



Multidimensional Impacts of Climate Change and Adaptation Strategies: An Empirical Study of Agricultural Households in the Mekong River Basin

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Executive Summary

Overview of the Study

Climate change increases temperature and precipitation variability globally, causing climate shocks such as droughts and floods, which negatively affect economic activities and quality of life. Low- and middle-income countries (LMICs) are particularly vulnerable to climate change, facing more risks of reduced agricultural productivity, food security crises, labor force losses, the spread of tropical diseases, and an increase in climate-induced refugees. Many LMICs rely heavily on agriculture for their economies, and farmers in LMICs have limited information and resources to respond to climate changes, which exacerbates the damage caused by climate change. This dynamic could intensify inequalities and undermine multiple dimensions of human well-being.

The Mekong River Basin, spanning six countries—Vietnam, Laos, Cambodia, Thailand, Myanmar, and China—is Asia’s largest trans-boundary river system. It provides agricultural, industrial, and domestic water resources to over 90 million people, including the Mekong Delta, one of the world’s most significant rice-producing regions. However, the basin is located in a monsoon climate zone, characterized by high annual rainfall variability. It is particularly vulnerable to climate change, with more frequent and severe climate disasters such as droughts, floods, and saline intrusion expected.

Given this context, the study aims to comprehensively examine the impacts of climate change in the Mekong River Basin, where high agricultural dependence and limited capacity magnify climate-related risks. Specifically, it investigates the determinants of farmers’ adoption of climate adaptation measures and evaluates the multidimensional impacts of these measures. This study seeks to identify effective adaptation strategies for farmers to address the global challenge of

climate change and provide policy insights to enhance climate resilience in the agricultural sector, thereby supporting the development of international cooperation models.

The objectives of this research include: (1) Conducting interdisciplinary, evidence-based climate change research; (2) Strengthening research capacity in LMICs; (3) Developing and disseminating evidence-based climate change response strategies; (4) Identifying and proposing effective international development cooperation models for climate change adaptation. Through these efforts, the study aims to offer practical policy recommendations to farmers and policymakers in climate-vulnerable LMICs. To achieve this, the study focuses on three key research areas: The impacts of climate change on agricultural productivity and variability, and the effectiveness of adaptation measures; The factors of farmers' decision-making in adopting climate change adaptation measures; The effects of climate change adaptation measures on farmers' quality of life.

(Sub-study 1) The Impacts of Climate Change on Agricultural Productivity and Variability, and the Effectiveness of Adaptation Measures

Sub-study 1 examines the impact of climate change on agricultural productivity, profitability, and variability, as well as the effectiveness of adaptation measures, using micro-level data from Vietnamese farmers, historical climate records, and future climate projections. It analyzes how climate change affects agricultural productivity, profitability, and variability, and explores how these changes influence farmers' decisions to adopt adaptation measures, such as crop selection and machinery investments. Additionally, it assesses the impact of climate change and farmers' adaptation measures on rice productivity and agricultural income, with a focus on neighborhood effects.

Climate change significantly affects rice productivity and farm profitability. Substantial increases in temperature reduce both productivity and profitability, while also decreasing the variability of rice yields. In contrast, increased rainfall

raises variability of rice productivity, and both factors contribute to increased variability of farm profitability. Extreme weather events exacerbate rice productivity and its variability, with the Mekong Delta region being particularly vulnerable in terms of variability of rice yields.

In response to climate change, Vietnamese farmers tend to increase the proportion of rice cultivation. Simulations based on future climate scenarios suggest that the shares of rice and fruit crops will rise, while the shares of other food crops, vegetables, and industrial crops will decline. Lower carbon mitigation efforts are associated with a greater increase in the proportion of rice cultivation. Climate change also influences machinery expenditure, with a consistent rise in per-unit-area machinery expenditure across various climate scenarios.

The analysis of rice productivity, incorporating adaptation measures such as increased rice cultivation area and higher machinery investments, shows that rising temperatures and rainfall negatively impact rice productivity. Extreme weather events further reduce yields. However, adaptation measures improve productivity, highlighting their potential as effective responses to climate change. Without adaptation, rice productivity is projected to decline significantly, with losses exceeding 40% under the SSP5-8.5 scenario by 2061–2080. Implementing adaptation measures could mitigate these losses or even result in productivity gains, reducing losses to around 5% when all forms of adaptation measures are implemented. The effects of these adaptation measures were more pronounced in scenarios with lower carbon emission reduction efforts. These measures are particularly crucial in the Mekong Delta, where is more vulnerable to climate change compared to other areas.

Higher temperatures and increased rainfall negatively affect agricultural income, though the magnitude of income loss is smaller compared to rice productivity loss. This is due to the offsetting effects of climate change on different crops and the positive impact of higher market prices resulting from reduced productivity. Nonetheless, climate change tends to reduce agricultural income. Adaptation

measures, particularly adjusting crop shares, can lead to income growth. Neighborhood effects highlight the spillovers of adaptation, where climate impacts and adaptation decisions by neighboring farms influence others, potentially amplifying effects (multiplier effects). Future climate simulations suggest that, although income losses are smaller than productivity losses, long-term reductions in income are likely without adaptation. This is likely due to heterogeneous responses between crops (diversification effects) and price effects results from market price changes caused by climate change. Furthermore, if farmers implement adaptation measures, agricultural income can improve in the long term, with changes in crop composition having the greatest impact on farm profitability. When all adaptation measures are implemented, profitability could increase by up to 9%. In particular, in the Mekong Delta region, adaptation measures could boost farm profitability by up to 50%, and adjusting crop composition is expected to play a crucial role in responding to climate change.

The findings suggest several policy implications. First, rice productivity is expected to decline, particularly in the Mekong Delta. To address this, climate change adaptation measures at the farm level, such as changes in crop composition and mechanization, need to be encouraged with policy support for drought and flood mitigation, crop variety improvement, and climate disaster prevention. Second, the impact of climate change on agricultural income from crop farming is relatively smaller than the reduction in rice productivity. This is because agricultural income focuses on income rather than productivity per unit area. The increase in market prices due to the reduction in productivity positively affects profitability, which partially offsets the negative impact of climate change on productivity. Nevertheless, climate change tends to worsen farm profitability. However, agricultural income may actually increase when farmers implement adaptation measures such as changing crop combinations and increasing investment in agricultural machinery. Therefore, education and financial support for crop change and infrastructure investment at the farm level are crucial. Third, the neighborhood effects, which represent the social effect between neighboring farmers in crop selection, were

found to be significant. This suggests that changes in crop selection and the formation of specialized production zones for specific crops create positive spillover effects, and education and training on crop selection can lead to positive externalities. Furthermore, regionally organized community-based programs are likely to deliver effective effective outcomes.

(Sub-study 2) The Factors of Farmers' Decision-Making in adopting climate change adaptation measures among Mekong River Basin Farmers

Sub-study 2 conducts a survey targeting farms in the Mekong Delta of Vietnam and the Mekong River Basin of Laos to analyze the factors influencing farms' decisions to implement climate change adaptation measures. Climate change responses are broadly categorized into adaptation and mitigation measures, with low- and middle-income countries mainly relying on adaptation measures due to limited climate change response capacity. Key climate change adaptation measures in agriculture include (1) adjusting cultivation schedules, (2) crop diversification, (3) changing seed varieties, (4) preparing agricultural land, (5) adjusting cultivation techniques, (6) managing water usage, (7) improving water infrastructure, (8) diversifying income sources, and (9) utilizing agro-climatic information. These adaptation measures serve as crucial strategies for farmers in the Mekong River Basin to effectively respond to climate change. The countries in the Mekong River Basin, in collaboration with international development cooperation programs like DeRisk South Asia, SAMIS, and LaCSA, provide government-led climate information services to enhance farmers' climate change response capabilities. These initiatives have improved access to farming techniques and information, contributing to strengthening farmers' climate change response capacities.

This study aims to analyze various factors influencing the decision-making process for implementing climate change adaptation measures by farms in the Mekong Delta of Vietnam and the Mekong River Basin of Laos. The goal is to understand the decision-making mechanisms behind the adoption of adaptation

measures and to propose effective policies and strategies for improving farmers' climate change adaptation capacity, which can contribute to increased agricultural productivity, food security, poverty alleviation, and improved quality of life, ultimately contributing to sustainable agriculture and rural development.

The household surveys were conducted through one-on-one face-to-face interviews in collaboration with local partners in Vientiane Province, Laos (308 households), and Tien Giang Province, Vietnam (319 households) in June and September 2024, respectively. The Vietnam survey built a panel data set based on a follow-up survey conducted in the same region in 2022.

The key dependent variables include (1) adoption of individual climate change adaptation measures, (2) adoption of adaptation measure groups classified by similar characteristics, and (3) climate change adaptation index, which measures the overall tendency to utilize climate change adaptation measures. Climate change adaptation measures are classified based on similar characteristics into categories such as (4) variety/crop diversification, (5) adjusting farming practices, (6) water use management/infrastructure improvements, (7) climate information utilization, (8) income diversification, and (9) insurance purchase. The climate change adaptation index was estimated using Principal Component Analysis (PCA). The main explanatory variables include demographic variables, socio-economic variables, access to climate information, resource and technical factors, climate change perception and damage experience, adaptation measure perception, social networks, and non-cognitive skills that may influence farmers' decisions to adopt climate change adaptation measures.

Survey results show that the majority of farmers in Vietnam and Laos recognized that climate change is occurring and had experienced damage from floods or droughts. Additionally, they anticipated future climate shocks such as droughts or floods due to climate change. Although most households had a positive perception of climate change adaptation measures, relatively fewer households actually utilized climate information in their adaptation efforts.

In terms of the current status of climate change adaptation measure adoption by farmers, Vietnam primarily adopted (4) agricultural land preparation, (5) adjustment of cultivation techniques, (9) utilization of agro-climatic information, and (7) individual water infrastructure improvements. In contrast, Laos mainly adopted (1) adjusting cultivation schedules, (3) changing seed varieties, (5) adjusting cultivation techniques, and (9) utilizing agro-climatic information. Both countries showed similar proportions of households possessing knowledge how to implement climate change adaptation measures and the actual adoption rates, but Vietnam exhibited a lower adoption rate relative to its knowledge compared to Laos.

The analysis of factors influencing the adoption of climate change adaptation measures by farmers in the Mekong River Basin revealed that no common factors universally affected the decision-making for all measures. However, agricultural extension services, access to agro-climate information, and self-efficacy were identified as key influencing factors.

These findings provide the following implications. First, to promote the adoption of climate change adaptation measures by farmers, policy support is needed to improve climate change-related knowledge and perception, support practical access to climate information, provide incentives to utilize this information, and identify and remove barriers. Second, education and training programs linked with agricultural extension services should strengthen farmers' climate-smart agricultural techniques and their implementation capabilities for adaptation measures. Third, it is essential to design regionally organized support measures tailored to farmers' non-cognitive skills, such as self-efficacy, and the characteristics of adaptation measures to effectively induce behavioral changes for adopting climate change adaptation measures. Fourth, efforts to enhance the climate change response capacities of LMICs should be strengthened through cooperation with various international development cooperation programs that utilize agro-climatic services.

(Sub-study 3) The Effects of Climate Change Adaptation Measures on Farmers' Quality of Life

Sub-study 3 aims to comprehensively analyze the various impacts of climate change adaptation measures on farmers' quality of life. Climate change has complex effects on the lives of farmers in LMICs, particularly threatening agricultural productivity and food security in the Mekong River Basin, thereby lowering the overall quality of life of farmers. Therefore, it is necessary to analyze the impact of climate change on various aspects of quality of life, such as income, consumption, and health, in addition to agricultural productivity. This provides an in-depth understanding required for establishing effective climate change response policies that can improve farmers' quality of life.

This study analyzes the effects of climate change adaptation measures on various aspects such as household income, agricultural income, household consumption expenditure, food consumption expenditure, and subjective quality of life, among farmers in the Mekong River Basin of Vietnam and Laos. By comparing the quality of life outcomes between farmers who adopted adaptation measures and those who did not, the study sheds light on the multidimensional effects of climate change adaptation measures. Using household survey data collected from Vietnam and Laos, the study employs methods such as Multiple Ordinary Least Squares regression, Panel Fixed-Effects analysis, and Endogenous Switching Regression (ESR) to estimate the impact of climate change adaptation measures on farmers' quality of life while mitigating biases caused by endogeneity. The study also examines how climate information services contribute to enhancing farmers' climate response capacities and alleviating the negative impacts of climate change through synergy effects with other adaptation measures.

The results show that in Laos, climate change adaptation measures had various effects on household income, consumption expenditure, and subjective quality of life. Adjusting farming practices showed positive effects by increasing household income and consumption expenditure, while income diversification enhanced

household income and optimism about future life. The use of climate information contributed to increasing household and agricultural incomes. On the other hand, the income-increasing effects of variety and crop diversification and water resource management were minimal, and insurance purchase was associated with income reduction and high anxiety about the future. The combination of climate information utilization and adjusting farming practices demonstrated effective synergies in increasing agricultural productivity and income. These results suggest that some adaptation measures, such as changing cultivation schedules or more actively utilizing climate information in agriculture, which can be implemented with relatively low costs and risks while maintaining the overall framework of current agriculture, may be more effective compared to high-cost and high-risk measures such as water resource management or variety and crop diversification.

In Vietnam, the ESR analysis results indicated that most climate change adaptation measures, except for insurance purchases, had positive effects on increasing household and agricultural incomes, and also showed positive effects in terms of household consumption expenditure, which well reflects the living standards of households. However, in terms of nutrition (food consumption expenditure) and subjective quality of life (satisfaction with current life and optimism about future life), different effects could be observed depending on the characteristics of the various types of climate change adaptation measures. This suggests that it is necessary to formulate and implement agricultural support policies and projects considering the objectives and characteristics of the target groups. It was also confirmed that in the case of insurance purchases, which might not directly increase current household income and agricultural income, there is a possibility that short-term negative impacts such as insurance premiums for insurance enrollment or moral hazards caused by insurance enrollment adversely affected household and agricultural incomes.

The key implications derived from this study are as follows. First, for farmers in LMICs with limited climate change response capacities, low-cost and low-risk

adaptation measures such as adjusting farming practices, utilizing climate information, and diversifying income sources, which have relatively low costs and difficulty of implementation, can be effective in improving the welfare and quality of life of farmers. Therefore, it is necessary to promote the active use of such adaptation measures by farmers, while high-cost and high-risk measures should be supported at the governmental or community level rather than at the individual farm level. Second, as agricultural extension services and access to finance have positive effects on increasing farmers' incomes, policies are needed to enhance farmers' capacities through community-based agricultural extension services and improve financial accessibility. Third, utilizing climate information is an important tool that can strengthen farmers' climate change response capacities and create synergy effects when combined with other adaptation measures, thus allowing farmers to respond more effectively to climate change. Therefore, policies to improve access to climate information services and provide technical support and capacity-building to actively utilize these services in agricultural activities are needed.

Proposal of a Sustainable International Development Cooperation Project Model

This study proposes a digital-based climate-smart agriculture international development cooperation project model, considering the long-term international development cooperation policies of the Korean government in the agriculture and climate change sectors, as well as the agricultural and climate change-related development strategies of Vietnam and Laos. Through this, the study seeks to promote sustainable agricultural and rural development and present guidelines applicable to the international development cooperation projects of the Korean government in these fields.

Vietnam has established a national strategy focused on agricultural digitization and technological innovation to respond to climate change in the agricultural sector. This policy aims to increase agricultural productivity and minimize the damage caused by climate change. Laos also has set the establishment of a

sustainable agricultural system and the enhancement of food security as the main goals of its national agricultural development strategy, implementing policies to strengthen the climate change adaptation capacity of rural areas.

By strengthening global networks and cooperation, we propose the following strategies to respond to the global challenge of climate change and improve global climate change capacities. First, we suggest to link with the Mekong Delta Region Development Policy Operation (Mekong DPO) project in Vietnam. A project to 'Increase Income through Improvement of Agricultural Product Distribution Systems' can be promoted in connection with the coastal road construction project in Tien Giang Province, involving the Asian Development Bank (ADB) and Korea Export-Import Bank for Mekong DPO. By utilizing the road being constructed, this project can be promoted to establish an agricultural product distribution system and form an agricultural value chain, enabling synergy effects through the linkage of grants (aid funds) and loans (non-aid funds) and the development of the BOP (Bottom of the Pyramid) market through private sector participation. Second, we propose to collaborate with the Asian Mega-Deltas (AMD) initiatives, being led by the Consultative Group on International Agricultural Research (CGIAR), for climate information projects such as 'Climate Change Resilience through the Automation of an Integrated Climate Change Information System.' Similarly, a digital platform providing agro-climatic information can be established in vulnerable areas such as the Mekong River Basin and central highlands to strengthen the climate change response capacity of the agricultural sector.

In addition, the following ODA models can be promoted in Vietnam and Laos respectively. In Laos, the advantages of agro-meteorological services such as SAMIS and LaCSA, which have already achieved significant results, can be utilized, and their limitations can be complemented to promote the nationwide expansion of these services. Alternatively, climate information services can be provided to climate-vulnerable areas, and regional tailored approaches can be considered to enhance the climate-smart agriculture capacity of farms and expand technical support. In Vietnam, while agro-meteorological services like DeRISK have made

meaningful contributions to the agricultural sector and received positive evaluations from the Vietnamese government, stable service provision is challenging without additional external support. Therefore, to provide long-term financially, technically, and capacity-wise sustainable climate information services, we suggest to develop a national-level Agro-Climatic Digital Platform (ACDP) that integrates data and information from various sources to provide services to farms. For the successful establishment and operation of the ACDP, it is necessary to prepare a technical foundation for development and maintenance, establish an effective delivery system for climate information and services, and create a systematic capacity-building program for system operation and utilization.

In promoting such ODA models in the agricultural and climate change sectors, we recommend the following considerations. First, the participation of vulnerable groups such as small farmers, women, youth, elderly, and disabled should be considered throughout the planning, implementation, and evaluation stages of a project. This ensures that the public objectives of ODA projects are achieved and that the project's outcomes are equitably distributed to vulnerable groups. Second, the active participation of local communities and farmer organizations should be encouraged to strengthen the capacity for self-reliance and sustainable project. Third, it is necessary to actively utilize the participation of the domestic private sector in Korea, with its technological capabilities and expertise. This can create new business opportunities such as exploring the BOP market, ensure the financial and economic sustainability of the project, and promote mutual development and co-prosperity between donor and recipient countries. Furthermore, cooperation between private sectors in Korea and partner countries can contribute to new market creation and the enhancement and development of local private sector capabilities. This approach will help achieve the public objectives of ODA projects in a sustainable manner while contributing to the mutual development of Korea and its partner countries.

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1. Research Overview

1.1. Background and Objectives of the Research

1.1.1. Research Background

Climate change is rapidly increasing the frequency and intensity of extreme weather events, such as drastic temperature fluctuations and changes in precipitation patterns. These changes directly impact human life and indirectly affect it through ecological disruption and socioeconomic transformations. The vulnerability of individuals or groups can exacerbate the impacts of climate change, potentially leading to severe inequalities. According to the 2023 report by the Intergovernmental Panel on Climate Change (IPCC), the rate of global temperature rise is progressing faster than anticipated, and low and middle income countries (LMICs) are particularly vulnerable to climate change due to limited financial resources. Countries in low latitudes, in particular, are expected to suffer greater damage from climate-related phenomena, such as rising sea levels, floods, and droughts (IPCC, 2023).

Most LMICs rely heavily on agriculture for their economies, raising significant concerns about potential losses in agricultural productivity due to climate change (Rosenzweig et al., 2014). Consequently, these impacts are likely to lead to social issues such as reduced farm incomes, increased poverty, and worsening food security. Such changes could, in turn, result in a decline in farmers' welfare across various aspects, including education, healthcare, and overall quality of life.

