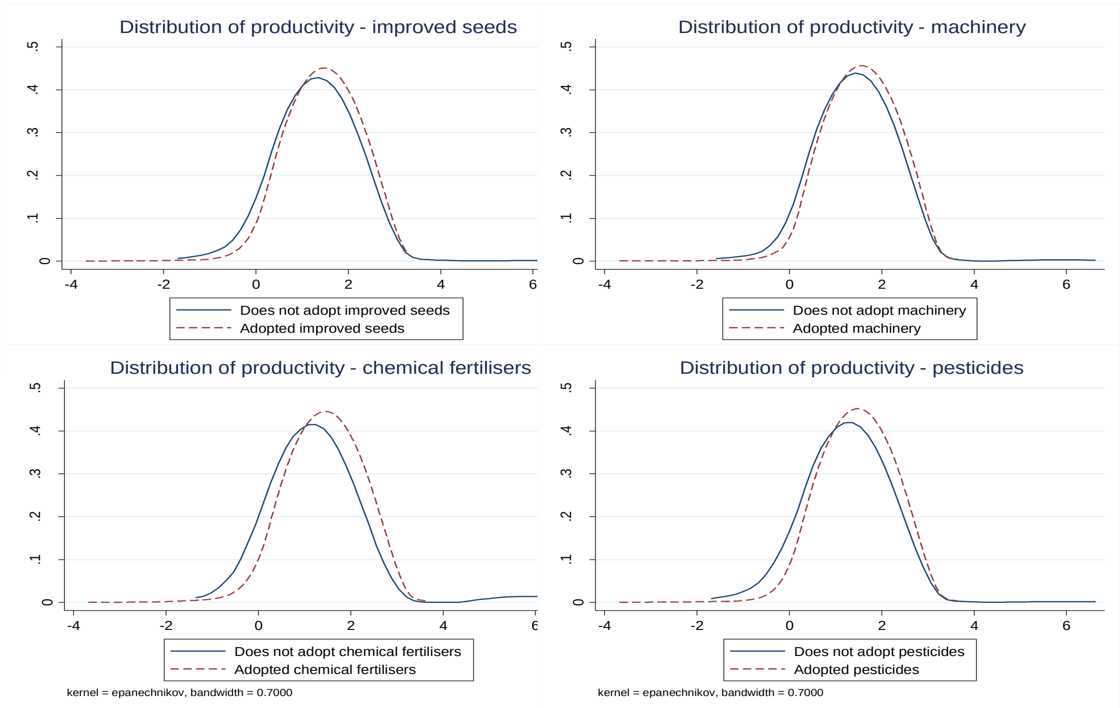
Collinearity Diagnostics

Variable	VIF	Tolerance	Variable	VIF	Tolerance
IMR1	1.26	0.7974	credit	1.41	0.7077
IMR2	2.49	0.4013	wage	1.05	0.795
IMR3	5.28	0.1894	urban	6.17	0.166
IMR4	1.1	0.7901	tenure	1.48	0.6738
hsize	1.25	0.7978	year1	1.76	0.5689
farmsize	1.31	0.7615	year3	3.5	0.286
labourw	7.18	0.1393	year2	2.04	0.4902
gateprice	1.88	0.5329	year5	4.71	0.2125
extension	1.73	0.5773	Mean VIF		2.47