The Mekong River Basin, covering an area of 795,000 km², is Asia's largest trans-boundary river, supplying agricultural, industrial, and domestic water resources to 90 million residents across neighboring countries, including Vietnam, Laos, Cambodia, Thailand, Myanmar, and China. Due to its location in a monsoon

climate zone where rainfall is highly concentrated in the summer, the basin experiences significant annual rainfall variability, making it highly vulnerable to climate change. Climate change projections indicate that wet-season rainfall variability could fluctuate between -16% and +17%, highlighting the considerable uncertainty in future climate predictions (Mekong River Commission, 2017). As a result, the Mekong Delta, one of the world's largest agricultural regions, is expected to face complex challenges from climate change, impacting agricultural productivity, food security, public health, and overall quality of life.

However, despite the severity of these impacts, information sharing on climate change issues, such as extreme weather events, remains limited. The Mekong River flows from upstream countries like China and Myanmar through downstream regions in Thailand, Laos, Cambodia, and Vietnam, often leading to conflicts of interest among countries over the use of the river and limiting effective information exchange. Member countries of the Mekong River Commission (MRC)—Cambodia, Laos, Thailand, and Vietnam—are making efforts to share information, but China and Myanmar have not joined as members. Furthermore, China's construction of dams upstream has altered the natural water flow downstream (increasing dry-season flow and reducing wet-season flow), which adds to the challenges. Thus, limited information sharing between China and the MRC hampers timely responses to climate crises affecting the Mekong River Basin, including extreme weather events.

Vietnam, Laos, and Cambodia, key ODA partner countries located in the Mekong River Basin, are particularly vulnerable to climate change impacts in the agricultural sector. Frequent droughts and floods lead to greater variability in the supply of agricultural water, resulting in unstable crop yields. Additionally, challenges such as reduced hydroelectric power generation, navigation blockages on the Mekong River, soil erosion from landslides, rising sea levels, and infrastructure damage from storms severely impact transportation and water supply infrastructure. These issues hinder market access and contribute to significant income losses for farming households.

This study aims to identify effective adaptive measures for farming households and derive policy implications to address climate change in agriculture, a global challenge. Focusing on rural areas in the Mekong River Basin—where high agricultural dependency amplifies climate change impacts—this interdisciplinary empirical research will comprehensively analyze the multidimensional effects of climate change and the effectiveness of adaptation measures adopted by farmers. Through this approach, the study seeks to provide valuable insights and recommendations for policy development in climate adaptation strategies for the agricultural sector.

1.1.2. Research Objectives

This study aims to strengthen research capacity in LMICs and **establish a sustainable research network** through partnerships with local institutions and researchers in the target regions. By conducting data-driven empirical research, the study seeks to **offer recommendations for climate change adaptation strategies** in rural areas of LMICs and **to inform international development cooperation policies**. The specific objectives are outlined as follows:



Conducting Interdisciplinary Evidence-Based Climate Change Research

This study will analyze the impacts of climate change and the effectiveness of adaptation measures in rural areas of Vietnam, Laos, and Cambodia¹⁾ within the

1) In the case of Cambodia, a limited, secondary study was conducted within the scope that

Mekong River Basin, a critical agricultural region highly vulnerable to climate change. The analysis will cover multiple dimensions, including: Economics (changes in productivity, income variability vulnerability); Agriculture (food security); Education; Quality of life. Additionally, it will explore factors influencing farmers' decision-making on climate adaptation and assess the effectiveness of adaptation measures. This empirical research will be conducted through a multidisciplinary partnership, involving fields such as agricultural and resource economics, development economics, meteorology, plant microbiology, and agronomy, to provide a comprehensive view of climate adaptation in agriculture.

Strengthening Research Capacity in LMICs

By establishing partnerships with local institutions and researchers in Vietnam and Laos, key ODA partner countries, the study seeks to leverage complementary strengths and address gaps, creating a synergistic effect through collaborative research. This partnership aims to enhance the research capacity of LMICs and build a sustainable research network.

Developing and Disseminating Evidence-Based Climate Change Response Strategies

Based on empirical research, the study will provide scientific evidence to formulate climate change adaptation strategies for rural areas in LMICs vulnerable to climate impacts. The study will also offer recommendations and insights for international development cooperation policy. Research findings will be shared with domestic and international stakeholders and disseminated through journal publications and conference presentations to broaden the impact of the outcomes.

allowed data collection and analysis without a local research partnership, incorporating feedback from the proposal review.

Identifying and Proposing International Development Cooperation Models

Based on the research findings, the study aims to identify effective ODA project models for climate change adaptation and collaborate with multinational international development networks to address and improve climate-related development challenges in rural areas of LMICs. It will evaluate international cooperation frameworks related to climate information services, recognized as innovative solutions for climate change adaptation, to identify ODA project models that can foster strategic partnerships between nations. This approach seeks to position our country as a leader in climate change adaptation through international development cooperation on the global stage.

The study's findings will be disseminated to a broad range of domestic and international stakeholders through submissions to high-impact journals and conference presentations. Leveraging these insights, the study will identify viable ODA project models and explore collaborative strategies with multinational development networks. This effort is expected to support the development of climate adaptation policies and solutions, contributing to resolving climate-related challenges in vulnerable rural areas of LMICs.

1.2. Scope of the Research

This study focuses on **Vietnam, Laos, and Cambodia** as primary research areas within the Mekong River Basin, selected to capture the region's diverse geographical, economic, social, and institutional characteristics (see Figure 1-1). Over the past decade (excluding the COVID-19 pandemic period), these countries have achieved an average annual economic growth rate of approximately 6.1% (World Bank, 2023). As of 2023, the GDP growth rates are 5.0% for Vietnam, 3.7% for Laos, and 5.4% for Cambodia. Prior to the pandemic in 2019, the GDP growth rates were 7.4% in Vietnam, 5.5% in Laos, and 7.1% in Cambodia. Although the share of agriculture, forestry, and fisheries in GDP has gradually decreased due to urbanization and industrialization, it still accounts for 12.0% to 21.5% of GDP across these countries. Similarly, while the employment contribution of these sectors (percentage of total employment in agriculture, forestry, and fisheries) is also on a declining trend, it continues to constitute a substantial portion of total employment.

Economic growth has led to a steady increase in greenhouse gas (GHG) emissions across the target countries. As of 2020, Vietnam's total GHG emissions reached 470,578 ktCO₂eq²⁾, more than ten times the emissions of Laos (30,491 ktCO₂eq) and Cambodia (42,363 ktCO₂eq). These countries have set ambitious Nationally Determined Contributions (NDCs) to reduce emissions and achieve "Net Zero" carbon emissions by 2050. Specifically in the agricultural sector, Vietnam plans to reduce total emissions by 56.4 million tons by 2050, Laos aims for an annual reduction of 128,000 tons by 2030, and Cambodia has set a goal of reducing 15.6 million tons by 2050.

However, like many other LMICs, these nations face resource and capacity constraints in addressing climate change³⁾, including greenhouse gas reduction.

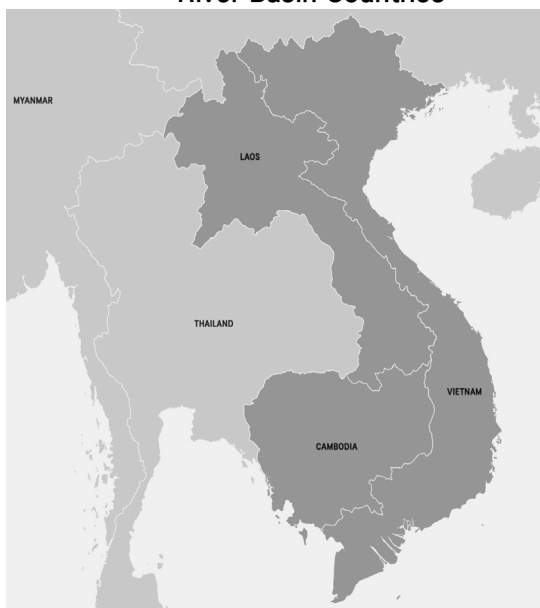
2) The unit used for greenhouse gas emissions, tons of CO₂ equivalent (tCO₂eq), represents the global warming impact of various greenhouse gases, equivalent to the impact of one ton of CO₂, as defined in Article 2, Section 9 of the Basic Act on Low Carbon Green Growth.

3) Mitigation and adaptation measures for addressing climate change in the agricultural sector will be discussed in detail in Section 3.2.

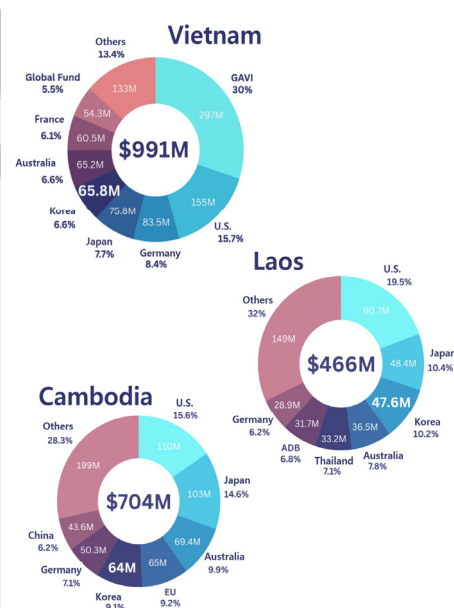
Implementing mitigation strategies at the farm level is particularly challenging. Additionally, due to their high dependency on the climate-sensitive agricultural sector, countries in the Mekong River Basin are especially vulnerable to climate change, making effective adaptation to extreme weather events and other climate impacts a critical challenge.

While both mitigation and adaptation measures are essential for addressing climate change, it is crucial to consider the unique conditions, capacities, and constraints of LMICs. Therefore, this study focuses on adaptation measures in the agricultural sector, examining the **impact of climate change on farming households in the Mekong River Basin** and the **effectiveness of climate adaptation measures**, with a specific focus on major crop productivity and variability. Additionally, the study will explore the **factors influencing farmers' decisions to adopt adaptation measures** and analyze the **multidimensional impacts of these adaptations on their livelihoods**.

[Figure 1-1] Map of the Three Mekong River Basin Countries



[Figure 1-2] ODA Grant Amounts (2022)



(Created by the authors / Data Source: OECD)

1.2.1. Major Economic Conditions, Agricultural Contribution, and Development Strategies of the Three Mekong River Basin Countries

〈Table 1-1〉 presents key economic conditions based on major economic indicators and household-level data for each country, providing an overview of the general economic status and household conditions in the three Mekong River Basin countries. 〈Figure 1-3〉 illustrates the trends in low urbanization rates and the high contribution of agriculture to employment in these countries. In Vietnam and Cambodia, the contribution of agriculture to employment decreased significantly from 2012 to 2022, but agriculture still accounts for over 30% of total employment. In Laos, the agricultural employment share initially declined but then increased again, reaching approximately 70% in 2022, comparable to the 2012 level. This confirms that **agriculture continues to play an important economic role** in the economies of the three Mekong River Basin countries. Additionally, an analysis of the ODA status, development strategies of the three Mekong countries, and South Korea's focused international development cooperation strategies for these countries provides a deeper understanding of the target countries and their primary development challenges. 〈Figure 1-2〉 and 〈Table 1-2〉 show the scale of ODA grants received by the three Mekong countries in 2022, along with the distribution by sector. South Korea has established the Country Partnership Strategy (CPS) as a medium- to long-term strategy and fundamental guideline for supporting partner countries. Separately, KOICA has developed the Country Plan (CP) to enhance alignment with CPS, meet the need for tailored support strategies, improve integrated project development, and leverage KOICA's comparative advantages over other aid organizations to maximize development effectiveness.

Socialist Republic of Vietnam

Vietnam's extensive agricultural regions, including the Mekong Delta, make a significant contribution to the national economy. Agriculture holds an essential place in Vietnam's GDP, with rice, coffee, and seafood as key export items. As of 2023, Vietnam's real GDP stands at approximately \$377.4 billion, with a per

capita GDP of \$3,817. This figure is lower than both the global average per capita GDP of \$11,567 and the LMIC average of \$5,337. Nonetheless, Vietnam's per capita GDP has been on a steady upward trend. In 2023, Vietnam's per capita GDP growth rate was 4.3%, outpacing both the global average of 1.8% and the LMIC average of 3.5%. Additionally, in 2018, the poverty rate in Vietnam, based on the national poverty line, was 20.7%, which is lower than the global average of 27.7% and the LMIC average of 30.4%. This indicates that the average income of Vietnamese households is increasing, and living standards are gradually improving. However, in 2018, Vietnam's poverty rate based on the national poverty line was 6.7%, with a stark contrast between urban and rural areas: urban poverty was at 1.5%, while rural poverty reached 9.6%. This rural poverty rate is approximately 6.4 times higher than in urban areas and 4.5 times higher than the national average. This disparity suggests that while living standards in urban areas have significantly improved, there is a substantial income imbalance between urban and rural regions in Vietnam.

Vietnam's economy remains heavily reliant on the agricultural sector. As of 2023, agriculture, forestry, and fisheries contribute 12.0% to Vietnam's GDP. Although this share is lower than that of manufacturing (23.9%) and services (42.5%), it remains high compared to the global average of 4.1% and the LMIC average of 9.0%. Additionally, the employment contribution of agriculture, forestry, and fisheries in Vietnam is 33.6% (as of 2022), closely aligned with the employment shares of industry (30.6%) and services (35.8%). This is also higher than the global average of 26.4% and the LMIC average of 32.3%, indicating that agriculture still plays a substantial role in national employment.

In 2022, Vietnam received \$991 million in ODA grants, with South Korea contributing approximately 6.6% of this amount (\$65.8 million). According to Vietnam's long-term national development strategy, the 2021–2030 Socioeconomic Development Strategy (SEDS)⁴, the country aims to become an emerging industrial nation and

4) Government Agencies: Central Committee of Communication(2021). CHIẾN LƯỢC PHÁT TRIỂN KINH TẾ - XÃ HỘI 10 NĂM 2021–2030.

upper-middle-income country by 2030 through advancements in science, technology, innovation, and digital transformation across economic, social, environmental, and political sectors. Within the economic sector, Vietnam has set strategic goals related to ‘regional economic and marine economic development and rural development revitalization’. In the environmental sector, it has focused on ‘environmental protection’, ‘climate change response’, ‘disaster prevention’, and ‘disaster management’, all of which are linked to **agriculture, rural development, and climate change**.

In the third phase (2021–25) of South Korea’s Country Partnership Strategy (CPS), priority sectors for support to Vietnam include transportation, healthcare and sanitation, environment, education, and public administration. Within the environmental sector, the CPS outlines targeted support strategies for climate change adaptation: (1) Strengthening climate resilience through eco-friendly infrastructure development and capacity building; (2) Expanding green energy and supporting smart city infrastructure to transition Vietnam toward a carbon-neutral society; and (3) Forest cooperation, waste management (solid and marine waste), and circular economy development to mitigate climate change impacts. Building on these strategies, South Korea plans to enhance **climate adaptation and mitigation support** through initiatives such as water resource management, irrigation projects, environmental management capacity building, and the development of smart and sustainable agriculture. These initiatives aim to provide eco-friendly infrastructure and forest cooperation to reduce climate impacts in vulnerable areas, including the Mekong Delta and the Red River regions, which face droughts, floods, and rising sea levels. KOICA’s Country Plan (CP) also prioritizes inclusive and sustainable rural development, with a focus on creating "Peace Villages" in rural areas to support the **agriculture, forestry, fisheries, and rural development** sectors in Vietnam.

Lao People's Democratic Republic

Laos, a landlocked country, relies heavily on agriculture and hydropower as its main industries. Hydropower, in particular, is a crucial element of the Laotian economy, with a high dependency on the Mekong River for energy production. In 2023, Laos' real GDP was approximately \$20.3 billion, with a per capita GDP of \$2,660 and a per capita GDP growth rate of 2.3%. This indicates that the average income level and economic growth rate of Laotian households are relatively low compared to other LMICs. The agriculture, forestry, and fisheries sector contributes 16.1% to Laos' GDP (as of 2023), significantly higher than the global average of 4.1% and the LMIC average of 9.0%. Additionally, the employment contribution of agriculture, forestry, and fisheries is 69.6% (as of 2022), more than twice the average for LMICs (32.2%). When compared to Laos' industrial employment share (7.2%) and service sector employment share (23.3%), it is evident that the majority of the Laotian population is engaged in agriculture.

In 2018, the poverty rate in Laos, based on the social poverty line, was 30.5%, roughly aligned with the LMIC average of 30.4%. According to the national poverty line, however, the rate was 18.3%, with a stark disparity between urban (7.0%) and rural areas (28.3%), where the rural poverty rate is more than seven times higher. Moreover, the poverty rate for wage workers was 4.5%, for non-agricultural self-employed workers 5.5%, and for the unemployed and economically inactive population 21.3%. In contrast, the poverty rate among agricultural workers was 24.6% (Lao Statistics Bureau, 2020), indicating that agricultural workers in Laos are more economically vulnerable than wage earners, non-agricultural self-employed individuals, and even the unemployed or economically inactive population. This highlights the need for government efforts not only to improve the overall standard of living in Laos but also to specifically target rural areas and farming households, which face higher economic vulnerability, to enhance their quality of life.

In 2022, Laos received \$466 million in ODA grants, with South Korea contributing approximately 10.2% of this amount (\$47.6 million). Laos has set a goal of achieving

upper-middle-income status through innovative, eco-friendly, and sustainable economic growth, based on its long-term development strategy, ‘Vision 2030 (2016–2030)’, and the ‘National Implementation Strategy (2016–2025)’ for a decade of social and economic development. Additionally, the ‘9th National Socio-Economic Development Plan (2021–2025)⁵⁾’ outlines national development strategies and priority policies by sector. Within the well-being sector, the plan aims to improve **quality of life** through enhancing living conditions at both individual and societal levels. In the environmental sector, it prioritizes **climate change adaptation** by achieving environmentally friendly development and disaster risk reduction. In 2022, Laos received approximately \$40.7 million in ODA grants in the agriculture, forestry, and fisheries sector, across 150 projects, representing about 9% of its total ODA grants. In the environmental sector, it received about \$10 million for 55 projects, accounting for around 2% of total ODA grants.

In the third phase of its CPS, South Korea has identified water management, healthcare and sanitation, energy, regional development, and education as priority support areas for Laos. Within the water management sector, specific support directions include strengthening policy capacity for integrated water management systems and building water resource management systems and infrastructure. In the regional development sector, the focus includes (1) reducing urban-rural development disparities, (2) improving rural environments to prevent climate disasters and enhance the quality of life for rural residents, and (3) supporting agricultural value chain enhancements to alleviate rural poverty and achieve food security. These strategies form the basis of South Korea’s support for **climate change adaptation, agricultural and rural development, and quality of life improvement** in Laos.

5) Lao PDR Ministry of Planning and Investment(2021). 9th Five-Year National Socio-Economic Development Plan (2021-2025).

Kingdom of Cambodia

In Cambodia, the abundant resources of the Mekong River Basin play a crucial role in the national economy. Agriculture and fisheries are core industries, with tourism also emerging as a significant sector in recent years. In 2023, Cambodia's real GDP was \$26.3 billion, with a per capita GDP of \$1,553 and a per capita GDP growth rate of 4.3%. While Cambodia has experienced rapid economic growth in recent years, its average household income level remains lower than not only the average for LMICs but also that of neighboring countries such as Vietnam and Laos. The agriculture, forestry, and fisheries sector contributes 21.5% to Cambodia's GDP (as of 2023), the highest among the three Mekong River Basin countries in this study. Furthermore, the sector's contribution to employment stands at 36.6% (as of 2022), highlighting its importance in national employment. Based on the national poverty line, Cambodia's poverty rate was 17.7% in 2012, with a marked income gap between urban (6.4%) and rural areas (20.8%). This disparity indicates a need for policies aimed at reducing income inequality between urban and rural regions.

In 2022, Cambodia received \$704 million in ODA grants, with South Korea contributing approximately 9.1% of this amount (\$64 million). Cambodia releases its top-level national development strategy, the Rectangular Strategy for Growth, Employment, Equity, and Efficiency (RS), on a five-year basis. In the fourth phase of the Rectangular Strategy (RS Phase IV, 2018–2023), inclusive and sustainable development was established as one of the four core strategies, prioritizing **agricultural and rural development, environmental sustainability, and climate change adaptation** as key development areas. To implement the Rectangular Strategy, Cambodia developed the National Strategic Development Plan (2019–2023), which focuses on 'enhancing productivity', 'diversification', and 'commercialization' in the agriculture sector, along with 'promoting livestock and aquaculture'. In the environmental sector, the plan emphasizes 'sustainable environmental practices' and 'partnership building' for development'. In 2022, Cambodia received approximately

\$60.4 million in ODA grants in the agriculture, forestry, and fisheries sector, covering 224 projects and accounting for about 9% of total ODA grants. In the environmental sector, Cambodia received around \$19.2 million across 79 projects, representing about 3% of total ODA grants.

In the third phase of its CPS, South Korea has identified transportation, water management, healthcare and sanitation, education, and regional (rural) development as priority support areas for Cambodia. In the water management sector, specific focus areas include ensuring stable water resource availability and supply. In the regional (rural) development sector, priorities include (1) expanding agricultural infrastructure to increase rural incomes and competitiveness, (2) strengthening agricultural value chains and improving product quality and competitiveness to facilitate exports, and (3) enhancing technical capabilities in rural areas. These priorities form part of South Korea's strategic support plan for **climate change adaptation and agricultural and rural development** in Cambodia. KOICA's Country Plan (CP) also designates inclusive and sustainable rural development as a key program, focusing on support for agriculture, forestry, fisheries, and rural development in Cambodia.

Agriculture plays a vital role in the economies of all three countries, yet the economic conditions in rural areas remain relatively poor. Climate change poses serious threats to the agricultural sector in these nations, underscoring the need for policy efforts that support the vulnerable agricultural sector and rural areas in adapting to climate impacts. To address this, it is essential to strengthen farmers' capacity to respond to climate change, improve agricultural productivity, and stabilize income levels, thereby enhancing overall quality of life and living standards. An examination of literacy rates among adults aged 15 and over, the percentage of the population with access to electricity, internet usage rates, and mobile subscriptions per 100 people reveals that all three countries possess the fundamental conditions necessary to improve farmers' climate resilience. Building on this foundation, it is crucial to promote the adoption of effective and efficient adaptation measures at the farm level. Such climate adaptation measures will help minimize

the impacts of climate change on the agricultural sector, support economic stability for farming households, and improve their quality of life, ultimately contributing to national economic growth.

〈Table 1-1〉 Statistical Indicators of Three Mekong Basin Countries

Indicators	World	LMICs	Vietnam	Laos	Cambodia
Real GDP (2023)	–	–	USD 377.36 billion	USD 20.3 billion	USD 26.31 billion
Real GDP per Capita (2023)	USD 11,567.2	USD 5,337.3	USD 3,817.2	USD 2,659.7	USD 1,552.8
GDP per Capita Growth Rate (2023)	1.8%	3.5%	4.3%	2.3%	4.3%
GDP Contribution of Agriculture, Forestry, and Fisheries (2023)	4.1%	9.0%	12.0%	16.1%	21.5%
GDP Contribution of Manufacturing (2023)	15.3%	20.5%	23.9%	9.2%	18.3%
GDP Contribution of Services (2023)	61.8%	53.1%	42.5%	44.0%	33.4%
Employment Contribution of Agriculture, Forestry, and Fisheries (2022)	26.4% (F:25.6%/ M:26.9%)	32.2% (F:32.6%/ M:32.0%)	33.6% (F:34.9%/ M:32.4%)	69.6% (F:70.0%/ M:69.5%)	36.6% (F:38.7%/ M:34.8%)
Employment Contribution of Industry ⁶⁾ (2022)	23.9% (F:17.2%/ M:28.3%)	24.3% (F:19.0%/ M:27.6%)	30.6% (F:26.7%/ M:34.3%)	7.2% (F:5.6%/ M:8.6%)	26.6% (F:23.7%/ M:29.1%)
Employment Contribution of Services (2022)	49.7% (F:57.2%/ M:44.9%)	43.5% (F:48.5%/ M:40.5%)	35.8% (F:38.5%/ M:33.2%)	23.3% (F:24.8%/ M:21.9%)	36.8% (F:37.5%/ M:36.1%)
Poverty Rate Based on National Poverty Line ⁷⁾ (2018)	–	–	6.7% (Urban:1.5%/ Rural:9.6%)	18.3% (Urban:7.0%/ Rural:28.3%)	17.7%(2012) (Urban:6.4%/ Rural:20.8%)
Poverty Rate Based on Societal Poverty Line ⁸⁾ (2018)	27.7%	30.4%	20.7%	30.5%	–
Life Expectancy at Birth (2022)	72.0 years	70.4 years	74.6 years	69.0 years	69.9 years
Government Expenditure on Health (% of GDP, 2021)	6.5%	2.8%	2.0%	0.7%	2.0%

Indicators	World	LMICs	Vietnam	Laos	Cambodia
Government Expenditure on Education (% of GDP, 2021)	4.2%	3.7%	2.9%	1.9%	1.7%
Adult Literacy Rate (15+, 2022)	87.0% (F:83.8%/ M:90.3%)	84.8% (F:81.0%/ M:88.7%)	96.1% (F:95.1%/ M:97.2%)	87.5% (F:83.4%/ M:91.6%)	83.8% (F:79.7%/ M:88.1%)
Population with Access to Electricity (2022)	91.4% (Urban:97.7%/ Rural:84.0%)	89.5% (Urban:96.9%/ Rural:82.6%)	100% (Urban:100%/ Rural:100%)	100% (Urban:100%/ Rural:100%)	92.3% (Urban:97.7%/ Rural:84.0%)
Internet Usage Rate (2021)	63.1%	57.1%	74.2%	62.0%	60.2%
Mobile Phone Subscriptions per 100 People (2021)	107.4	103.0	138.9	65.0	120.0
Total ODA Support from South Korea (2022)	KRW 3,824.76 billion	–	KRW 147.11 billion	KRW 110.04 billion	KRW 178.9 billion
Bilateral Grant ODA Support from South Korea (2022)	.	–	KRW 59.73 billion	KRW 45.53 billion	KRW 52.96 billion
KOICA ODA Support from South Korea (2022)	.	–	KRW 45.13 billion	KRW 29.61 billion	KRW 36.52 billion

(Created by the authors / Data Source: World Development Indicators, World Bank)

-
- 6) The industry sector includes mining and quarrying, manufacturing, construction, and public utilities (electricity, water, and gas).
- 7) The poverty rates in urban and rural areas of Vietnam are based on data from the General Statistics Office of Vietnam (2019), for Laos from the Lao Statistics Bureau (2020), and for Cambodia from the ADB (2015).
- 8) The poverty headcount ratio at the societal poverty line represents the proportion of the population in poverty according to the World Bank's societal poverty line, which is adjusted to each country's median income, considering real purchasing power.

〈Table 1-2〉 ODA Grant Amounts Received by the Three Mekong River Basin Countries in 2022

Total Amount of ODA Grants Received in 2022		Vietnam (\$991M)			Laos (\$466M)			Cambodia (\$704M)		
Sector		Amount	# Projects	Percentage	Amount	# Projects	Percentage	Amount	# Projects	Percentage
 Agriculture, Forestry, & Fishing		\$40.8M	222	4%	\$40.7M	150	9%	\$60.4M	224	9%
 Banking & Financial Services		\$14.3M	85	1%	\$10.1M	37	2%	\$4.4M	45	1%
 Communications		\$2.9M	53	<1%	\$4.4M	41	1%	\$10.8M	454	2%
 Education		\$124M	292	13%	\$74.7M	193	16%	\$95.7M	292	14%
 Energy		\$47.2M	63	5%	\$3.9M	37	1%	\$7.6M	37	1%
 General Environment Protection		\$55.5M	167	6%	\$10.0M	55	2%	\$19.2M	79	3%
 Government & Civil Society		\$112M	703	11%	\$91.2M	500	20%	\$139.0M	659	20%
 Health		\$481M	356	49%	\$84.1M	252	18%	\$195.0M	336	28%
 Humanitarian Aid		\$4.7M	60	<1%	\$5.2M	55	1%	\$11.7M	60	2%
 Industry, Mining & Construction		\$9.7M	88	1%	\$6.4M	50	1%	\$11.0M	62	2%
 Transport & Storage		\$10.3M	50	1%	\$52.3M	43	11%	\$27.1M	51	4%
 Water & Sanitation		\$12.2M	95	1%	\$24.2M	62	5%	\$33.0M	113	5%
 Other/Unspecified		\$76.4M	369	8%	\$58.5M	220	13%	\$89.4M	304	13%

(Created by the authors / Data Source: OECD)

[Figure 1-3] Urbanization Rate and Employment Contribution of Agriculture in the Three Mekong River Basin Countries

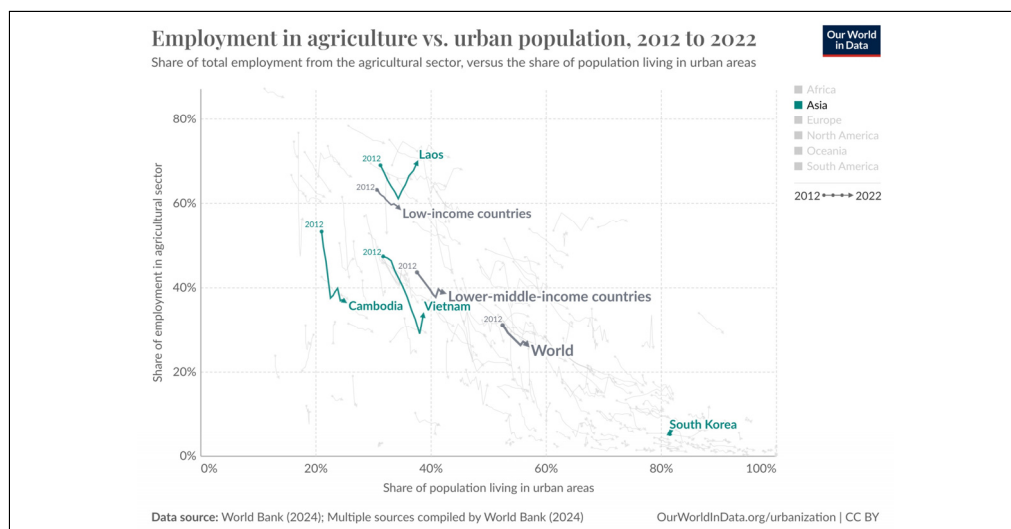


Figure Source: Our World in Data

1.2.2. Climate Change Adaptation Capacity in the Mekong River Basin Countries

Vietnam, Laos, and Cambodia, the key countries in the Mekong River Basin, are highly dependent on the agricultural sector and have vulnerable rural populations. As climate change progresses, these nations are likely to experience significant economic and social impacts due to their high reliance on agriculture, with a substantial portion of the population relying on agriculture for their livelihoods. Agricultural productivity is directly affected by climate change, underscoring the need for policies to strengthen climate change adaptation capacities. However, these countries currently face limitations in their adaptation capacities.

The ND-GAIN Index (Notre Dame Global Adaptation Initiative) assesses national vulnerability, resilience, and adaptation readiness to climate change, incorporating various factors such as water availability, food security, and education levels. As of 2020, Vietnam ranked 100th, Laos 121st, and Cambodia 144th out of 185 countries, placing them in the lower-middle ranks, **indicating low climate change adaptation capacities**. This suggests that farming households in these countries may struggle to effectively respond to climate-induced environmental changes, potentially leading to adverse impacts on the well-being of local residents in the Mekong River Basin.

Vietnam has steadily expanded its policy efforts to address climate change through medium- and long-term national development strategies, achieving some progress in infrastructure development and climate change adaptation planning. Despite this, Vietnam is still ranked as the 58th most vulnerable country globally in terms of adaptation capacity. Issues related to water availability and food security remain pressing challenges. Frequent droughts and floods severely impact agricultural productivity, exacerbating economic vulnerabilities in rural areas. Consequently, measures to strengthen farmers' climate change adaptation capacity are essential.

In Laos, the impacts of climate change are particularly pronounced in the

agriculture and water resource management sectors. Low educational levels in rural areas and a lack of basic infrastructure further hinder adaptation capacity. Given Laos' agriculture-centered economy, the country is highly vulnerable to declines in agricultural productivity caused by climate change, resulting in worsened food security and income instability for farming households. Policy support to aid farmers in adapting to climate change is crucial.

Similarly, Cambodia faces threats of reduced agricultural productivity and food security risks due to climate change, with very low readiness for adaptation. The risks from climate change to the agricultural sector extend beyond decreased productivity and have the potential to affect the national economy as a whole. Therefore, expanding investments in climate adaptation for farmers and implementing innovative response strategies are urgently needed. Given Cambodia's high vulnerability to productivity declines caused by climate change, a strategic, government-led approach to strengthening adaptation capacity is essential.

The three countries in the Mekong River Basin, along with neighboring nations, form a critical agricultural hub in Southeast Asia, underscoring both their economic importance and their pronounced vulnerability to climate change. This highlights that climate change is not merely an environmental issue but one with far-reaching implications for livelihoods and quality of life across the region. Against this backdrop, this study seeks to conduct a comprehensive analysis of the impacts of climate change and adaptation measures on the agricultural sector and the livelihoods of farming households in the Mekong River Basin. The research aims to provide foundational data to aid national and regional governments, as well as farming communities, in formulating more efficient and effective climate adaptation strategies and to support practical decision-making on the ground. Ultimately, this study aspires to enhance the climate adaptation capacity in the Mekong River Basin and to contribute to the sustainable development of rural areas in the region.

1.2.3 Sub-study Topics

This study focuses on Vietnam and Laos within the Mekong River Basin to analyze the **multidimensional impacts of climate change on farming households** and evaluate the **effectiveness of climate adaptation measures**. Through this, it aims to contribute to **developing strategies for climate change adaptation** and **international development cooperation policies** for resource-limited LMICs. To this end, three detailed research topics have been established, covering the impacts of climate change on agricultural productivity and its variability, factors influencing farmers' decisions to adopt climate adaptation measures, and the evaluation of the effectiveness of climate information services.

01

Sub-study 1

The Impacts of Climate Change on Agricultural Productivity and Variability, and the Effectiveness of Adaptation Measures



02

Sub-study 2

The Factors of Farmers' Decision-Making in adopting climate change adaptation measures among Mekong River Basin Farmers



03

Sub-study 3

The Effects of Climate Change Adaptation Measures on Farmers' Quality of Life



[Sub-study 1] The Impacts of Climate Change on Agricultural Productivity and Variability, and the Effectiveness of Adaptation Measures

In Sub-study 1, we will use micro-level farm data from Vietnam to analyze the impact of climate change on the productivity and profitability of major crops, as well as the effectiveness of key climate adaptation measures. Focusing on the expected value and variability of productivity per area or household, this study aims to measure the **economic uncertainty induced by climate change** and assess

the **effectiveness of adaptation measures** accordingly. Rather than merely examining average productivity changes, this research emphasizes understanding farmers' strategies in response to productivity variability and income instability caused by climate change.

Additionally, it will address the issue of **efficient crop mix selection** as a climate change adaptation strategy. By analyzing how climate change and adaptation measures influence crop choices, the study aims to assist farmers in developing optimal agricultural strategies. To this end, data from the Vietnam Household Living Standard Survey (VHLSS) will be used, and climate variables will be sourced from databases like the National Oceanic and Atmospheric Administration (NOAA) and WorldClim to incorporate projections of future climate variables into the analysis.

[Sub-study 2] The Factors of Farmers' Decision-Making in adopting climate change adaptation measures among Mekong River Basin Farmers

In Sub-study 2, we will examine the **factors influencing the decision-making process for adopting and implementing climate change adaptation measures** among farming households in the Mekong Delta of Vietnam and the Mekong River Basin in Laos. This analysis will consider demographic characteristics (age, gender, education level), socio-economic variables (income, assets, employment status), and farmers' knowledge, perception, attitudes, and practices regarding climate change and adaptation measures. Particular focus will be placed on factors such as access to climate information and non-cognitive abilities of farmers (such as self-efficacy) to assess their impact on the adoption of adaptation strategies. Through this comprehensive analysis, the study aims to deepen the understanding of farmers' decision-making mechanisms regarding climate adaptation, providing valuable insights to inform policy development.

[Sub-study 3] The Effects of Climate Change Adaptation Measures on Farmers' Quality of Life

In Sub-study 3, we will conduct a comprehensive analysis of how climate change and climate adaptation measures affect the quality of life of farming households. Using survey data collected from farmers in Vietnam and Laos, the study will examine various aspects, including: (1) Household Income (per capita income); (2) Agricultural Productivity (per capita agricultural income); (3) Living Standards (per capita consumption expenditure); (4) Health/Nutrition (per capita food consumption expenditure); (5) Quality of Life (subjective happiness, optimism about the future). A key focus will be on how **the use of climate information services** in implementing adaptation measures affects farmers' quality of life, exploring how the use of climate information services can help mitigate the adverse impacts of climate change. Additionally, we will assess the synergy between climate information services and other adaptation measures. This analysis aims to understand the multidimensional effects of adopting adaptation measures at the household level, providing insights and recommendations for developing effective climate adaptation policies.

1.3. Research Methodology

The research methodology employed in this study is divided into two main components: a literature review and a household survey. First, a literature review was conducted to gather baseline information and analyze the current status of the target countries. Micro-level household data were obtained through local research partnerships and utilized in the analysis. Additionally, household surveys were conducted with farming households in Vietnam and Laos to collect data from the target regions, which were then used for quantitative analysis.

1.3.1. Literature Review

The literature review, a method of gathering information from existing data sources, was conducted to obtain accurate data on the baseline conditions and current status of the study regions. This review provided insights into economic indicators, national development strategies, and climate change-related policies, forming a comprehensive background on the key development challenges in each country and supporting the design of the survey.

In this study, a foundational analysis was conducted on the Mekong region's agricultural, forestry, and fisheries output, household quality of life, and climate change patterns. Climate change impact cases reported in the Mekong Delta and neighboring areas were analyzed to refine the research methodology. To assess the climate change situation in each country, raw data from national household surveys—VHLSS (Vietnam), AHS (Laos), and CSES (Cambodia)—as well as agricultural census data were collected and analyzed. Climate variable data were sourced from databases such as NOAA, and future climate projections from WorldClim were also utilized.

〈Table 1–3〉 Household Survey Data by Country

Data	Description
Vietnam Household Living Standard Survey (VHLSS)	Conducted by the World Bank and the General Statistics Office of Vietnam, this survey aims to assess the living standards of Vietnamese households and the impact of poverty policies. Collected biennially since 2002, it includes a sample of over 30,000 households, covering demographic and socio-economic information, economic conditions, education, and health (World Bank, n.d.).
Annual Household Survey (AHS)	Conducted by the Lao Statistics Bureau, this survey aims to estimate national accounts and assess household living standards in Laos. Collected biennially since 2004, it includes a sample of over 2,000 households, with questions on demographic and socio-economic information of household members, labor input, and consumption expenditure (ISHN, n.d.).
Cambodia Socio-Economic Survey (CSES)	Conducted by the National Institute of Statistics of Cambodia, this survey seeks to assess poverty status and living standards among Cambodian households. It has been conducted irregularly since 1993, with a sample of over 3,000 households. The survey includes questions on demographic and socio-economic information, education, health, and consumption expenditure (ISHN, n.d.).

In addition, strategy documents and statistical data for the target countries identified during the literature review, along with additional climate and meteorological data collected, were used to assess the current state of climate change impacts, adaptation capacity, and relevant policy objectives for the target countries and regions. These resources provided foundational information for conducting household surveys.