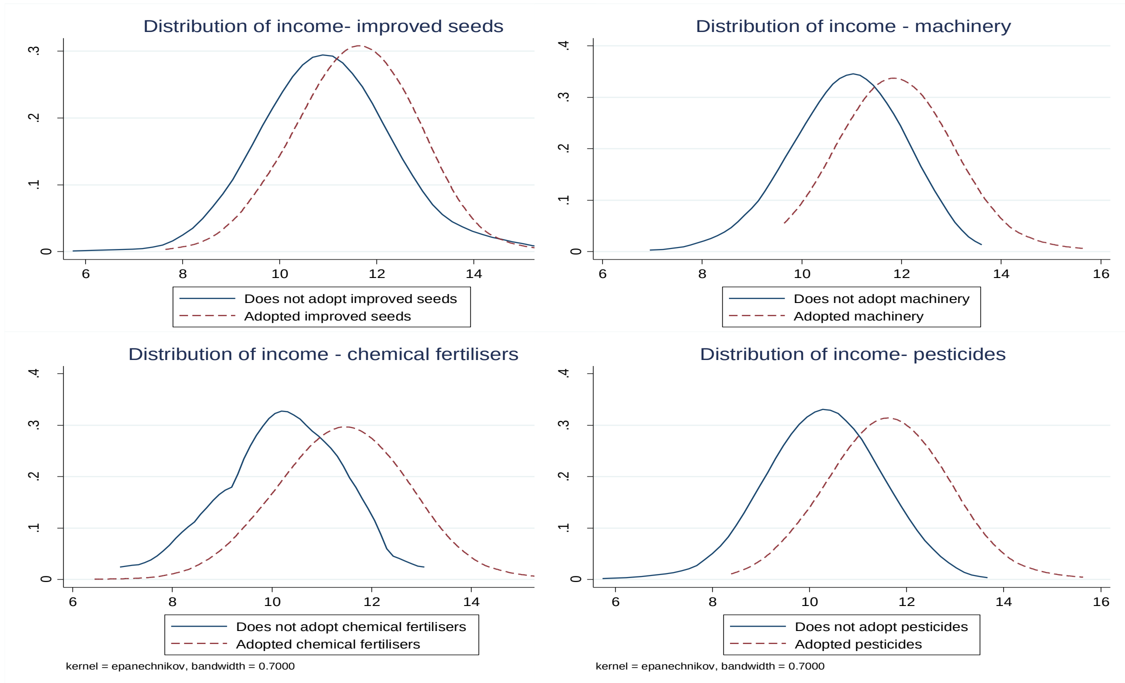
Heteroskedasticity Diagnostics *(Breusch-Pagan hettest H_0: no heteroskedasticity)*

	Seed use equation	Fertilisers use equation	Pesticides use equation	Machinery use equation
Chi2(1):	241.2***	208.0***	266.6***	168.7***

Appendix 2D: A shift in the distribution of productivity in relation to the adoption of agricultural technologies adopted in the sample



Appendix 2E: A shift in the distribution of income in relation to the adoption of agricultural technologies adopted in the sample



Appendix 2F: Pairwise correlations between variables

	IMR1	IMR2	IMR3	IMR4	hsize	farmsize	labourprice	gateprice	extension	credit	wage	urban	tenure	year1	year3	year2	year5	year6
IMR1	1																	
IMR2	0.1753	1																
IMR3	0.3724	-0.1139	1															
IMR4	-0.5678	-0.0605	-0.6013	1														
hsize	0.0532	-0.0833	0.0507	0.0786	1													
farmsize	0.0968	-0.0614	-0.0874	0.0408	0.1151	1												
labourprice	-0.5424	-0.0642	-0.569	0.6189	-0.0569	-0.0906	1											
gateprice	0.0038	-0.0646	-0.183	0.2814	-0.0082	0.1045	0.1918	1										
extension	-0.1402	-0.3958	0.2462	-0.1081	0.0367	0.0934	-0.015	-0.0641	1									
credit	0.0172	-0.1427	-0.0176	0.0667	0.05	0.0809	0.1033	0.0399	0.0394	1								
wage	-0.5238	0.1604	-0.1324	0.2777	-0.044	-0.0052	0.5802	0.3329	-0.2174	0.1502	1							
urban	-0.2298	0.193	-0.1405	0.6055	-0.0026	0.0528	0.445	0.3117	-0.3237	0.1922	0.223	1						
tenure	-0.0833	-0.4364	-0.0109	-0.0329	0.0667	-0.0024	-0.0473	0.0041	0.0924	-0.0508	-0.0121	-0.0076	1					
year1	0.168	-0.1928	0.2797	-0.2812	0.0475	-0.0332	-0.0189	-0.1313	0.2023	-0.0363	-0.4033	-0.4147	-0.0297	1				
year3	0.5129	0.1352	0.2636	-0.3405	0.0413	0.134	-0.4473	-0.1417	-0.038	0.0604	-0.3036	-0.0244	0.0222	-0.0876	1			
year2	0.173	0.0089	-0.4114	0.2114	0.0253	0.002	0.1556	0.1279	-0.2234	0.0911	0.2854	0.4506	-0.0234	0.0647	0.1181	1		
year5	-0.3035	0.1822	-0.3931	0.4828	-0.0503	-0.0401	0.2917	0.1392	0.0185	0.0015	0.5714	0.4029	-0.0082	-0.1054	-0.2567	0.1602	1	
year6	0.1128	-0.0105	0.2377	-0.232	-0.0465	0.0163	-0.3572	-0.156	-0.0471	-0.2028	-0.3046	-0.2801	0.0376	0.0514	0.1615	-0.0149	0.1088	1

Appendix 2G: The estimated results of marginal effects for two-stage procedure

Variable	Improved seed	Fertilisers	Pesticides	Machinery
Household size	0.00465	0.00524	0.00088	-0.02148
	0.0091	0.0095	0.009	0.0121
Farm size	0.00000665***	0.00000467**	-1.42E-06	-0.0000056**
	1.89E-06	1.96E-06	2.18E-06	2.29E-06
Tenure	0.11283**	0.1846***	0.12284**	0.03666
	0.0573	0.0295	0.0502	0.1019
Credit	0.02801	0.03046	-0.04562	0.03458***
	0.0236	0.0169	0.0229	0.0174
Labour wages$_{(t-1)}$	0.00039	0.00005	0.002***	0.002***
	0.0004	0.0002	0.0005	0.0005
Farm-gate price$_{(t-1)}$	0.00826*	0.0078**	0.00767**	0.00089
	0.0041	0.0025	0.0024	0.0036
Extension	0.0403*	0.0644***	0.02214	-0.01672
	0.0245	0.0187	0.0255	0.0307
Real agricultural wage	0.45976***	0.04248*	0.02632	0.20737***
	0.0426	0.0239	0.0472	0.0565
Urban population	0.12083***	-0.02494	0.03592**	0.04004**
	0.0136	0.01	0.0142	0.0181

Appendix 3A: Details of homogeneity tests for climate series

Suppose that we have a series of the meteorological variable of a sequence x_1, x_2... x_n with mean ($\bar{x}$) and standard deviation σ. L is the length of that series and k is likely to be the year of a break or change point.

Standard normal homogeneity test (Alexandersson 1986)

The test calculates the statistic value T_k by comparing the mean (M) of the first k records with that of the remaining (n-k) records (Jaiswal et al., 2015). k will be considered as a break point if maximising T_k:

$$T_k = kM_1^2 + (n-k)M_2^2,$$

where M_1 and M_2 are calculated as follows:

$$M_1 = \frac{1}{k}\sum_{i=1}^{k}\frac{(x_i - \overline{x})}{\sigma}$$

$$M_2 = \frac{1}{n-k}\sum_{i=k+1}^{n}\frac{(x_i - \overline{x})}{\sigma}$$

Pettitt's test (Pettitt, 1979)

Consider the two subsamples: x_1, x_2... x_t and x_{t+1}, x_{t+2}... x_L, where t is likely to be the change point. The U_t index is calculated as follows:

$$U_t = \sum_{i=1}^{t}\sum_{j=t+1}^{n} sign(x_t - x_j),$$

$$\text{where: } sign(x_t - x_j) = \begin{cases} 1, \ if \ (x_t - x_j) > 0 \\ 0, \ if \ (x_t - x_j) = 0 \\ -1, \ if \ (x_t - x_j) < 0 \end{cases}$$

If there is a change point *t*, $|U_t|$ will reach the maximum value K_L at that point:

$$K_L = \max_{1 \le t \le L} |U_t|$$

Then the probability that *t* is the change point is approximated by (Pettitt, 1979):

$$p = 1 - \exp\left[\frac{-6K_L^2}{L^2 + L^3}\right]$$

Buishand's test (Buishand, 1982)

The cumulative deviation from the mean for k^{th} observation of a sequence $x_1, x_2 \ldots x_n$ with mean ($\bar{x}$) is defined as the adjusted partial sum (*S*):

$$S_k^* = 0 \text{ and } S_k^* = \sum_{i=1}^{k} (x_i - \bar{x}) \quad k = 1, \ldots., n$$