〈Table 1–4〉 List of Literature Reviewed

Category	List of References
Overview Data by Country (Economic Indicators, etc.)	Domestic – Korea Agro-Fisheries & Food Trade Corporation. 2022. 2022 Vietnam National In-Depth Survey Report. – Korea Agro-Fisheries & Food Trade Corporation. 2021. 2021 Cambodia National In-Depth Survey Report. – Ministry of Foreign Affairs. 2018. Vietnam Overview, March 2018. – Ministry of Foreign Affairs. 2019. Laos Overview Report. – Ministry of Foreign Affairs. 2019. Cambodia Overview Report. – Choi Won-ho. 2015. Overview of Vietnam's Agriculture. World Agriculture. Issue 163. Naju: Korea Rural Economic Institute. – Choi Won-seop. 2014. Overview of Vietnam's Agriculture. World Agriculture Issue 163. Korea Rural Economic Institute.

Category		List of References
		- Korea Institute for Curriculum and Evaluation. 2012. Vietnam: National Overview and Education System. - Joint Ministries, 2023. Laos Country Partnership Strategy. - Joint Ministries, 2023. Vietnam Country Partnership Strategy.
	International	- World Bank National Accounts Data. - FAO & WFP. 2020. Special Report: 2019 FAO/WFP Crop and Food Security Assessment Mission (CFSAM) to the Lao People's Democratic Republic. FAO. - FAO. 2016. Country Programming Framework for Lao PDR 2016~2021. - ADB (Asian Development Bank). 2018. Agriculture, Natural Resources, and Rural Development Sector Assessment, Strategy, and Road Map. - Nam Bui Hai. 2019. Information on Agricultural and Rural Situation in Vietnam. NIAPP.
Policy Data by Country	Domestic	- KOICA. 2015. Laos Agriculture ODA Expert Report. Korea International Cooperation Agency. - Joint Ministries, 2021. Third Comprehensive Basic Plan for International Development Cooperation (Draft) (2021–2025). - Joint Ministries, 2024. ASEAN Development Cooperation Strategy (Draft). - Joint Ministries, 2023. Agriculture Development Cooperation Promotion Strategy (Draft). - Joint Ministries, 2023. Revised Country Partnership Strategy for Five Priority Cooperation Countries (Draft) – Laos, Vietnam, Tanzania, Ethiopia, Uganda. - Joint Ministries, 2022. New Government's International Development Cooperation Direction (Draft). - Jung Ki-hwan. 2013. Cambodia's Agricultural Potential and Policy Direction. - Heo Jang & Lee Mina, 2020. Development of International Development Cooperation Strategy for Priority Countries in Agriculture and Forestry (Year 3): Laos. - Lee Yo-han, 2012. ODA Status in Laos' Human Resource Development Sector and Korea's Support Strategy. Korea Institute for International Economic Policy.
	International	- Vietnam Socioeconomic Development Strategy (SEDS) 2021–2030. - Vietnam National Program for New Rural Development 2021–2025. - Laos Vision 2030 (2016–2030). - Laos National Socio-Economic Development Plan 2021–2025. - Cambodia Rectangular Strategy for Growth, Employment, Equity, and Efficiency, Phase IV (RS Phase IV 2018–2023). - Cambodia National Strategic Development Plan (NSDP 2019–2023).

Category		List of References
Statistical Data by Country		- Vietnam Household Living Standard Survey (VHLSS). - Annual Household Survey (AHS). - Cambodia Socio-Economic Survey (CSES). - Mekong River Commission. 2017. MRC Council Study: Climate Change Discipline Report. - The World Bank Group & Asian Development Bank. (2021). Climate Risk Profile: Vietnam. - WHO. 2023. Lao PDR officials tackle the effects of climate change on health. - USAID. 2022. Mekong Delta Climate Resilient Agriculture Activity Design. - UNDP. 2022. Agricultural transformation model adapting to climate change in the Mekong Delta. - ADB (Asian Development Bank). 2017. Country Partnership Strategy: Lao People's Democratic Republic. 2017-2020 More Inclusive and Sustainable Economic Growth. - OECD. 2024. OECD Development Co-operation Peer Reviews: Korea 2024. OECD Development Co-operation Peer Reviews.
	Domestic	- Agrifood Export Information. 2016. Vietnam Ministry of Agriculture and Rural Development (MARD). - Bae Jin-ho, 2017. Changing Vietnamese Agriculture: Gaining More From Less. World Agriculture, Issue 201. Naju: Korea Rural Economic Institute. - Integrated Reporting System for Official Development Assistance.
	International	- NOAA ESRL Physical Sciences Division (PSD) Climate Hazards Group InfraRed Precipitation with Station (CHIRPS). - SIMVA(Social Impact Monitoring and Vulnerability Assessment). - IPCC. 2022. Climate Change 2022: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. - IPCC. 2021. Climate Change 2021: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. - ADB. 2009. The Economics of Climate Change in Southeast Asia: A Regional Review, Asian Development Bank (ADB). - IPCC. 2014. Climate Change 2014: impacts, adaptation, and vulnerability. In: Field CB, Barros VR, Dokken DJ, Mach KJ, Mastrandrea MD, Bilir TE, Chatterjee M, Ebi KL, Estrada YO, Genova RC, Girma B, Kissel ES, Levy AN, MacCracken S, Mastrandrea PR, White LL (eds) Part A: global and sectoral aspects. Contribution of Working Group II to the Fifth Assessment Report of the intergovernmental panel on climate change. Cambridge University Press, Cambridge.

1.3.2. Household Survey

Based on the data collected from the literature review and stakeholder interviews, survey questions were developed, and a household survey was conducted to build a dataset for analysis. This survey targeted farming households in the Mekong Delta region of Vietnam and the Mekong River Basin in Laos. Its purpose was to cross-verify information obtained from the literature and existing data, while also identifying additional details not sufficiently covered in previous studies, thereby establishing a comprehensive dataset for analysis.

Furthermore, the survey aimed to assess the direct and indirect impacts of climate change on the quality of life of local residents, as well as the effects and sustainability of climate information services for farming households. The survey was conducted in several stages as follows.

(Survey Design) The survey was designed based on the analysis focus of Detailed Research 1, as well as the findings from the literature review and interviews. Questions were crafted to capture various types of information—such as fact-checking, information acquisition, knowledge, attitudes, opinions, and behavior—in alignment with the survey's objectives, including individual data usage and index or indicator development. A mix of open- and closed-ended questions was used, incorporating nominal, ordinal, and interval scales to ensure the most suitable responses could be gathered effectively.

The primary survey questions focused on measuring the education level, health status, assets, income, subjective quality of life, and decision-making influence of household heads and members. Additional questions covered aspects such as agricultural productivity, climate change adaptation behaviors, risk preferences, and self-efficacy of farming households. To incorporate the unique characteristics of Vietnam (MDRI, CIAT, Institute of Agro-Meteorology) and Laos (CIAT, FAO, National University of Agriculture), the survey was co-reviewed in collaboration with local research partners. The finalized questionnaire was then translated into

local languages by the local research partnerships, with a double-translation review process to ensure accuracy.

(Survey Target Selection) The survey was conducted in Tien Giang Province in the Mekong Delta region of Vietnam and Vientiane Province in the Mekong River Basin in Laos.

Tien Giang Province in Vietnam, located in the lower Mekong River area, has a population of 1.97 million and covers an area of 2,510 km². This region is well-suited for agriculture and contributes 55% of Vietnam's rice production as part of the Mekong Delta. However, since 2015, it has faced increasingly severe climate impacts, particularly drought (Nghia et al., 2022). Notably, climate change has led to a shift in crop selection from rice to fruits and vegetables, making it a suitable area for analyzing the effectiveness of climate adaptation measures. Additionally, Tien Giang was part of the DeRisk program led by organizations such as the World Meteorological Organization (WMO), the International Center for Tropical Agriculture (CIAT), and the University of Southern Queensland (USQ) over the past five years, providing an opportunity to assess the impact of climate information services as well.

Therefore, this study selected five districts in Tien Giang Province affected by recent saline intrusion and drought as the survey target areas. In each district, two communes were randomly selected, and in each commune, two villages were also randomly chosen, resulting in a survey conducted across a total of five districts, 10 communes, and 20 villages. This area overlaps with regions previously surveyed by the research team in 2022. The data collected from this study were combined with previously gathered survey data⁹⁾ to build a panel dataset, leveraging the advantages of this panel data for conducting panel analysis.

9) This survey data was collected as part of the project titled "Development and Utilization of a Climate Change Adaptation Model for Vietnam's Agricultural Sector through Research Partnerships (2021-2023)," under KOICA's "Research Project for Global Crisis Response through Partnerships with Developing Countries."

Vientiane Province in Laos, located in the northern part of the country, has a population of 460,000 and covers an area of 16,875 km². Its location in the Mekong River Basin makes it suitable for observing climate change impacts. This region frequently experiences floods and droughts linked to climate change and utilizes climate information provided through the LaCSA system, developed as part of the UN FAO's SAMIS project. In Vientiane, the survey was conducted in three districts, selected from LaCSA project areas recently affected by climate impacts. Two villages in each district were randomly selected, totaling six villages for the survey.

A total of 627 households participated in the survey across both countries (319 in Vietnam and 308 in Laos). In Vietnam, some households from the 2022 survey were re-surveyed to build a panel dataset, accounting for an attrition rate of 70% due to migration or refusal to participate. Aiming to survey 300 households, the final survey included 319 households. In Vientiane Province, Laos, 308 households were surveyed through random household visits in pre-selected villages.

(Ensuring Research Ethics) To ensure adherence to research ethics, the survey received approval from the Institutional Review Board (IRB) of Seoul National University (IRB Approval No.: 2407/003-008). Throughout the study—including survey content, participant recruitment procedures, and analysis models—measures were taken to protect research participants and ensure transparency in data collection across all phases of the research.

(Survey Preparation) The translated questionnaires were coded into the mobile survey platform SurveyCTO¹⁰) to enable data collection via mobile devices in areas with limited or no internet access. Subsequently, training sessions were conducted in Vietnam and Laos for local partner institutions and survey enumerators, covering topics such as the survey's purpose and objectives, the meaning of survey

10) SurveyCTO is a widely used survey platform employed by numerous international organizations, research institutions, universities, and NGOs, including the World Bank, J-PAL, IPA, and Oxfam. It facilitates survey implementation in regions without internet connectivity, making it a valuable tool for evaluating the impact of international development cooperation projects.

questions, sampling methods, participant identification, survey administration, and the use of SurveyCTO.

(Survey Method) The survey was conducted by locally hired enumerators through one-on-one interviews using mobile devices with SurveyCTO, in collaboration with the research team and local partners. During the survey, GPS information for key local facilities and market data were also collected. Real-time monitoring of responses was carried out at the device level, even in offline conditions, following a pre-coded protocol. Additionally, automated monitoring records for data uploaded to the server ensured data quality and the reliability of research outcomes and outputs.

(Survey Sampling) The sample size for the survey was determined with budget constraints in mind, while ensuring sufficient statistical power at a specified significance level to detect the minimum effect size necessary for meaningful analysis (Glennerster and Takavarasha, 2013; Faul et al., 2009; Cohen, 1988). To achieve the desired Minimum Detectable Effect Size (MDE), the sample was drawn at the household level rather than the group level, ensuring the effectiveness and impact of the study could be statistically identified.

In this study, a minimum sample size of 300 households per country was determined to achieve an MDE (Minimum Detectable Effect) of 0.03 standard deviations at a 5% significance level (95% confidence) and 80% power. This sample size ensures that, when set to 300 households, the difference in average outcomes (e.g., household income) between two groups can be detected as statistically significant if it exceeds 0.0263 standard deviations after controlling for covariates in a multiple regression analysis, as indicated by power analysis. Consequently, with a target sample of over 600 households across the two countries, the survey was completed with 319 households in Vietnam and 308 households in Laos.

■ **Example of Minimum Detectable Effect Size (MDE)**

- With a sample size of 300, the difference in the mean outcome (e.g., household income) between two groups must be at least 0.3245 standard deviations for the effect size to be statistically detectable. Additionally, for methodologies such as multiple regression analysis or difference-in-differences and matching methods based on multiple regression, the MDE with a sample size of 300 is 0.0263 standard deviations.

Sample Size	Simple Regression / Mean Comparison (MDE Indicator : d)	Multiple Regression (MDE Indicator: f^2)	Analysis of Variance (MDE Indicator: f)
100 people	0.5659	0.0801	0.2829
200 people	0.3981	0.0396	0.1991
300 people	0.3245	0.0263	0.1623
400 people	0.2808	0.0197	0.1404
500 people	0.2511	0.0158	0.1255

(Survey Implementation) In Laos, the research team visited the target areas to conduct direct training for local survey enumerators. Working in collaboration with researchers from the Faculty of Agriculture at the National University of Laos, the survey questions were finalized to fit the local context, and the survey was completed with a total of 308 households (as of June 28, 2024). An overview of the field survey in Laos is as follows.

〈Table 1–5〉 Overview of Survey in Laos

Section		Content
Over-view	Location	■ Vientiane Province, Lao PDR
	Period	■ 2024.6.17. ~ 2024.6.21. (Departure & Arrival Dates)
	Personnel	■ Inae Kim, Taesoo Choi (Department of Agricultural Economics and Rural Sociology, Seoul National University)
	Survey Content	■ Assess the agricultural and climate change status in the study area through on-site visits, including policy responses and farm adaptation to extreme weather events like droughts and floods ■ Conduct an interview with FAO consultant to understand the status of the LaCSA project ■ Conduct a preliminary survey and refine the questionnaire ■ Consult with a local agricultural expert (Professor Phommavong, Laos National University, College of Agriculture) for survey question adjustments and translation ■ Review the current status of the DeRisk project (interview with CGIAR) ■ Conduct training for survey enumerators

Section		Content	
Details	Survey Schedule	2024.06.17.	☐ Departure ☐ Interview with FAO consultant
		2024.06.18.	☐ Meeting with local survey coordinator ☐ Meeting with local agri. experts and questionnaire revision ☐ Field visit to Vientiane for preliminary survey with local farmers
		2024.06.19.	☐ Internal meeting for questionnaire review and refinement ☐ Translation adjustments based on feedback from local coordinator and agricultural expert
		2024.06.20.	☐ Interview with CGIAR stakeholders ☐ Survey coding revision with feedback from local coordinator/experts
		2024.06.21.	☐ Enumerator training for survey administration ☐ Return
Survey Site Photos			
		Interview with FAO consultant	Interview with agricultural expert and revise questionnaire
			
		Conduct preliminary survey with farmers in vientiane	Enumerator training for survey
			
	Enumerator training for survey	Visit to Laos National University, College of Agriculture	

In Vietnam, survey questions were finalized to fit the local context through regular virtual meetings with the Mekong Development Research Institute (MDRI), with whom a local partnership was established. The recruitment and training of enumerators for the survey were led by the local partner organization, with additional training sessions provided by the research team to support capacity-building within the partner institution.

During enumerator recruitment, priority was given to applicants with prior household survey experience, agricultural experience, familiarity with data collection using tablet PCs, and knowledge of the survey areas. From the applicant pool, 12 enumerators were selected through application review, a written test, and a mock interview assessment. These selected enumerators underwent four days of in-person training from September 5 to September 8. The training covered topics such as: (1) Survey structure and objectives; (2) Field survey principles and procedures; (3) Tablet operation; (4) Data collection using the mobile survey platform (SurveyCTO); (5) Survey quality and data management; (6) Survey guidelines; and (7) Final assessment of enumerators. Following the training, a survey was conducted from September 10 to September 19, 2024, covering a total of 319 households. Since a household survey was also conducted in the same area in 2022 in collaboration with MDRI, building a panel dataset was facilitated.

〈Table 1-6〉 Overview of Survey in Vietnam

Section		Content
Over-view	Location	■ Tien Giang Province, Vietnam
	Period	■ 2024.9.10. ~ 2024.9.19.
	Partner	■ Mekong Development Research Institute (MDRI)
	Target	■ 319 Households in Tien Giang Province
	Survey Content	■ Demographic information / Household income and asset levels ■ Agricultural productivity and income for major crops ■ Awareness and attitudes toward climate change / Implementation of climate change response measures ■ Accessibility to climate change information ■ Self-efficacy and social networks ■ Subjective quality of life

Section		Content
Details	Survey Sample	■ To build a panel dataset, a total of 319 households completed the survey, excluding those who migrated to other regions or declined participation among the 422 households initially surveyed in 2022 ■ Respondents were evenly selected from 5 districts, 10 communes, and 20 villages in Tien Giang Province, Vietnam ■ The survey included at least 62 households in each district
Survey Site Photos		 Enumerator training for survey  Enumerator training for the survey, including interview practice

1.4. Research Partnerships

This study was conducted in collaboration with domestic researchers and several local partner institutions in Vietnam and Laos. In Vietnam, partnerships were established with the Mekong Development Research Institute, CIAT-Vietnam, and CGIAR, while in Laos, collaborators included the National University of Laos, FAO, CIAT-Laos, and The Green Company. Through these partnerships, foundational data for climate change research were obtained, including the Vietnam Household Living Standard Survey (VHLSS) in Vietnam, the Lao Agriculture Census (LAC) in Laos, and local meteorological data. During the survey process, local characteristics were incorporated through joint reviews with local partners. In-person and virtual meetings were held to facilitate the ongoing exchange of information necessary for evaluating the effectiveness of climate change adaptation measures and climate information services, ensuring active collaboration with the local partners.

Mekong Development Research Institute (MDRI)

MDRI, a local partner institution in Vietnam, is an economic research institute with extensive experience in climate change studies, including research on the influence of climate change on women (UN Women Vietnam, 2021) and the impact of climate change on inequality in Vietnam (Oxfam Vietnam, 2021–2022). MDRI is regarded as one of the top institutions in Vietnam in terms of academic capacity in research.¹¹⁾

International Center for Tropical Agriculture (CIAT)

CIAT is an international collaboration center promoting climate change adaptation, playing a significant role in Vietnam's DeRisk project and Laos' SAMIS project. CIAT provided advisory support throughout this study and offered information and necessary literature related to DeRisk and SAMIS.

11) IDEAS: According to the Economics and Finance Research indicators, MDRI ranks within the top 10 economic research institutions in Vietnam.

National University of Laos

Professor Phomma Thammavong of the National University of Laos, an expert in agricultural economics and regional development, has conducted numerous studies on Lao farming households. For this study, he played critical role in survey design and meticulously developing and refining survey questions. He was instrumental in recruiting and professionally training survey enumerators, and subsequently managed the comprehensive field survey and monitoring process with rigorous oversight.

Food and Agriculture Organization (FAO) Laos

The FAO Laos country office, particularly through the expertise of agricultural specialist Phommachanh Phothichanh, provided essential data and resources, including the Lao Agriculture Census (LAC), the Annual Economic Report, and the Lao Census of Agriculture report. The research team, in partnership with FAO and the Lao Statistics Bureau, accessed the 3rd Lao PDR Agriculture Census (LAC III, 2019/2020). Also, FAO offered valuable insights on climate information services, such as SAMIS and LaCSA, which were instrumental in shaping the survey design.

The Green Company

The Green Company, a consulting organization in Laos with substantial experience in household surveys and research projects, partnered in survey preparation, enumerator training, questionnaire review, and the pilot survey. They facilitated interviews with local stakeholders and secured survey approvals from local governments. Additionally, The Green Company led the implementation and monitoring of the household survey.