If a series is homogenous with no change point detected, $S_k^* = 0$ because any variation from the mean will fluctuate around that mean. However, if a break exists at k^{th} observation in the series, S_k^* will reach a maximum or minimum value and these values could be rescaled to (*R*) by the standard deviation σ to test for the significance of the change point:

$$R = (\max_{0 \le k \le n} S_k^* - \min_{0 \le k \le n} S_k^*) / \sigma$$

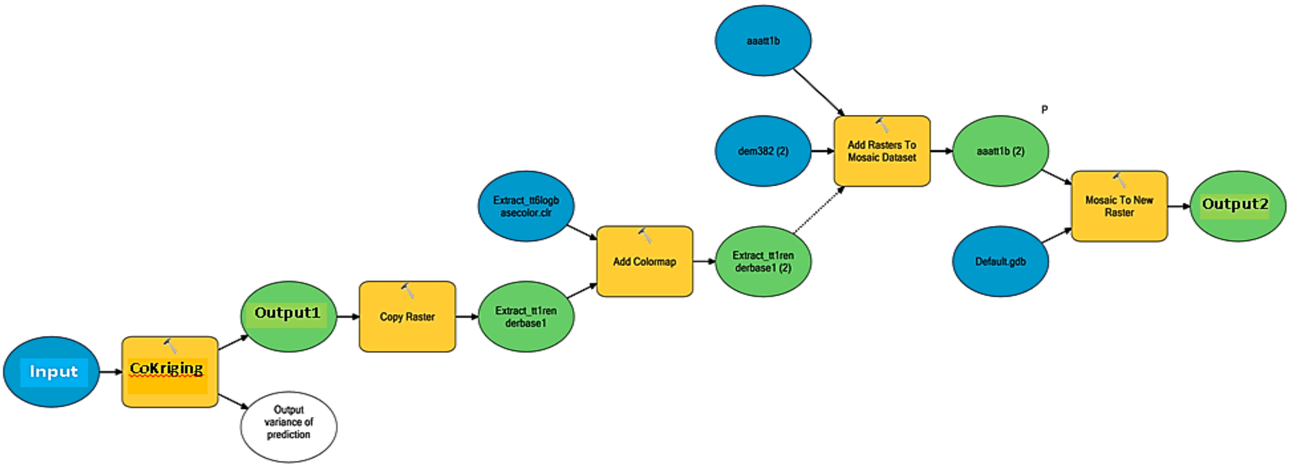
Von Neumann's test (Wijngaard et al., 2003)

The Von Neumann's test defines the ratio N as the difference between the year-to-year mean square and the variance of data series:

$$N = \frac{\sum_{i=1}^{n-1} (x_i - x_{i-1})^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2}$$

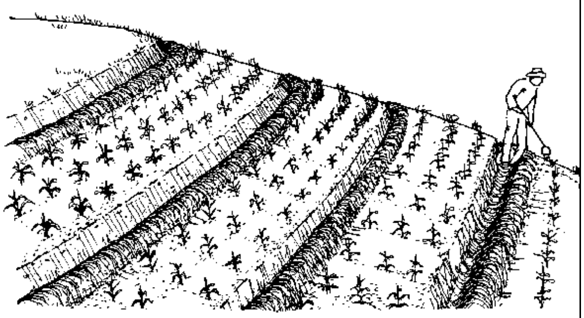
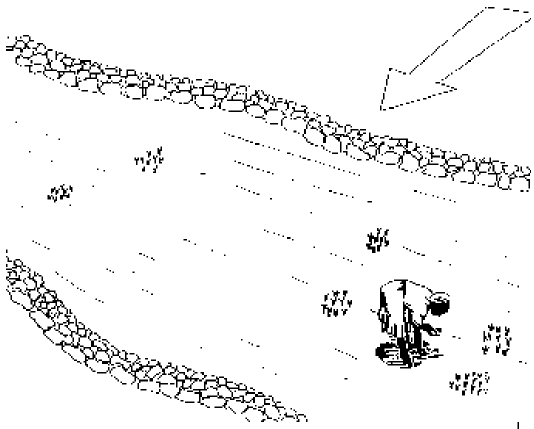
If a series is homogenous, the expected value of N=2. When there is a break point, N will have a value that is lower than $E(N)$ (Buishand, 1982).

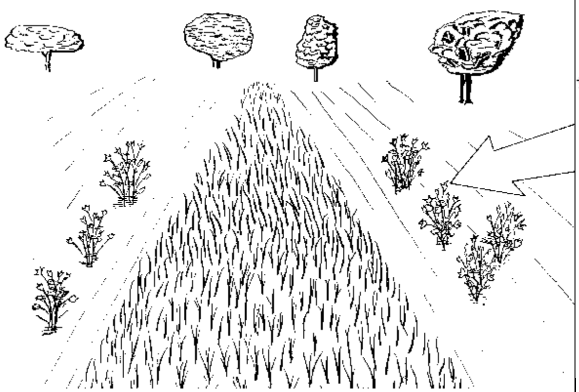
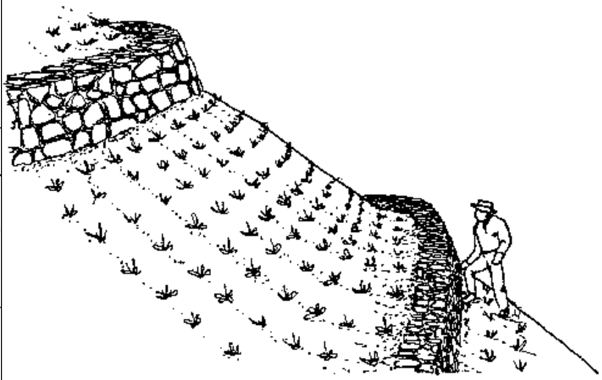
Appendix 3B: An example of the interpolation process of climatic variables



Appendix 4A: Land and water conservation technologies

Note: Land and water conservation technologies adapted from FAO (Critchley, 1991; Crozier and Corps, 1986), Sustainable Sanitation and Water Management (SSWM), and (Recha et al., 2014)

 Soil bunds	 Rock bunds

 Grass lines	 Terraces

Conservation technologies	Description
Soil bunds / Rock bunds	Bunds are often applied to land areas with slight slope below 5%. Bunds are usually constructed either with soil or rocks for the purpose of preserving runoff, preventing soil erosion, and increasing soil moisture. These methods are widely used in many areas with harsh climatic conditions.
Grass lines	Grass lines are planted along contours to reduce the amount of water flowing down the slope and conserve soil. Fodder grass and natural grass can be used to construct grass lines.
Terraces	Terracing is the process of reducing the length and/or steepness of a slope in a planted zone using soil embankments and channels built along the slope. The change in slope profile reduces runoff speed - especially on erosion-prone uneven lands - thus reducing soil erosion. It also allows infiltration.

Appendix 4B: Methods of calculation

Growing degree-days (GDDs) (McMaster and Wilhelm, 1997)

GDDs are calculated by taking the average of the daily maximum and minimum temperatures compared to the lower threshold or base temperature (T_{base} = 8 °C for rice in this case) during the growing season. As a formula:

$$GDD = \frac{T_{\max} + T_{\min}}{2} - T_{\mathrm{base}}.$$

The GDD for a day is equal to T_{base} subtracted from the daily average temperature if this average is greater than the threshold temperature T_{base}. If the daily mean temperature is lower than the base temperature T_{base} then GDD=0. Adding the daily GDD of all the days in the growing season will produce accumulated GDDs for a plant during its growing season. The concept of GDDs assumes that there is a base or lower threshold temperature which limits a plant to grow or grow very slowly.

Standardised Precipitation Index (SPI)

The SPI is determined by normalising the precipitation for a given weather station after it has been fitted to a probability density function as described by McKee *et al.* (1993). The SPI is calculated by dividing the difference between normalised seasonal amount of rainfall at a location and its long-run seasonal mean by the standard deviation as follows:

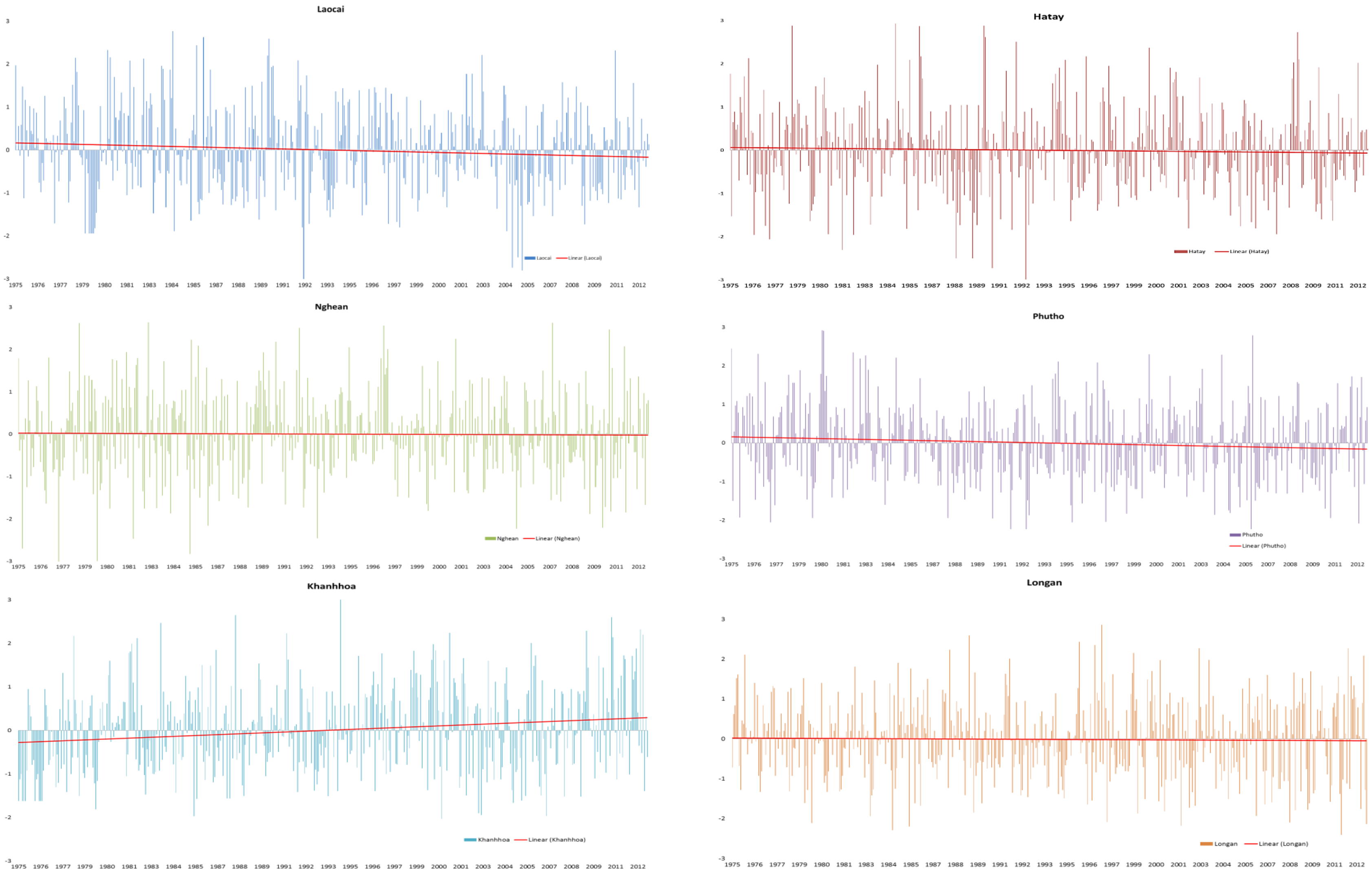
$$SPI = \frac{x_i - \overline{x_\iota}}{\sigma},$$

where σ is the standard deviation, x_i is seasonal precipitation at the ith weather station, $\overline{x\iota}$ is long-term mean precipitation during the study period at the same location.

SPI classification

2.0+	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-.99 to .99	Near normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2 and less	Extremely dry

Appendix 4C: The Standardised Precipitation Index (SPI) across 6 study provinces (1975-2012)



Appendix 4D: Description of outcome, control, and explanatory variables (1992-2012)