Additionally, the Department of Crop Production at Vietnam's Ministry of Agriculture and Rural Development and the Asian Mega-Deltas (AMD) initiative participated in needs assessments through written interviews, providing feedback and advisory support on the household survey questions. Through comprehensive

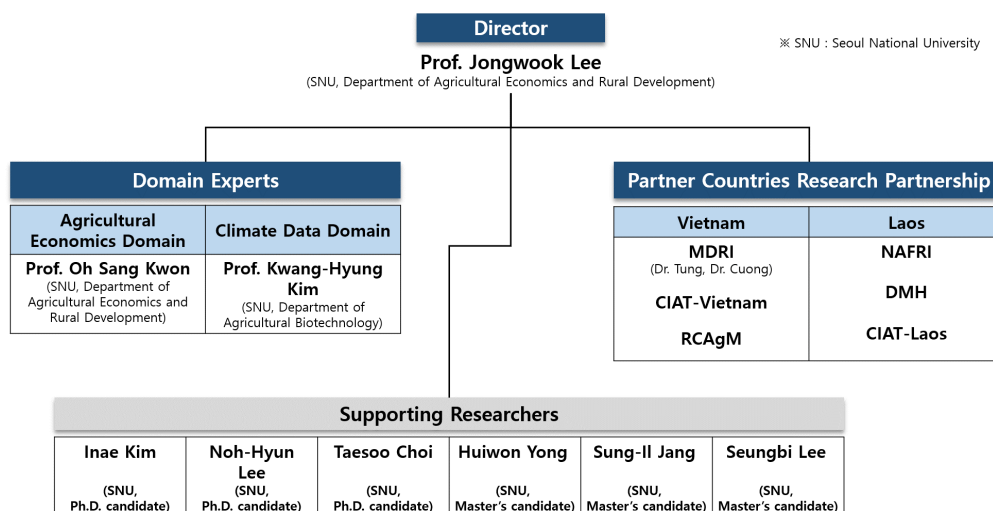
research partnerships with local institutions and researchers, close collaboration was maintained across all research stages—from study design, survey design, and data collection to analysis and publication. This partnership also contributed to strengthening the research capacities of local partner institutions and researchers.

Throughout each research stage, regular meetings and workshops were held between domestic researchers and local research partners using virtual meeting platforms, along with capacity-building training sessions. A continuous communication system was established, allowing for ongoing exchange of feedback, sharing of field experiences, and practical application of partnership-based research capabilities. During the research process, additional consultations and collaborations were carried out with local research networks, including universities and companies, laying a foundation for expanding long-term local research partnerships.

1.5. Research Implementation Framework

1.5.1. Research Execution Structure

[Figure 1–4] Organizational Chart



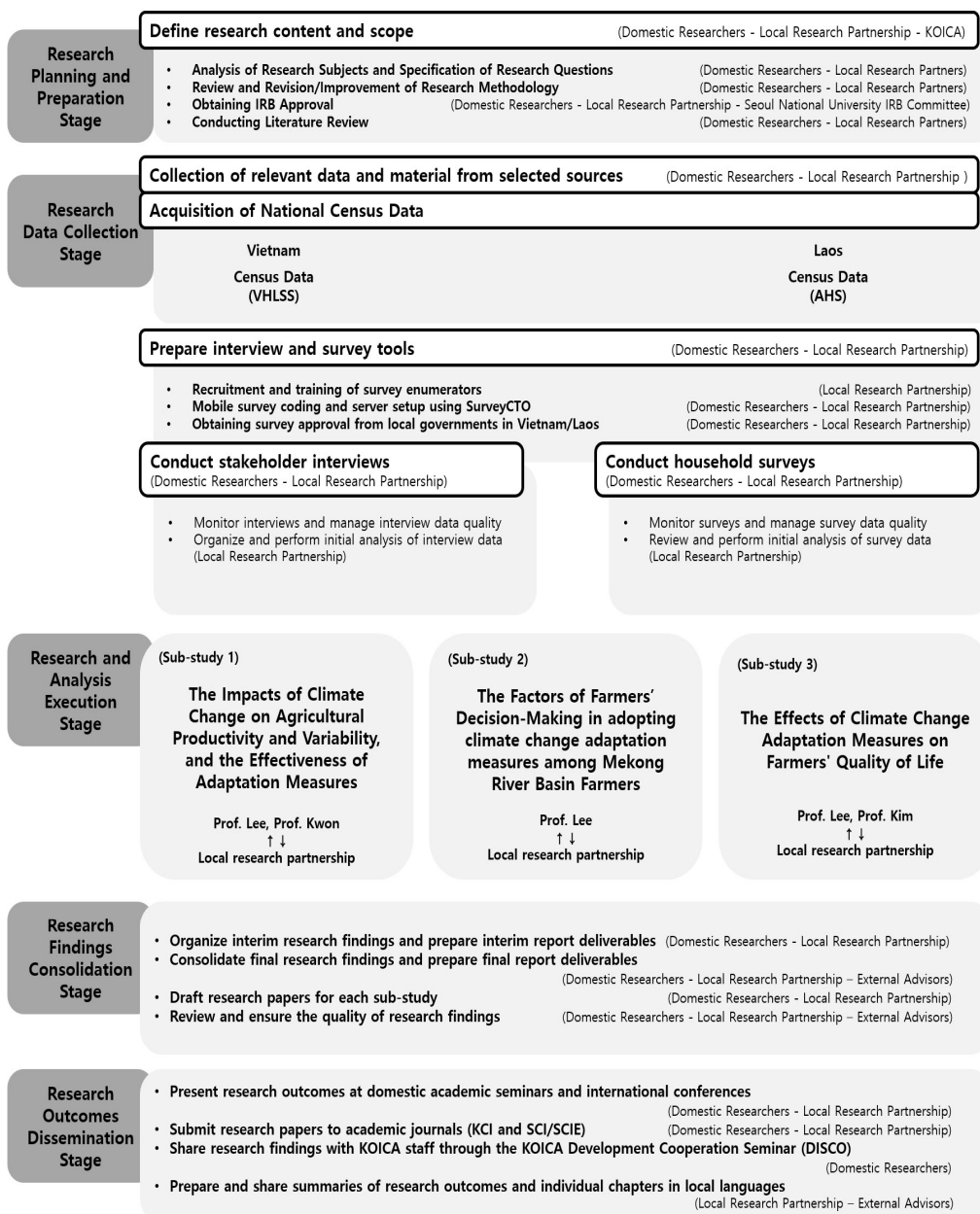
〈Table 1–7〉 Research Team Composition and Roles

Category		Responsibilities
Domestic	Prof. Jongwook Lee (Principal Investigator)	Project Lead, Co-Research for Sub-Study 1, Lead and Conduct Research for Sub-Study 2 & 3
	Prof. Oh Sang Kwon (Co-Investigator)	Lead and Conduct Research for Sub-Study 1
	Prof. Kwang-Hyung Kim (Co-Investigator)	Co-Research for Sub-Study 3
	Inae Kim (Research Associate, Ph.D. Program)	Conduct Research and Data Collection/Management for Sub-Study 2 & 3, Manage Overall Project and Report Writing
	Noh-Hyun Lee (Research Associate, Ph.D. Program)	Conduct Research and Data Collection/Management for Sub-Study 3, Review Climate Information Service Content

Category			Responsibilities
Domestic	Taesoo Choi (Research Associate, Ph.D. Program)		Conduct Research and Data Collection/Management for Sub-Study 2 & 3, Manage Local Research Partnerships
	Huiwon Yong (Research Associate, M.A. Program)		Conduct Research and Data Collection/Management for Sub-Study 1, Manage Feedback and Outcome Sharing
	Sung-il Jang (Research Associate, M.A. Program)		Conduct Research and Data Collection/Management for Sub-Study 2 & 3, Literature Review
	Seungbi Lee (Research Associate, M.A. Program)		Conduct Research and Data Collection/Management for Sub-Study 2 & 3, Manage Household Surveys
International	Vietnam	MDRI	Overall Management of Vietnam Local Survey and Feedback
		CIAT-Vietnam	Support for Vietnam Local Survey and Feedback, Provide Literature and Expert Opinions on Climate Information Services
	Laos	CGIAR	Provide Research Consultation and Connection with DeRISK Project
		Laos National University	Review Survey Questions for Laos Household Survey and Support Local Preliminary/Main Survey
		FAO	Provide Basic Data Required for Agricultural Census Research (e.g., AHS), Information on Climate Information Provision Projects, and Review/Consult on Survey Questions
		CIAT-Laos	Provide Literature on Laos Climate Information and Consultation on Surveys
		The Green Company	Support Local Household Survey Consulting (Enumerator Training, Conducting Preliminary/Main Local Surveys, and Support Interviews with Local Governments in Survey Target Areas)

1.5.2. Outcomes by Research Phase

[Figure 1–5] Outcomes by Research Phase



This study was conducted through a systematic, phased approach, with the key outcomes from each phase as follows:

Phase 1: Research Planning and Preparation

In the initial phase, a comprehensive plan for the research was established. The study's objectives and scope were clearly defined, and detailed plans were developed for each specific research area and methodology. The necessary human and material resources were identified, with plans for efficient allocation. Particular emphasis was placed on role assignments within the research team and on creating a detailed schedule to ensure systematic execution. Throughout this process, ongoing consultations with local partner institutions were held, culminating in the signing of partnership agreements and obtaining IRB approval to ensure research ethics compliance.

Phase 2: Data Collection

In the second phase, relevant domestic and international data were collected for each specific research topic. Existing studies, policy documents, and statistical data related to the target countries were gathered and systematically analyzed, with key resources identified for collection. National household survey data and agricultural census data for each country were obtained. Through close collaboration with local research partners, stakeholder interviews and preliminary and main household surveys were conducted, along with case studies of similar projects both domestically and internationally.

Phase 3: Research Analysis

Based on the data collected in Phase 2, a research methodology suitable for this study was developed. An appropriate research model was created to achieve the study's objectives, and the design for empirical analysis was conducted. Specific details such as data collection methods, analytical tools, and key variables were defined to ensure the validity and reliability of the research. Econometric analysis was performed using agricultural census data and household survey data collected directly by the research team, empirically testing the research questions outlined in Phase 1.

Phase 4: Compilation of Research Findings

The results of the empirical research were comprehensively analyzed, yielding meaningful insights. The academic significance and policy applicability of the findings were assessed, and a model for international development cooperation projects in the agricultural sector to address climate change was proposed. Emphasis was placed on presenting practical strategies for applying the research outcomes in real-world contexts within developing countries.

Phase 5: Dissemination of Research Outcomes

Following the interim report, the research results, incorporating feedback from the collaborative team and review panel, were presented at the Asian Association of Environmental and Resource Economists (AAERE) Conference (August 26–27, 2024, Taiwan). This platform allowed the research team to gather feedback from numerous experts, enhancing the study’s quality. After the final report, further findings from the research will be presented at domestic and international conferences or submitted to academic journals to share results and contribute to the research community. Additionally, the outcomes will be shared with KOICA staff at the KOICA Development Cooperation Seminar (DISKO) to support the development and formation of practical models for international development cooperation projects.

Following this, the research findings will be translated into the local languages and disseminated in the target countries, Vietnam and Laos, through the institutions with whom research partnerships were established. This approach aims to effectively share the research outcomes with academic communities, development cooperation practitioners, and local stakeholders in the target countries. It is anticipated that these efforts will provide a foundation for formulating practical policies and implementing projects that contribute to the sustainable development of Asian developing countries.

2. The Impacts of Climate Change on Agricultural Productivity and Variability, and the Effectiveness of Adaptation Measures

2.1. Introduction

Climate change directly affects crop production and is especially likely to affect farm incomes significantly in developing countries, with their high dependence on agricultural income. How, and to what extent climate change affects productivity varies by the type of crop and as well as the crop-producing region. This sub-study estimates the impact of climate change on the productivity and agricultural income of major crops in the Mekong region by applying econometric methods to micro-level data from Vietnam. In the process, we select and modify existing models to best reflect the characteristics of our data. In addition, unlike previous studies, this study attempts to quantitatively analyze how farmers' adaptation behavior will be affected by climate change and, as a result, how such adaptation measures contribute to reducing the productivity and agricultural income of rice crops. We also explicitly analyze the impact of climate change on agricultural production and income, as well as their variability.

2.1.1. Literature Review

The impacts of climate change on agricultural production and agricultural income have been studied by various disciplines using different methodologies. These analyses can be roughly grouped into two types: those that reflect market equilibrium and those that do not. Equilibrium analysis employs a structural model of the mechanism where climate change affects not only agricultural productivity and farm income, but also prices of non-agricultural goods and non-farm incomes through demand-side factors. Direct models, on the other hand, provide a more micro-level analysis using a reduced-form method that directly derives how climate change affects the productivity of specific crops or farmers' incomes.

Equilibrium analysis methods are categorized into the agricultural sector model (Chang 2002; Park et al. 2015), which focuses on the agricultural sector only and derives its demand and supply system as well as equilibrium conditions, and the computable general equilibrium (CGE) analysis (Moore et al. 2017; Kwon and Lee 2013), which analyzes the equilibrium of the economy as a whole. These equilibrium analysis methods have the merit of analyzing the effects of climate change on the entire economy, not being limited to a single item. However, for equilibrium analysis, it is first necessary to estimate the effect of climate change on productivity using the direct analysis method which will be outlined below. Rather than an equilibrium analysis, this study applies a direct analysis, econometric analysis to be specific, which uses micro-level data.

Direct analysis methods are categorized into agronomic and econometric analyses. In crop science, a crop model or biophysical analysis method is a scientific approach which uses a mathematical model to represent the environmental conditions that affect crop production (sunlight, water availability, air and soil temperature, CO₂ concentration, air humidity, etc.) For example, Rosenzweig et al. (2014) projected the global productivity changes of rice, maize, soybean, and wheat from 2070 to 2099 compared to 1980 to 2010 by simulating many existing crop models under IPCC climate change scenarios. Crop model analysis has also been applied by Korean researchers for major agricultural crops (Kim et al., 2015). Crop modeling has the advantage of capturing precise pathways through which climate change affects crop production, but it is only applied to a few major food crops and is essentially a simulation technique which does not have an econometric basis.

Econometric methods are the most common methods of direct analysis used by economists. As outlined by Ortiz-Bobea (2021), this approach includes several different methods, all of which attempt to estimate an econometric model. The dependent variable in the estimation equation is either crop yields, agricultural income, or land prices, and the explanatory variables are climate/weather variables and a number of indicators reflecting regional and time-specific characteristics.

Econometric methods attempt to distinguish between long-term climate factors and short-term weather variables. The first approach is to use cross-sectional data of climate variables over a long period of time (e.g., 30 years) to analyze the impact of regional climate differences on land prices or agricultural income (Mendelsohn et al. 1994; Mendelsohn and Massetti 2017). This method, also known as the Ricardian model, can reflect the impact of long-term climate variables, but it analyzes the impact of climate change under the assumption that a sufficient degree of adaptation measures has been introduced, and therefore does not derive the difference in climate change impact with and without adaptation. In addition, this method is known to suffer from significant omitted variable bias, as short-term weather variables or other key explanatory variables are not included in the model (Ortiz-Bobea, 2021).

The omitted variable bias of cross-sectional data analysis can be resolved by applying fixed effect estimation to panel data comprising of multi-year data from multiple regions. Well-known studies, such as Deschenes and Greenstone (2012) and Fisher et al. (2012), have attempted to resolve the omitted variable bias by using panel data estimation, where every individual yield data for each region is represented by annual weather variables and other explanatory variables. However, this sub-study mainly focuses on the impact of relatively short-term weather variables on yield rather than long-term climate change, and therefore does not properly reflect the impact of adaptation. In addition, such an analysis may show that regional and annual effects mainly affect yield rather than short-term weather variables.

An approach that has been introduced to mitigate the limitations of these two methods is a methodology that incorporates both short-term weather variables and long-term climate variables (Moore and Lobell 2014; Mérel and Gammans 2021; McIntosh and Schlenker 2006).¹²⁾ In this method, both long-term climate change and short-term weather variables are taken into account, and can also

12) A more detailed analysis procedure is described in Section 2.2.2.

utilize panel data, which can improve the problems of the two previous methods. In addition, by estimating the difference between the effects of long-term climate variables and short-term weather variables, the effects in the presence of appropriate adaptation can be distinguished from the effects in the absence of adaptation.

The econometric estimation methods described above have improved significantly over a relatively short period, and their application has greatly expanded as well. However, apart from the relatively early Ricardian model, most studies have focused on developed countries such as the U.S. and Europe rather than developing countries. Studies that focus on countries in the Mekong region are scarce with some exceptions, such as Trang's (2016) work on Vietnamese rice. In Korea, there have been similar studies with a focus on rice by Kwon and Kim (2008), and Cho and Kwon (2014).

Also, previous studies usually use data at the regional level, such as U.S. counties. Aggregating data by region allows for the construction of panel data, but such a method is reliable only when a sufficient number of observations per region is available. Household surveys or agricultural census in the Mekong Delta have a small number of surveyed households per administrative region, making it difficult to assume that these households are representative of the region. Additionally, due to the relatively short time series of available data, using regional average data reduces the degrees of freedom of the estimated model.

Another limitation of previous studies is that they reflect producers' adaptation to climate change only in an implicit manner. The Ricardian model assumes the existence of sufficient adaptation as it utilizes only cross-sectional data of long-term climate variables. Moore and Lobell (2014) and Mérel and Gammans (2021), which use both climate and weather variables, implicitly assume the presence or absence of adaptation effects based on whether the impact of the squared deviation of weather from climate is taken into account or not. Therefore, these studies do not explicitly explain how adaptation is taken into account or its effect.

Furthermore, previous studies have limitations in analyzing how climate change affects the variability in yield or profitability. Climate change not only alters the expected value of climate variables but also affects their variability, increasing the frequency of extreme weather events. Moore and Lobell (2014) and Mérel and Gammans (2021), which incorporate both climate and weather variables, take into account the squared deviation of short-term weather from the long-term climate in their models, thus allowing for an evaluation of the impact of climate instability on productivity or profitability. However, such an approach focuses on analyzing the impact of "climate variability" on the "mean productivity and income," rather than on the variability of productivity or profitability. For a decision maker, it would be essential to understand not only the change in mean yield/profitability but also changes in its variability and the impact of climate change on this variability.

Our sub-study addresses these four limitations of previous studies. First, to address the limitation of crop yield models being mainly employed in developed countries, this sub-study uses economic data from the Mekong Delta region to derive relevant insights.

Second, the issue of using regional average data is addressed by utilizing individual farm-level data from the Vietnam Household Living Standard Survey (VHLSS) data, which is a survey on relatively large number of households. Although this data is a repeated cross-sectional data rather than a panel data, we account for omitted variable bias by adding additional explanatory variables apart from climate and weather variables.

Third, to analyze specific adaptation measures and their effects, this sub-study applies a two-step analysis method. In the first step, this study identifies adaptation measures of the producer side that can be identified by observed data and analyzes how climate change impacts the farmer's endogenous decision making process related to such measures. The second step then estimates a yield/profitability equation that includes these endogenous adaptation measures as well as implicit

adaptation. This approach enables us to separate the direct effects of climate change on yield/profitability without adaptation from the effects when accounting for changes in levels of adaptation measures.

Lastly, this sub-study explicitly analyzes the impact of climate change not only on the average outlook of yield/profitability but also on its variability. For this purpose, this sub-study modifies a Just-Pope (1978) type of stochastic production function to assess how climate change affects the variability of rice yields and agricultural income in Vietnam.

2.1.2. Climate Change Adaptation Measures

There are various adaptation measures that can be implemented in the agricultural sector to address climate change. Some of these measures can be directly undertaken by individual farmers, while others belong to the public sector such as national governments, public institutions, or the international community. <Table 2-1> is a summary of the climate change adaptation measures proposed by the European Environmental Agency (EEA, 2019), which apply to either the public sector such as international and national governments, or individual agricultural producers of this sub-study.