	Full sample (mean/sd)						**Adopters** (mean/sd)						**Non-adopters** (mean/sd)					
	1992	**1998**	**2006**	**2008**	**2010**	**2012**	**1992**	**1998**	**2006**	**2008**	**2010**	**2012**	**1992**	**1998**	**2006**	**2008**	**2010**	**2012**
Land conservation	0.71	0.58	0.65	0.81	0.84	0.83	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	0.46	0.49	0.48	0.39	0.36	0.38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SPI45	-0.43	-0.43	-1.26	-0.21	-0.05	-0.06	-0.40	-0.44	-1.25	0.24	-0.09	-0.06	-0.51	-0.44	-1.27	-0.06	0.01	-0.11
	0.45	0.87	0.81	0.71	0.54	0.34	0.37	0.90	0.82	0.50	0.49	0.32	0.60	0.80	0.80	0.69	0.56	0.20
Drought	0.61	0.89	1.29	1.42	0.63	1.13	0.64	0.93	1.35	1.46	0.68	1.11	0.53	0.87	1.17	1.21	0.37	1.00
	1.26	1.47	1.92	2.31	1.22	1.91	1.31	1.53	2.01	2.42	1.33	1.90	1.14	1.41	1.74	1.85	.92	1.95
GDDs	4412.7	4475.6	4286.5	4333.1	4499.3	4487.2	4384.1	4456.6	4256.4	4278.6	4319.2	4445.0	4469.2	4482.2	4330.3	4416.5	4654.7	4480.9
	362.9	386.3	470.7	381.7	471.3	424.8	301.1	409.3	437.2	464.4	462.2	392.7	473.8	343.3	517.5	452.1	353.8	433.1
AGDDs	3977.6	3946.4	4075.4	4093.5	4115.7	4130.5	3905.4	4006.0	4006.5	4149.3	4061.0	4051.0	4132.1	3834.1	4170.0	4282.7	4229.1	4215.4
	482.1	563.8	496.2	482.8	475.2	470.2	437.8	544.1	455.1	455.0	410.2	444.8	537.7	567.3	542.8	504.4	441.1	424.7
Household size	4.97	4.81	4.75	4.64	4.46	4.38	4.97	4.75	4.89	4.77	4.46	4.46	5.05	4.98	4.47	4.64	4.63	4.33
	2.00	1.78	1.53	1.51	1.62	1.67	1.92	1.88	1.52	1.55	1.61	1.64	2.15	1.59	1.53	1.75	1.67	1.69
Credit	0.48	0.52	0.69	0.52	0.57	0. 61	0.44	0.53	0.71	0.53	0.59	0.70	0.54	0.53	0.65	0.64	0.63	0.41
	0.50	0.50	0.46	0.50	0.50	0.20	0.50	0.50	0.46	0.50	0.49	0.22	0.50	0.50	0.48	0.49	0.49	0.30
Experience	12.24	11.85	11.63	13.11	14.70	16.58	12.26	12.92	11.36	13.42	14.8	16.81	12.19	10.37	12.12	13.80	11.60	15.52
	5.29	8.68	4.63	4.40	4.36	4.51	5.15	8.99	3.83	4.66	4.18	4.41	5.64	8.03	5.84	4.92	6.50	4.86
Farmsize	4141.4	2219.5	3821.5	3715.9	3585.7	3751.7	3524.2	2432.6	3972.1	4311.8	3973.9	3250.4	5624.0	1928.3	3649.5	4328.0	3280.9	6122.1
	600.9	4979.3	5046.3	5865.2	5884.8	7034.9	5063.1	5080.7	7599.4	7268.0	6658.4	6019.6	7799.1	4841.4	7949.9	4768.1	3986.4	7359.9
Information	0.63	0.68	0.36	0.03	0.43	0.53	0.73	0.69	0.39	0.06	0.49	0.55	0.38	0.67	0.29	0.00	0.56	0.67
	0.48	0.47	0.48	0.18	0.50	0.50	0.44	0.47	0.49	0.23	0.50	0.50	0.49	0.47	0.46	0.00	0.51	0.47
Labour wages	4.81	18.62	23.52	63.49	84.64	126.44	5.02	18.36	22.98	55.94	77.59	130.23	4.28	18.92	24.57	60.30	81.47	119.86
	1.62	1.92	6.11	17.69	29.42	50.11	1.64	1.68	6.07	15.70	24.86	53.50	1.46	2.13	6.08	12.63	23.52	41.56
Farm-gate price	1.20	1.77	2.45	4.43	5.58	6.18	1.20	1.74	2.43	4.86	6.40	6.21	1.20	1.80	2.49	2.31	4.82	5.90
	0.30	0.34	0.31	3.56	5.11	4.42	0.23	0.33	0.27	3.48	7.40	4.66	0.43	0.36	0.38	1.95	0.34	0.86