<Table 2-1> Classification of Climate Change Adaptation Measures by the European Environment Agency (EEA, 2019)

Category	Adaptation Measures
Public (international/ national government)	• Evaluation and monitoring of climate change impacts on the agricultural sector, assessment of vulnerability • Facilitation of information exchange and accessibility on climate change impacts • Development of a climate change data management system • Strengthening institutional capacity and coordination for adaptation and resource accessibility • Development and preservation of new varieties of crops, fruit trees, livestock, and fish that are adapted to climate conditions • Establishment of links between climate change, agriculture, and rural development

Category	Adaptation Measures
	• Dissemination of policies for adaptation/mitigation, sustainable land/water management, and biodiversity conservation • Raising awareness and providing guidance on climate change • Support for risk management and disaster insurance • Management of irrigation facilities
Individual producers	• Use of drainage systems that consider ecosystem impact / Enhancement of irrigation efficiency / Rainwater storage and utilization • Expansion of precision agriculture and sustainable facility-based agriculture (e.g., smart farming) • Sustainable land management (e.g., reduced tillage, low-input farming) • Adjusting farming calendar (e.g., modifying planting schedules) • Selection and cultivation of climate-adaptive crops • Tillage or minimum tillage practices • Diversification of crops and crop rotation • Maintenance of farmland boundaries (to reduce water runoff and soil erosion) • Genetic improvement of livestock • Improvement of pasture and grazing areas • Prevention of livestock disease outbreaks • Diversification of agricultural income sources

Among the climate change adaptation measures that can be undertaken by farmers or the public sector, this study focuses on farmers' decision making as they are well-identified in the VHLSS data of this study. By comparing and testing identifiable variables, this sub-study selects 1) crop switching behavior and 2) agricultural machinery purchase as the two most important adaptation measures. Crop switching behavior encompasses several adaptation measures listed by the EEA, such as 'diversification of crops,' 'diversification of agricultural income sources,' 'Adjusting farming calendar,' and 'selection and cultivation of climate-adaptive crops.' The second adaptation measure, the use of agricultural machinery is not a direct adaptation measure emphasized by the EEA, but was selected due to its significant role in water and soil management in developing countries where the agricultural infrastructure is relatively weak.

2.1.3. Analysis Plan

This sub-study, with the objectives and characteristics outlined above, consists of four sub-analyses:

- Analysis 1: The impact of climate on the expected value and variability of productivity/profitability
- Analysis 2: The impact of climate on farm's decision-making
- Analysis 3: The impact of climate on rice productivity and the effectiveness of adaptation measures
- Analysis 4: The impact of climate on agricultural income and analysis of neighborhood effects

These analyses focus on two main outcomes: rice, which is the most important crop in the Mekong Delta, and agricultural income of crop production. The data on production and income are obtained from individual farm-level data (i.e., households with positive agricultural income) in the Vietnam Household Living Standard Survey (VHLSS). Historical climate data are obtained from NOAA ESRL Physical Sciences Division (PSD) and Climate Hazards Group InfraRed Precipitation with Station (CHIRPS), while future climate projections are processed from WorldClim data.

In 'Analysis 1', we simultaneously estimate the impact of climate on the expected value and variability of rice yield (productivity) and agricultural income (profitability) reflected in a single model. The Just-Pope (1978) function is applied for this purpose, and we incorporate both climate and weather variables to estimate and interpret the results of climate change.

'Analysis 2' corresponds to the first step of the two-step approach used in this study to assess the impacts of climate change. In this step, we analyze the choices of rice farmers regarding the proportion of farmland allocated to rice production and the expenditure on agricultural machinery for rice production. Similarly, for agricultural income, we estimate the decisions related to selecting crop types and

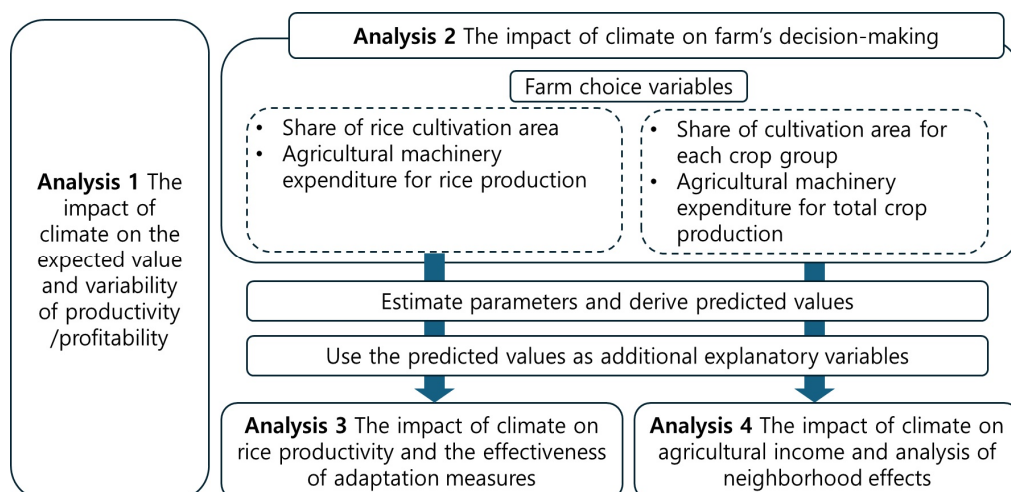
expenditure on agricultural machinery. For this analysis, we incorporate climate/weather variables, farm household characteristics, and regional characteristics. This estimation helps to understand the influence of climate change on farm decisions and provides several insights. In the case of share of crop area, which takes the form of multivariate fractional data, we apply a model that accounts for such characteristic.

‘Analysis 3’ corresponds to the second step of the two-step approach, specifically, in analyzing the impact of climate variables on rice yield. In this analysis, we focus on the adaptation strategy of rice farmers of choosing the proportion of land allocated to rice cultivation and expenditure on agricultural machinery for rice production. This analysis includes long-term climate variables, short-term weather variables, and deviations between the two, to estimate their impact on individual farms’ rice yield. The effects of adaptation measures are divided into cases where no adaptation occurs, where adaptation of switching rice shares is taken into account, and when adaptation of choosing machinery expenditure is taken into account. Additionally, we project the mitigation effect of these adaptation measures under the four IPCC climate scenarios.

In ‘Analysis 4’, the methods applied in Analysis 3 for rice yield are extended to agricultural income of crop production. In the case of agricultural income, the impact of climate change on each crop type varies. Therefore, the direct impact of climate/weather variables on income is represented in a relatively simple form. Instead, we place higher emphasis on choosing crop shares and expenditure on agricultural machinery in response to climate change, and thus propose a model that allows for a more detailed analysis of such factors. This study also recognizes that crop selection is influenced not only by household characteristics, but also regional factors and neighboring farms, thus discovering the existence of neighborhood effects. The statistical significance of the neighborhood effect is tested and incorporated into deriving the effects of adaptation measures. Similar to rice yield, the effects of adaptation measures on agricultural income are projected under different climate change scenarios.

The relationships between these four analyses are illustrated in <Figure 2-1>.

[Figure 2-1] Visualization of the Sub-analyses of Sub-study 1



This sub-study combines the estimation results of each sub-analysis with the SSP (Shared Socioeconomic Pathways) scenario, a future climate change scenario, to simulate how key variables (e.g., crop share, productivity, profitability) will change under future climate conditions. In particular, this sub-study focuses on the Mekong Delta region of Vietnam, which has a high dependence on agriculture and is identified as vulnerable to climate change. The results for the Mekong Delta region of Vietnam are presented in comparison with national-level simulation results.

2.2. Sub-analysis Methods

2.2.1. The Impact of Climate on the Expected Value and Variability of Productivity/Profitability (Analysis 1)

This analysis examines the pure effect of climate on productivity or profitability. In analyzing the impact of climate, this analysis not only focuses on how climate change affects the expected value of farm productivity/profitability but also the variability, or uncertainty, associated with it. It also incorporates the impact of the variability in climate itself on productivity/profitability, distinguishing it from the models in ‘Analysis 2’, ‘Analysis 3’, and ‘Analysis 4’. While this analysis does not explicitly reflect adaptation measures, it assumes that adaptation occurs implicitly by including long-term climate variables as explanatory variables.

Specifically, ‘Analysis 1’ estimates the Just-Pope (1978) type of climate-adaptation response function of Equation (2-1). Both the expected value and variance of productivity/profitability depend on climate variables, with the variability represented by a stochastic variable with mean 0 and variance 1. The dependent variable y_{it} , defined as rice productivity per unit area or agricultural income per unit area of farm i at time t , is expressed as a logarithmic variable. The expectation part of y_{it} , $f(\mathbf{X}_{it} : \beta)$, is modeled as a quadratic function, while the variability part of y_{it} , $h(\mathbf{Z}_{it} : \gamma)$, is expressed as the form of an exponential function so its value is always positive.

$$(2-1) \quad y_{it} = f(\mathbf{X}_{it} : \beta) + h(\mathbf{Z}_{it} : \gamma)\epsilon_{it}$$

Equation (2-1) indicates that the mean of y_{it} is $f(\mathbf{X}_{it} : \beta)$ and its variance $h(\mathbf{Z}_{it} : \gamma)^2$, where $\mathbf{X}_{it}$ is the vector of variables that affect the mean and $\mathbf{Z}_{it}$ is the vector of variables that affect the variance. $\mathbf{X}_{it}$ and $\mathbf{Z}_{it}$ include climate variables and other explanatory variables, and their variables can partially or completely overlap. In

this analysis, we choose $\overline{Temp}_i$ (the 30-year mean of temperature), $\overline{Rain}_i$ (the 30-year mean of precipitation), $\overline{Temp}_i^2$, $\overline{Rain}_i^2$, D_r (regional dummies), t (time), and ED_{it} (extreme weather) dummies, explained below) for $\mathbf{X}_{it}$. For $\mathbf{Z}_{it}$, we use $\overline{Temp}_i$, $\overline{Rain}_i$, D_r , t , and ED_{it} . The squared term of temperature and rainfall is not included in $\mathbf{Z}_{it}$. Thus, the functional form of f and h is specified as the following:

$$(2-2) \quad f(\mathbf{X}_{it} : \beta) = \beta_0 + \beta_1 \overline{Temp}_i + \beta_2 \overline{Rain}_i + \beta_3 \overline{Temp}_i^2 + \beta_4 \overline{Rain}_i^2 \\ + \beta_{ED}(ED_{it}) + \delta_i t + \sum_r (\delta_r D_r + \delta_{rt} D_r \times t)$$

$$(2-3) \quad h(\mathbf{Z}_{it} : \gamma) = \exp(\gamma_0 + \gamma_1 \overline{Temp}_i + \gamma_2 \overline{Rain}_i + \beta_{ED}(ED) + \delta_i t \\ + \sum_r (\delta_r D_r + \delta_{rt} D_r \times t))$$

In equations (2-2) and (2-3), ED_{it} is an extreme weather dummy variable which indicates if the weather of farm i in time t is an extreme weather. Extreme weather is normally understood as a weather event that deviate significantly from normal climate, and from a meteorological perspective, it is common to define extreme weather as the tail end of weather distributions, assuming that the distribution of weather variables follows a normal distribution.

This analysis follows this perspective and defines extreme weather as weather that exceeds ± 2 standard deviations of weather variables, following the specifications of Rahmstorf and Coumou (2011), Roh et al. (2012), and Cho et al. (2014). The VHLSS data used in this sub-study is biennial data from 2004 to 2018. So, calculating the standard deviation of weather, the annual average temperature and total rainfall for each district are obtained from climate data from 2004 to 2018 (including odd years), and if either temperature or rainfall of a certain year exceeds ± 2 standard deviations from the mean, it is considered that an extreme weather event occurred in that district in that year.

We use a maximum likelihood estimation method to estimate the parameter

vectors β and γ . Assuming that the error term ϵ_{it} follows a standard normal distribution, so that $\epsilon_{it} \sim N(0,1)$, the log-likelihood function is defined as Equation (2-4). So, this analysis estimates β and γ that maximizes this log-likelihood function.

$$(2-4) \quad \ln L = -\frac{1}{2} \left[N \ln(2\pi) + \sum_{i=1}^N \ln(h(\mathbf{Z}_i, \gamma))^2 + \sum_{i=1}^N \frac{(y_i - f(\mathbf{X}_i, \beta))^2}{h(\mathbf{Z}_i, \gamma)^2} \right]$$

N = number of observations

2.2.2. The Impact of Climate on Farms' Decision-Making (Analysis 2)

As shown in <Table 2-1>, farmers are not passive recipients of climate change, and climate change adaptation in the agricultural production sector can be implemented in various forms by both individual farmers and the public sector. One of the most effective adaptation measures is crop switching. By changing crop combinations in response to changes in production conditions including climate conditions, farmers can reduce damage caused by those changes or even increase productivity/profitability. Compared to infrastructure improvements or the development of new crop varieties which require significant financial and time investments, crop switching is a relatively easy adaptation strategy for producers in developing countries like those in the Mekong River Basin.

In addition to crop switching, decisions regarding the amount of capital invested in agricultural production can also be considered an adaptation measure to climate change. This study analyzes the effects of these adaptation measures, which are specified into the land share of each crop group and expenditure on agricultural machinery. Since this analysis distinguishes between farmer's choice in overall agricultural production and in rice production, there are four types of dependent variables in 'Analysis 2' as follows: the land share of crop groups, total agricultural machinery expenditure used in agricultural production, land share of rice, and agricultural machinery expenditure for rice production.

Analysis of Farmers' Crop Selection Behavior

Among the few studies on crop selection as an adaptation to climate change, Rising and Devineni (2020) used county-level data from the United States from 1949 to 2009. They analyzed the extent to which climate variables affect the productivity of six crop types and projected the productivity of these crops under the RCP 8.5 scenario for the year 2070. They predicted that the total profit from the six crops would decrease by 31% due to climate change by 2070, but if optimal crop selection behavior were adopted, the loss could be reduced by half.

Crop selection as an adaptation measure to climate change can be a useful strategy for both developed and developing countries. However, most of the econometric models analyzing the impacts of climate change on agriculture and the effectiveness of adaptation measures have focused on estimating the functional relationship between climate variables and productivity under the assumption that existing crop selections would remain unchanged (Ortiz-Bobea, 2021). The study by Rising and Devineni (2020) above also has the limitation that it is not an empirical estimation of crop selection behavior with actual data but instead an optimization model to derive future optimal crop selection based on linear programming.

This analysis uses long-term data from Vietnam's VHLSS to estimate how individual farmers' crop selection decisions are influenced by climate variables and other explanatory variables. Our estimation results provide valuable insights by quantifying the impacts of various variables on crop selection, and it allows us to project how crop selection will change under future climate conditions. In the context of a two-step analysis which incorporates 'Analysis 2,' 'Analysis 3,' and 'Analysis 4,' the predicted values of the adaptation variables in the productivity/profitability equations of 'Analysis 3' and 'Analysis 4' allows for analyzing how these variables affect productivity/profitability while mitigating the endogeneity issues typically associated with choice variables.

Suppose that a farm can choose among K types of crop (groups). Then we can

define s_{it}^h as the share of crop acreage (or production value) in time t for farm i ($i = 1, \dots, N$). This is a multivariate fractional data that takes a value between 0 and 1. ‘Analysis 2’ estimates how this multivariate fractional data is affected by explanatory variables which also include climate variables. For estimation, this analysis uses individual farm level data, as in all the other analyses.

In estimating a model with a fractional response variable, at least three methods can be applied (Murteira and Ramalho 2016). The first method is to transform the fractional variable into a log-odds ratio, $\ln(s_{it}^h/s_{it}^1)$, and apply a SUR (seemingly unrelated regression) method to a system of $K - 1$ equations as the log-odds ratio can take any value between $(-\infty, \infty)$. The second method is to assume that s_{it}^h follows a Dirichlet distribution and apply maximum likelihood estimation. However, these two methods do not allow for corner solutions, so one must impose a quite cumbersome assumption that every individual assigns a small amount of land for every type of crop. For this reason, this study uses a quasi-maximum likelihood (QML) method for estimating fractional data, which is an extension of the model of Papke and Wooldridge (1996) for univariate fractional data to the multivariate case.

Denote the vector of explanatory variables of farm i by $X_i = (X_{1i}, \dots, X_{Ki})$, and define s_i^h as the acreage share for crop h in farm i . We do not impose any assumptions on the distribution of s_i^h and assume that the conditional mean functions take the form of $E(s_i^h|X_i) = G_i(X_i; \beta) = (G_{1i}(X_i; \beta), \dots, G_{Ki}(X_i; \beta))$, where

$G_{ki} \geq 0$, $\sum_{k=1}^K G_{ki} = 1$. In this analysis, we assume a multinomial logit (MNL) functional

form $G_{hi} = \frac{\exp(X_{hi}\beta)}{1 + \sum_{k=1}^{K-1} \exp(X_{ki}\beta)}$, so that the log likelihood for farm i is the following:

$$(2-5) \quad \ln L_i(\beta) = \sum_{k=1}^K s_i^k \ln G_{ki} = \sum_{k=1}^{K-1} s_i^k \ln \left(\frac{G_{ki}}{G_{Ki}} \right) + \ln G_{Ki}$$

As we do not impose a distributional assumption, estimates are obtained by QML estimation. It is known that if the functional form of $G(\cdot)$ is appropriately chosen, the QML estimate $\hat{\beta}_{QML}$ is a consistent and asymptotically normal estimator regardless of the true conditional distribution of s_i^h (Gouriéroux et al., 1984).

This analysis also estimates a model for univariate fractional data with $K=2$, where the dependent variable is the share of rice acreage and the share of non-rice acreage. This univariate fractional data is used in 'Analysis 2' to analyze the impact of climate change on rice productivity. Also, it is used to assess the robustness of the analysis by comparing the univariate result to the result derived from multivariate fractional data.

Analysis of Farms' Machinery Expenditure Behavior

As machinery expenditure is a money metric, it is nonnegative, so we estimate a Tobit model. In the Tobit model, the dependent variable y is observed $y = y^*$ if it exceeds a certain threshold (in our study, the threshold is zero). However, when y^* is below the threshold then $y = 0$. Since the vector of explanatory variables, x , is always observed, the estimation data is a type of censored data. In the case of censored data, the model is specified as Equation (2-6).

$$(2-6) \quad y = \begin{cases} y^* & \text{if } y^* > 0 \\ 0 & \text{if } y^* \leq 0 \end{cases}, \quad y^* = x'\beta + \epsilon, \quad \epsilon \sim N(0, \sigma^2)$$

If one estimates the parameters of the model using ordinary least squares (OLS) not taking into account the characteristics of censored data, the parameter estimates suffer from censoring bias. Thus, this analysis applies a censoring regression method to include observations where $y=0$ as well. Parameter estimates are obtained through a maximum likelihood method where the log likelihood function is given as follows.

$$(2-7) \quad \ln L(\beta, \sigma^2) = \sum_{i=1}^N \left[-\frac{1}{2} \ln \sigma^2 - \frac{1}{2} \ln 2\pi - \frac{1}{2\sigma^2} (y_i - x_i'\beta)^2 - \ln \Phi(x_i'\beta/\sigma) \right]$$

When obtaining expected values of expenditure, $E[y|x]$, $E[y|x] \neq x'\beta$ since the marginal effect $\frac{\partial y_i}{\partial x_i}$ does not equal θ . Instead, expected values should be obtained by the relationship below.

$$(2-8) \quad E[y|x, y > 0] = x'\beta + E[\epsilon > -x'\beta] = x'\beta + \sigma\lambda(\omega), \quad \lambda(\omega) = \frac{\phi(\omega)}{\Phi(\omega)}, \quad \omega = x'\beta/\sigma$$

2.2.3. The Impact of Climate on Rice Productivity and the Effectiveness of Adaptation Measures (Analysis 3)

‘Analysis 3’ focuses on the impact of climate variables on farm productivity, particularly on rice productivity, which is a major agricultural product in Vietnam. While crop productivity can be analyzed through natural science estimation or simulation methods such as Rosenzweig et al.’s (2014) crop model, a statistical approach utilizing actual farm production data is also actively used, as in the case of this sub-study. For example, define y_{it} as the productivity or profitability of farm i at time t , $\mathbf{Z}_{it}$ the vector of climate variables, $\mathbf{X}_{it}$ the vector of adaptation measures from the producer or the government. Then, the regression equation would be defined as follows (ϵ_{it} has mean zero and variance σ_ϵ^2).

$$(2-9) \quad y_{it} = \alpha_i + \gamma_t + f(\mathbf{Z}_{it} : \beta) + \omega(\mathbf{Z}_{it}, \mathbf{X}_{it} : \delta) + \epsilon_{it}$$

$f(\mathbf{Z}_{it} : \beta)$ = Pure effect of climate change

$\omega(\mathbf{Z}_{it}, \mathbf{X}_{it} : \delta)$ = Interaction effect of climate and adaptation

y_{it} , a variable indicating yield or income, is represented by price of agricultural land, agricultural income, yield per unit land, crop-specific variables, or the entire profit of a farm. For $\mathbf{Z}_{it}$, the vector of climate or weather variables, growing season temperature (maximum, minimum, etc.), precipitation, amount of sunlight, or CO₂ concentration is used. For $\mathbf{X}_{it}$, the vector of adaptation measures, variables such as farming methods, irrigation water supply, selection of variety and crop type, or other investments in infrastructure can be used. α_i and γ_t reflect the

cross-sectional and time-series effects of panel data, respectively. So, (2-9) is estimated by a two-way fixed effect panel estimation method.

Equation (2-9) has been used in several studies to estimate the impact of climate change on productivity, but it primarily estimates the short-term relationships between the explanatory variables and the productivity variable. However, climate change is a relatively long-term phenomenon and producers can take adaptive measures in response to it. This requires an estimation equation that accounts for the long-term effects of climate variables and the adaptive actions of producers, which are difficult to express with specific variables. Moore and Lobell (2014), Mérel and Gammans (2021), and other studies have specified their estimation equations on theoretical backgrounds for reflecting long-term variables considering this issue. Assuming that the climate variable z_{it} in Equation (2-9) is a one-dimensional variable for the sake of simplicity, the following estimation equation is derived.¹³⁾

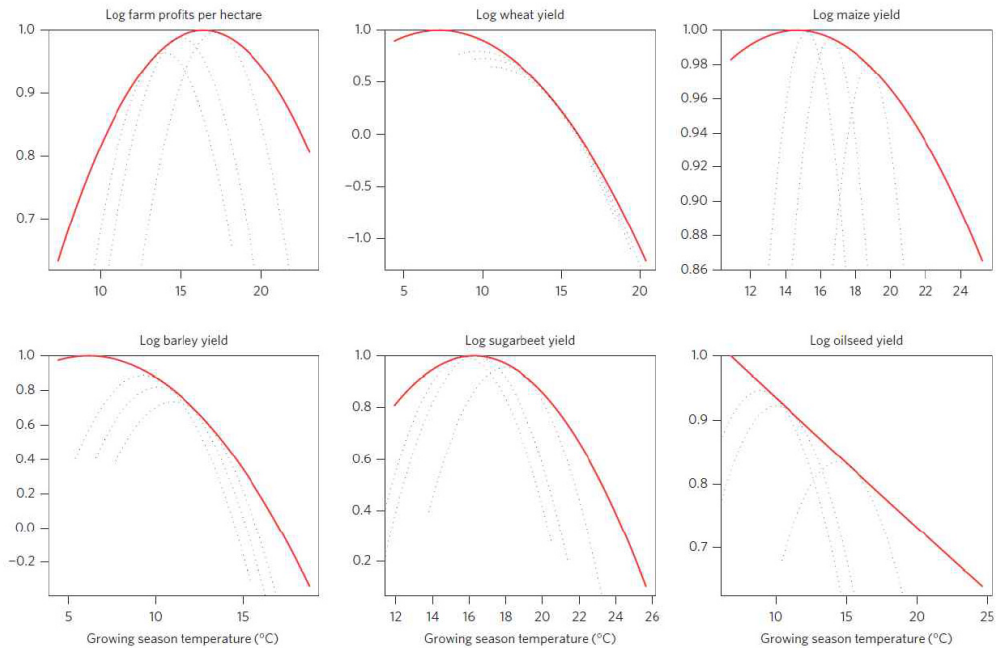
$$(2-10) \quad y_{it} = \mu_i \beta_1 + \mu_i^2 \beta_2 + (z_{it} - \mu_i)^2 \beta_3 + \omega(\mathbf{X}_{it} : \delta) + g(\alpha_i, t) + \epsilon_{it}$$

The weather variable of each farm is assumed to take a stationary distribution, so that $E[z_{it}|i] = \mu_i$. In Equation (2-10) the impact of climate change is represented by the impact of a long-term climate variable μ_i on y_{it} . At the same time, the short-term impact of the weather variable of time t is also reflected in the equation through the term $(z_{it} - \mu_i)^2 \beta_3$. $\omega(\mathbf{X}_{it} : \delta)$ represents other explanatory variables other than climate/weather variables, and $g(\alpha_i, t)$ represents regional effects and time trends.

13) This analysis uses both the Moore and Lobell (2014) model of Equation (2-10) as well as a modified version of the Mérel and Gammans (2021) model, which places greater emphasis on the role of short-term weather variables. However, since our individual farm data is not a panel data, the Mérel and Gammans (2021) model does not fully take advantage of the benefits of a panel model in our study. Also, the long-term deviation parameter β_3 in this model does not completely capture the long-term adaptation of farms, yielding unstable results. Therefore, we report only the results derived from the Moore and Lobell (2014) model.

Using the term $(z_{it} - \mu_i)^2 \beta_3$, one can distinguish between the long-term and short-term impact of climate change. This difference is understood to stem from producers' delayed understanding of, or time lag in responding to climate change. Since long-term responses can differ from the rather constrained short-term responses, and previous studies have shown that it is reasonable to expect the former to be larger, the model presumes that the estimate of β_3 will have a negative value. Since the productivity function of Equation (2-10) is a quadratic function of the climate variable μ_i and thus has a U-shape form (normally inverted), we expect the long-term response curve to be an upper envelope around the short-term response curve as shown in <Figure 2-2>.

**[Figure 2-2] Examples of short-term and long-term response functions
: Moore and Lobell (2014)**



Suppose the estimate of β is b , and the expected climate shifts from μ_{0i} to μ_{1i} (under future climate change scenarios). In the long run, where farmers adapt optimally to climate change, the expected value of y_{it} for each of the periods is the following. ($K(\cdot)$ represents the non-climate terms in the model)

$$E_{LR}[y_{kit}] = b_1\mu_{ki} + b_2\mu_{ki}^2 + b_3E[z_{kit} - \mu_{ki}]^2 + K(\cdot) = b_1\mu_{ki} + b_2\mu_{ki}^2 + b_3\sigma_{ki}^2 + K(\cdot), k = 0, 1$$

However, in the short run, the $(z_{1it} - \mu_{0i})$ term remains, so the expectation of y_{it} now becomes

$$\begin{aligned} E_{SR}[y_{1it}] &= b_1\mu_{1i} + b_2\mu_{1i}^2 + b_3E[z_{1it} - \mu_{1i} + (\mu_{1i} - \mu_{0i})]^2 + K(\cdot) \\ &= b_1\mu_{1i} + b_2\mu_{1i}^2 + b_3(\sigma_{1i}^2 + (\mu_{1i} - \mu_{0i})^2) + K(\cdot) \end{aligned}$$

Thus, the expectations of the long run and short run impact of climate change are expressed by the following formulae:¹⁴⁾

$$(2-11a) \quad E[\Delta y_i]_{LR} = b_1(\mu_{1i} - \mu_{0i}) + b_2(\mu_{1i}^2 - \mu_{0i}^2) + b_3(\sigma_{1i}^2 - \sigma_{0i}^2)$$

$$\begin{aligned} (2-11b) \quad E[\Delta y_i]_{SR} &= b_1(\mu_{1i} - \mu_{0i}) + b_2(\mu_{1i}^2 - \mu_{0i}^2) + b_3(\sigma_{1i}^2 - \sigma_{0i}^2) + b_3(\mu_{1i} - \mu_{0i})^2 \\ &= E[\Delta y_i]_{LR} + b_3(\mu_{1i} - \mu_{0i})^2 \end{aligned}$$

If $\hat{\beta}_3$ is estimated to be statistically insignificant or positive, we can assume that adaptation to climate change in the long term does not exist.¹⁵⁾ In such cases, the role of $(z_{it} - \mu_i)^2\beta_3$ is in removing the omitted variable bias of the model incorporating both the short-term variable z_{it} and the long-term variable μ_i , rather than allowing for distinction between the long run and short run effect. Since $\hat{\beta}_3$ was estimated to be negative in this analysis, $E[\Delta y_i]_{LR} \geq E[\Delta y_i]_{SR}$ always holds in our future climate change simulations, which indicate the existence of farms' unobservable long-term adaptation behavior.

The term $(z_{it} - \mu_i)^2\beta_3$ of Equation (2-10) captures the difference between the long

14) This may correct the error of Moore and Lobell (2014) in not accounting for changes in the variance of climate variables between the two time periods. However, the actual simulation later in this paper fails to reflect the change in variance as future climate projections are presented as an average value within 20-year-long intervals rather than year-by-year, thus making it impossible to calculate its variance. This issue will be accounted for later on by developing a method of obtaining the projected change in variance.

15) Some studies that account for both short-run and long-run effects like Equation (2-10) estimate the parameter of the deviation term to be statistically insignificant, positive, or negative with a very small magnitude.

run and the short run, assuming that farms act in a behavior to maximize productivity in the long run and that farms in the short run are limited in their ability to fully adapt to climate change. Thus, Equation (2-10) is a regression equation that identifies individual farm's adaptation without a specific variable to account for adaptation and instead derives the effect of implicit adaptation. So, this model cannot analyze the effect of individual farm-specific decision-making. To address this limitation, 'Analysis 3' takes into account farm's crop selection and machinery purchase by adding them in the $\omega(\mathbf{X}_{it} : \delta)$ part of Equation (2-10). In other words, estimating 'Analysis 3' allows some part of the unobserved adaptation to be expressed as observable variables, thereby enabling a comparison between the effect of unobserved adaptation and observable adaptation (crop selection and machinery purchase) in response to climate change.

Accounting for such adaptation measures in 'Analysis 3' means that producers actively modify crop choices and capital input in response to changes in climate variables and other conditions, thereby including these variables as determinants of productivity. In particular, when analyzing the impact of crop selection, the predicted proportion of rice from 'Analysis 2' is included as an additional explanatory variable in 'Analysis 3', thus reflecting the effects of specialization, economies of scale, and other factors on rice productivity. This allows for estimating adaptation effects while distinguishing the effects of rice cultivation scale, mechanization, and implicit adaptation.

So, $\omega(\mathbf{X}_{it} : \delta)$ includes the predicted values from the rice share equation and the machinery expenditure (on rice) equation estimated in 'Analysis 2.' Since the first-stage estimates are included as explanatory variables of $\mathbf{X}_{it}$, the statistical significance in the second-stage estimation may be biased. Therefore, this analysis uses a bootstrapping strategy, which repeatedly executes the first-stage estimation of 'Analysis 2' and the second-stage estimation of 'Analysis 3,' to determine the statistical significance of the second-stage estimates. This bootstrapping approach also applies to 'Analysis 4' on agricultural income analysis.

2.2.4. The Impact of Climate on Agricultural Income and Analysis of Neighborhood Effects (Analysis 4)

Following ‘Analysis 3,’ which analyzes how the productivity of rice, the most important crop for Vietnamese farmers, responds to climate change, ‘Analysis 4’ focuses on how agricultural income reacts to climate variables. So, the y_{it} variable of Equation (2-10) is now the agricultural profit per square meter of acreage for farm i in time t (in logarithms).¹⁶⁾ While ‘Analysis 3’ specified the effect of climate z_{it} as z_{it} , z_{it}^2 , and $(z_{it} - \mu_i)^2$, such a specification is not adequate for ‘Analysis 4’ where heterogeneous agricultural products are aggregated and thus make it hard to precisely estimate the effect of various different climate variables. Thus, ‘Analysis 4’ only takes into account the linear impact of climate on profitability (agricultural income per square meter of acreage).¹⁷⁾ For $\omega(\mathbf{X}_{it} : \delta)$, which includes explanatory variables other than weather/climate variables, we use the land shares of four crop types for each farm and machinery expenditure. These variables are obtained from the predicted variables of ‘Analysis 2’, $\hat{s}_{it}^h$ ($h \in \{1, 2, 3, 4\}$) and $\hat{c}_{it}$. This analysis specifies the model to incorporate neighborhood effects related to land shares of each crop type, so that it accounts for the impact of neighboring farms in the same region increasing the area for a particular crop type.

Define $v(i)$ as the district that farm i belongs to, and $g_{v(i), t}$ the term that contains regional variables of $v(i)$ and time trends. Given an information set Ψ_i , this farm

16) Unlike the common practice of combining crop income and livestock income to define agricultural income, this study defines agricultural income as crop income. This is due to the fact that the area of land used for livestock production is not recorded in the VHLSS data, the high heterogeneity between crop production and livestock production, and limited land-use changes between crops and livestock. Crops in this study are divided into four categories: rice, other food crops and vegetables, industrial crops, and fruit, which will be further discussed in Section 2.3.

17) This analysis reflects the non-linear effects of climate variables in the model to be discussed later, resulting in statistically significant climate parameter estimates. However, the response curves derived from these estimated parameters exhibit little non-linearity, indicating that climate variables have a linear effect on profitability. Therefore, this analysis presents the estimation results from a linear model regarding the impact of climate variables on profitability.

forms expectations about the income of neighboring farms in the same district. Then, we can define $\frac{1}{|v(i)-1|} \sum_{j(\neq i) \in v(i)} E[y_j|\Psi_i]$ as the regional average of expected income. Then, the income equation accounting for neighborhood effect becomes the following, where ϵ_i is a random variable.

$$(2-12) \quad y_{it} = \alpha_0 + \sum_{h=2}^4 \alpha_h \hat{s}_{it}^h + \alpha_c \hat{c}_{it} + \theta_z z_{it} + \theta_g g_{v(i),t} + \beta \frac{1}{|v(i)-1|} \sum_{j(\neq i) \in v(i)} E[y_j|\Psi_i] + \epsilon_i$$

All parameters except θ_g are scalar variables, and θ_g is a vector of parameters. If β is estimated to be statistically different from zero, a neighborhood effect exists in choosing crop types within a region. The term $\frac{1}{|v(i)-1|} \sum_{j(\neq i) \in v(i)} E[y_j|\Psi_i]$, the average income expectation by farm i is an endogenous variable as it is an expected value and not observed by data. To estimate a model where the parameter β is identified, this analysis applies the identification of Manski (1993), Ioannides (2013), and Kwon and Kang (2013). These studies assume the existence of a social equilibrium and that the expected value of y_{it} in Equation (2-12) equals $\frac{1}{|v(i)-1|} \sum_{j(\neq i) \in v(i)} E[y_j|\Psi_i]$. As a result, we obtain the following equation.

$$(2-13) \quad \frac{1}{|v(i)-1|} \sum_{j(\neq i) \in v(i)} E[y_j|\Psi_i] = \alpha_0 + \sum_{h=2}^4 \alpha_h \tilde{s}_{it}^h + \alpha_c \hat{c}_{it} + \theta_z z_{it} + \theta_g g_{v(i),t} + \beta \frac{1}{|v(i)-1|} \sum_{j(\neq i) \in v(i)} E[y_j|\Psi_i]$$

In this equation, $\tilde{s}_{it}^h$ is the average of the share of a crop type h in region $v(i)$ excluding farm i , i.e., $\frac{1}{|v(i)-1|} \sum_{j(\neq i) \in v(i)} s_{jt}^h$. Solving for $\frac{1}{|v(i)-1|} \sum_{j(\neq i) \in v(i)} E[y_j|\Psi_i]$ and substituting it into Equation (2-12), we obtain Equation (2-14), a model that is nonlinear with respect to its parameters.

$$(2-14) \quad y_{it} = \frac{\alpha_0}{1-\beta} + \sum_{h=2}^4 \alpha_h \hat{s}_{it}^h + \alpha_c \hat{c}_{it} + \sum_{h=2}^4 \frac{\beta}{1-\beta} \alpha_h \tilde{s}_{it}^h + \frac{\theta_z}{1-\beta} z_{it} + \frac{\theta_g}{1-\beta} g_{v(i),t} + \epsilon_i$$

If neighborhood effect exists and the effect of this neighborhood effect reaches a stable equilibrium through a multiplier effect, $0 < \beta < 1$ should hold. For example, if the climate variable z_{it} changes by one unit, its direct impact on farm i 's income is θ_z . However, taking into account the feedback effect of neighboring farms affected by the same change, the total impact on income becomes $\theta_z + \beta\theta_z + \beta^2\theta_z + \dots = \frac{\theta_z}{1-\beta}$. Thus, the multiplier effect of regional characteristics (e.g., climate variables) is $\frac{1}{1-\beta}$. If $\tilde{s}_{it}^h$, the average of the share of a crop type h excluding farm i , changes by one unit, its (multiplier) effect on the dependent variable is $\alpha_h \frac{\beta}{1-\beta}$. 'Analysis 4' takes into account such neighborhood effect and simulates the impact of future climate on farm profitability.

2.3. Data

Farm characteristics (productivity, cultivated area, adaptation measures, regional characteristics, etc.) are obtained from VHLSS, a household-level survey in Vietnam. Historical values of climate variables are from the NOAA ESRL Physical Sciences Division (PSD) and Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), and future climate projections are processed based on WorldClim data.

The Vietnam Household Living Standard Survey (VHLSS) is a household-level survey conducted by the World Bank and the Vietnam General Statistics Office (GSO). It aims to assess living standards and the impact of poverty policies on Vietnamese households. The survey has been conducted biennially since 2002, with a total sample size of over 30,000 households. The survey includes demographic and socio-economic information, economic status, education, and health status of each household. In this study, we analyze eight rounds of the VHLSS survey data from 2004 to 2018. Vietnam's administrative divisions are classified into provinces, districts, and communes. This study directly uses household-level responses from the VHLSS data, but the historical climate variables are matched at the commune level and future climate projection variables are matched at the district level due to the lack of spatial resolution in climate data. All price variables were converted to real prices using Vietnam's GDP deflator (2010=100).

To calculate productivity and cultivation area in the VHLSS dataset, we use production data for 54 agricultural products (55 in the 2004, 2006, and 2008 data). In the VHLSS data, these are categorized into four product groups, as shown in <Table 2-2>. Although the VHLSS data classifies livestock, forestry and surface aquaculture, byproducts, etc. as a part of agricultural income, our sub-study excludes these from agricultural income. That is, agricultural income in our sub-study specifically refers to crop income. This is based on the assumption that crop production has unique characteristics that distinguish it from livestock, etc.,

which leads to differing patterns in how each type of production is influenced by climate variables.

〈Table 2-2〉 Classification of Agricultural Products in VHLSS Data

Name of Group	No.	Name of Agricultural Product
1. Rice	1	Year-round ordinary rice
	2	Winter-spring ordinary rice
	3	Summer-autumn ordinary rice
	4	Tenth-month or autumn-winter rice
	5	Ordinary rice planted in terraced field
	6	Year-round glutinous rice
	7	Year-round specialty rice
2. Other food crops and vegetables	8	Maize (corn)
	9	Sweet potato
	10	Cassava/manioc
	11	Other staple food crops
	12	Potato
	13	Morning glory vegetable
	14	Kohlrabi
	15	Cabbage, cauliflower
	16	Cruciferous vegetables
	17	Edible beans
	18	Tomato
	19	Seasoning herb
	20	Other edible vegetables, fruits and roots
	21	Other annual crops (green, black and red bean, flowers, decorative plants, plants for animal feed and manure, etc.)
3. Industrial crops	22	Soya bean/soybean
	23	Peanut/groundnut
	24	Sesame
	25	Sugarcane
	26	Tobacco, rustic tobacco
	27	Cotton
	28	Jute, ramie (China grass)
	29	Sedge
	30	Other industrial annuals

Name of Group	No.	Name of Agricultural Product
	31	Tea
	32	Coffee
	33	Rubber
	34	Pepper
	35	Coconut
	36	Mulberry
	37	Cashew
	38	Other industrial perennials
4. Fruit	39	Citrus
	40	Pineapple
	41	Banana
	42	Mango, horse mango
	43	Indian jujube
	44	Grape
	45	Plum
	46	Papaya
	47	Longan, lychee, rambutan
	48	Sapodilla
	49	Sugar-apple, soursop
	50	Jackfruit, durian
	51	Mangosteen
	52	Other fruit trees
	53	Other perennials
	54	Seedlings
	55	Bonsai

Bonsai (item no.55) is included in 2004, 2006, and 2008 surveys only.

Regarding regional specifications, Vietnam is normally classified into eight regions as in <Table 2-3>. The eight regions can be classified into northern regions and southern regions with respect to how many times rice is harvested in a year. (1) Red River Delta, (2) Northeast, (3) Northwest is in the northern region. (4) North Central Coast, (5) South Central Coast, (6) Central Highland, (7) Southeast, and (8) Mekong Delta is in the southern region.

〈Table 2-3〉 Regions of Vietnam

No.	Region	Map of Vietnam
1	Red River Delta	
2	Northeast	
3	Northwest	
4	North Central Coast	
5	South Central Coast	
6	Central Highlands	
7	Southeast	
8	Mekong Delta (Mekong River Delta)	

Vietnam's administrative divisions were reshaped between 2004 and 2018. In this study, the regional specification is based on the ‘old’ classification. The ‘farms’ that we analyze are defined as households with positive agricultural profit (=total value of agricultural products – total cost of agricultural products). Since the households surveyed in the VHLSS change with each survey, the data used in this sub-study is repeated cross-sectional data rather than panel data. Therefore, all sub-analyses in our sub-study utilize repeated cross-sectional data at the individual farm level. 〈Table 2-4〉 summarizes the number of farms in each of the eight regions by year.

〈Table 2-4〉 Number of farms of each region by year

No.	1	2	3	4	5	6	7	8	Total
Region	Red River Delta	North east	North west	North Central Coast	South Central Coast	Central Highlands	South east	Mekong Delta	
2004	1,149 (25.7%)	900 (20.2%)	256 (5.7%)	662 (14.8%)	428 (9.6%)	176 (3.9%)	200 (4.5%)	696 (15.6%)	4,467
2006	1,110 (25.9%)	884 (20.6%)	248 (5.8%)	653 (15.2%)	435 (10.2%)	174 (4.1%)	162 (3.8%)	620 (14.5%)	4,286
2008	1,098 (26.3%)	877 (21.0%)	248 (5.9%)	614 (14.7%)	429 (10.3%)	170 (4.1%)	150 (3.6%)	596 (14.3%)	4,182
2010	1,110 (27.1%)	888 (21.7%)	234 (5.7%)	608 (14.8%)	410 (10.0%)	174 (4.3%)	120 (2.9%)	552 (13.5%)	4,096

No.	1	2	3	4	5	6	7	8	Total
Region	Red River Delta	North east	North west	North Central Coast	South Central Coast	Central Highlands	South east	Mekong Delta	
2012	1,038 (26.1%)	865 (21.8%)	228 (5.7%)	607 (15.3%)	416 (10.5%)	180 (4.5%)	116 (2.9%)	521 (13.1%)	3,971
2014	976 (25.6%)	856 (22.4%)	218 (5.7%)	570 (14.9%)	379 (9.9%)	180 (4.7%)	120 (3.1%)	518 (13.6%)	3,817
2016	805 (24.8%)	743 (22.8%)	201 (6.2%)	532 (16.4%)	318 (9.8%)	171 (5.3%)	82 (2.5%)	401 (12.3%)	3,594
2018	878 (24.4%)	828 (23.0%)	209 (5.8%)	585 (16.3%)	364 (10.1%)	170 (4.7%)	101 (2.8%)	459 (12.8%)	3,253
Total	8,164 (25.8%)	6,841 (21.6%)	1,842 (5.8%)	4,831 (15.3%)	3,179 (10.0%)	1,395 (4.4%)	1,051 (3.3%)	4,363 (13.8%)	31,666 (100%)

The numbers in parentheses indicate each region's share of the total number of farms.

‘Analysis 4,’ which aims to analyze not only the impact of climate variables on agricultural income but also the neighborhood effect, defines neighborhood effect at the district level. If the number of farms within a district is too small, it may not sufficiently represent data when estimating neighborhood effects. Thus, ‘Analysis 4’ limits the sample to farms within districts that contain at least five farms.

‘Analysis 2’, which analyzes how farms’ decision-making processes are affected by climate variables, focuses on these four types of variables: (1) crop shares, (2) rice share, (3) machinery expenditure on total agricultural production, and (4) machinery expenditure on rice production. For variables other than climate variables, this analysis uses the ethnic minority dummy, the poverty dummy of the household’s commune in the previous year, the age and education status of the household head, the area of the household’s commune, regional dummies, and a year variable. Vietnam has a long shape stretching from north to south and displays considerable heterogeneity due to its diverse geography, such as river basin areas, coastal regions, and mountainous areas. To address regional heterogeneities, this analysis uses regional dummy variables. Ethnic minorities, which refer to ethnicities other than the Viet (the majority ethnicity), tend to cluster

in certain regions such as the northern midlands and central highlands, which may affect farmers' crop choices. As income status is also a factor that influences crop choice, a poverty dummy variable based on the poverty status at the commune level is also used as a choice variable. <Table 2-5> contains descriptive statistics of variables related to farms' decision-making behavior.

'Analysis 3' and 'Analysis 4' focus on farms' productivity and profitability, so the dependent variables are the logarithm of rice yield and the logarithm of agricultural profit per acreage, respectively. Rice yield is calculated by dividing the produced weight of rice in a year by the total acreage of land used in that year to produce rice. For example, suppose that a double cropping farm produced 50kg of rice on 100m² of land in the first season, and then produced 45kg of rice on that same amount of land. Then, the yield of this farm is $(50+45)/(100+100)=0.475$. Profitability (agricultural profit per acreage) is calculated in a similar manner, so it is obtained by dividing the agricultural profit (= agricultural production value – agricultural production cost) of a year by the total acreage of that year. Descriptive statistics of rice yield and profitability are in <Table 2-6>. Rice yield shows an increase with time, but there is no consistent time trend in the case of profitability.

<Table 2-5> VHLSS descriptive statistics for 'Analysis 2'

Variable		Mean	Std. dev.	Min.	Max.
Acreage (m ²)		12,981	20,938	216	640,000
Crop shares	1. Rice	0.61	0.39	0	1
	2. Other food crops and vegetables	0.22	0.31	0	1
	3. Industrial crops	0.12	0.27	0	1
	4. Fruit	0.05	0.20	0	1
Machinery expenditure per acreage (VND/m ²)		116	202	0	115,371
Ethnic minority		0.15	0.36	0	1
Poverty		0.26	0.44	0	1
Commune area (m ²)		30.10	41.24	0.32	511.38
Age of household head		48.79	13.03	15	104

Variable		Mean	Std. dev.	Min.	Max.
Highest level of education received by household head	No degree	0.26	0.44	0	1
	Primary school	0.27	0.44	0	1
	Secondary school	0.40	0.49	0	1
	Elementary vocational school	0.04	0.20	0	1
	Intermediate vocational school or Vocational college	0.03	0.17	0	1
	College and above	0.01	0.10	0	1
	Others	0.00	0.02	0	1

1) Acreage refers to the total crop production area of a year. Crop shares and Machinery expenditure per acreage are calculated with respect to this acreage.

2) Ethnic Minority =1 if household head is an ethnic minority, =0 if otherwise.

3) Poverty =1 if the commune of the household was classified as a poor one in the previous year, =0 if otherwise.

〈Table 2-6〉 Annual trend of rice yield, profitability, and mean crop shares

Year	Rice yield (kg/m ²)				Profitability (VND/m ²)			
	Mean	Std. dev.	Min.	Max.	Mean	Std. dev.	Min.	Max.
2004	0.46	0.12	0.02	1.17	2,349	6,514	10	386,353
2006	0.48	0.12	0.01	1.23	2,926	28,538	9	1,961,603
2008	0.49	0.12	0.03	1.00	2,962	9,217	1	471,023
2010	0.48	0.13	0.03	1.62	2,498	4,359	28	168,125
2012	0.51	0.12	0.04	1.10	2,159	3,259	6	79,114
2014	0.51	0.17	0.05	6.06	2,433	5,997	3	312,444
2016	0.52	0.14	0.05	4.20	2,530	4,661	33	125,890
2018	0.52	0.14	0.06	3.48	2,996	10,959	29	573,807
Year	Crop shares (annual mean)							
	1. Rice		2. Other food crops and vegetables		3. Industrial crops		4. Fruit	
2004	0.61		0.21		0.12		0.05	
2006	0.66		0.18		0.11		0.05	
2008	0.65		0.19		0.11		0.05	
2010	0.65		0.19		0.11		0.04	
2012	0.60		0.22		0.12		0.05	
2014	0.59		0.23		0.13		0.05	
2016	0.57		0.24		0.13		0.06	
2018	0.56		0.23		0.14		0.07	

To reflect the regional effects in Vietnam, this study uses regional dummy variables. Using VHLSS data, Vietnam's regions can be categorized in two ways. The VHLSS data itself divides the country into eight regions, as shown in <Table 2-3>. However, when using the rice production seasons from the 2004 VHLSS survey operational handbook, the regions can be classified into five groups, as shown in <Table 2-7>. By using the latter classification, we can group regions with similar production characteristics as well as account for the issue of uneven regional household proportions, as some highland regions have very few farm households. Therefore, all regional variables in this analysis are based on the 'Group' classification of <Table 2-7>.

In 'Analysis 1,' which examines the expected value and variability of rice productivity, part of 'Analysis 2,' which analyzes rice-related decision-making, as well as in 'Analysis 3,' which analyzes rice productivity, the climate variables are calculated using rice production information from <Table 2-7>. The months when rice is not produced in any region of the country—October and November—are excluded, and the average temperature and total rainfall are calculated for the remaining months.

<Table 2-7> Classification of region based on rice production characteristics

Group	Region	Northern or Southern region	Rice production period
Group 1	Red River Delta	North (two harvests a year)	{2, 3}, {7, 8}
Group 2	Northeast		{3, 4}, {8, 9}
	Northwest		
Group 3	North Central Coast	South (three harvests a year)	{1, 2}, {5, 6}, {8, 9}
	South Central Coast		
Group 4	Central Highlands		{2, 3}, {6, 7}, {8, 9}
	Southeast		
Group 5	Mekong Delta		{12, 1}, {4, 5}, {7, 8}

Months grouped by {} in the last column make up each growing season of rice. For example, in "Group 1", February and March are months when winter-spring season rice is cultivated

All analyses of this sub-study use a combination of VHLSS data and climate data. This sub-study uses VHLSS responses at the individual farm level, and since the farm's region is specified to the commune level, climate variables at the commune level are merged with VHLSS data. For historical climate data, we used daily minimum and maximum temperatures from NOAA ESRL Physical Sciences Division (PSD) and daily rainfall data from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). <Table 2-8> provides the descriptive statistics of annual maximum temperature, minimum temperature, and total rainfall during 2004-2018 (biennial).

<Table 2-8> Descriptive statistics of past climate data

Year	Maximum temperature (°C)	Minimum temperature (°C)	Total precipitation (mm)			
			Mean	Std. dev.	Max.	Min.
2004	36.7	3.3	1,419	524	2,955	360
2006	36.3	2.5	1,437	598	2,806	341
2008	36.0	2.2	1,497	561	3,357	325
2010	37.3	4.3	1,453	746	3,883	428
2012	37.3	3.1	1,592	730	2,731	339
2014	36.7	1.0	1,384	423	3,082	346
2016	38.4	1.9	1,616	746	3,410	364
2018	36.2	5.2	1,617	495	3,158	394

While analyzing the impact of past climate on crop share or yield is insightful in itself, it is also important to project how crop share or yield will change under future climate conditions. For this purpose, this study uses projections of temperature and precipitation processed from WorldClim (<https://www.worldclim.org/>). Our future climate data consist of district-level projections of monthly maximum temperature, monthly minimum temperature, and monthly total precipitation from seven global climate models (GCMs) for SSP scenarios SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5. Among the seven GCMs, this study uses projections from the MIROC6 model, but it is possible to compare the results using projections from GCMs other than MIROC6 in future analysis.

〈Table 2-9〉 Summary of GCM models

Name of model	Institution	Country, Year
BCC-CSM2-MR	Beijing Climate Center (BCC)	China, 2017
CanESM5	Canadian Centre for Climate Modelling and Analysis (CCCma)	Canada, 2019
CNRM-CM6-1	Centre National de Recherches Meteorologiques and Centre Europeen de Recherche et de Formation Avancee en Calcul Scientifique (CNRM-CERFACS)	France, 2017
CNRM-ESM2-1	Centre National de Recherches Meteorologiques and Centre Europeen de Recherche et de Formation Avancee en Calcul Scientifique (CNRM-CERFACS)	France, 2017
IPSL-CM6A-LR	Institute Pierre-Simon Laplace (IPSL)	France, 2017
MIROC6	MIROC consortium JAMSTEC AORI NIES RCCS (MIROC)	Japan, 2017
MIROC-ES2L	MIROC consortium JAMSTEC AORI NIES RCCS (MIROC)	Japan, 2018

The SSP (Shared Socioeconomic Pathways) scenarios are climate change scenarios introduced in the IPCC's 6th Assessment Report and consist of five scenarios. The scenarios used in this study—SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5—represent the expected (or targeted) levels of climate change under different greenhouse gas reduction efforts: SSP1-2.6 corresponds to the scenario where maximum efforts are made to reduce greenhouse gas emissions; SSP2-4.5 represents a scenario with moderate efforts; SSP3-7.0 reflects a scenario with limited efforts; and SSP5-8.5 corresponds to a scenario where the current greenhouse gas emission trend continues. Furthermore, the analysis period for future climate is divided into three intervals: 2021–2040, 2041–2060, and 2061–2080.

The projections of each of the seven GCMs are on a 10 km × 10 km grid, and when several point data are included in one district, the arithmetic mean of the data was applied. In this study, future climate was calculated for four SSP scenarios and three analysis periods from one of the seven GCM projections (MIROC6), then was used to simulate changes in crop mix and rice yield. The table below shows the descriptive statistics of future climate projections. The change in rainfall varies across the climate scenarios, with a tendency to increase and then decrease (SSP1-2.6, SSP5-8.5)/steadily increase (SSP2-4.5)/steadily decrease (SSP3-7.0), while temperature, represented by mean annual temperature, tends to increase over time in all scenarios, with the highest rate of increase in the SSP5-8.5 scenario.

〈Table 2-10〉 Descriptive statistics of climate projections (MIROC6)

Annual precipitation (mm)					
SSP Scenario	Year	Mean	Std. dev.	Min.	Max.
SSP1-2.6	2021-2040	1813.0	319.3	1065.3	3336.9
	2041-2060	1845.6	345.6	1061.5	3433.8
	2061-2080	1837.4	330.5	1113.4	3416.5
SSP2-4.5	2021-2040	1793.8	318.3	1044.9	3282.8
	2041-2060	1809.2	326.9	1032.1	3253.1
	2061-2080	1857.0	332.6	1095.6	3386.6
SSP3-7.0	2021-2040	1776.0	314.2	1081.5	3381.0
	2041-2060	1764.3	315.2	1041.5	3351.0
	2061-2080	1757.1	312.2	1049.6	3345.8
SSP5-8.5	2021-2040	1776.5	320.6	995.6	3382.5
	2041-2060	1801.5	326.3	1073.4	3503.8
	2061-2080	1793.7	317.1	1082.5	3397.7
Average temperature (°C)					
SSP Scenario	Year	Mean	Std. dev.	Min.	Max.
SSP1-2.6	2021-2040	25.1	2.3	16.9	28.4
	2041-2060	25.5	2.2	17.4	28.6
	2061-2080	25.7	2.1	17.6	28.6
SSP2-4.5	2021-2040	25.2	2.3	17.0	28.5
	2041-2060	25.6	2.3	17.5	28.8
	2061-2080	25.9	2.2	17.8	28.9
SSP3-7.0	2021-2040	25.0	2.3	16.8	28.3
	2041-2060	25.6	2.3	17.3	28.8
	2061-2080	26.3	2.3	18.0	29.5
SSP5-8.5	2021-2040	25.3	2.3	17.1	28.6
	2041-2060	26.0	2.2	17.8	29.0
	2061-2080	27.0	2.2	18.7	30.0

To obtain the long-term impact of climate change on rice yield, information on the mean and variance of future weather for each district may be required. Since the projections for future weather are averaged over the periods 2021-2040/2041-2060/2061-2080, the projections themselves are climate variables rather than weather variables, so these values are directly used as the mean of future weather. However, obtaining the variance from such data is infeasible, so this study ignores the effect of variance change.

2.4. Key Findings

2.4.1. The Impact of Climate on the Expected Value and Variability of Productivity/Profitability (Analysis 1)

The results of analyzing the impact of climate variables on farm productivity and profitability using the Just-Pope function are shown in the table below.

〈Table 2–11〉 Estimation results – a Just–Pope production function of farm productivity/profitability

Variable (β, γ)	$y_{it} : \ln (\text{Rice yield (kg/m}^2\text{)})$		$y_{it} : \ln (\text{Profitability (1,000VND/m}^2\text{)})$	
	$f(\mathbf{X}_{it} : \beta)$	$h(\mathbf{Z}_{it} : \gamma)$	$f(\mathbf{X}_{it} : \beta)$	$h(\mathbf{Z}_{it} : \gamma)$
Temperature	0.8652*** (0.0526)	-0.2514*** (0.0060)	0.7424*** (0.0729)	0.0434*** (0.0037)
Temperature ²	-0.0157*** (0.0011)		-0.0137*** (0.0015)	
Rainfall	-0.0004*** (0.0000)	0.0003*** (0.0000)	0.0006*** (0.0001)	0.0001*** (0.0000)
Rainfall ²	5.39e-08*** (1.71e-08)		-1.82e-07*** (2.02e-08)	
Extreme weather	-0.0373*** (0.0094)	0.0507* (0.0275)	0.0390* (0.0221)	-0.0126 (0.0223)
Group 1	0.3408*** (0.0160)	-1.5084*** (0.0328)	0.2866*** (0.0317)	-0.3704*** (0.0261)
Group 2	0.2068*** (0.0174)	-1.1301*** (0.0379)	0.1179*** (0.0331)	-0.0965*** (0.0281)
Group 3	0.0280** (0.0142)	-0.3524*** (0.0294)	0.0137 (0.0285)	-0.2796*** (0.0246)
Group 4	-0.0755*** (0.0184)	-0.1818*** (0.0389)	0.0905** (0.0375)	0.2659*** (0.0287)
Group 1 $\times$ t	-0.0329*** (0.0021)	0.0209*** (0.0059)	-0.0125** (0.0056)	0.0079 (0.0048)
Group 2 $\times$ t	-0.0151*** (0.0023)	-0.0220*** (0.0060)	-0.0025 (0.0055)	-0.0397*** (0.0046)
Group 3 $\times$ t	-0.0160*** (0.0024)	-0.0130** (0.0059)	-0.0299*** (0.0056)	-0.0229*** (0.0048)
Group 4 $\times$ t	0.0095*** (0.0036)	-0.0223*** (0.0080)	0.0384*** (0.0075)	-0.0357*** (0.0055)
Year (t)	0.0364*** (0.0020)	-0.0205*** (0.0048)	-0.0100** (0.0050)	0.0580*** (0.0036)

Variable (β, γ)	$y_{it}: \ln(\text{Rice yield (kg/m}^2\text{)})$		$y_{it}: \ln(\text{Profitability (1,000VND/m}^2\text{)})$	
	$f(\mathbf{X}_{it} : \beta)$	$h(\mathbf{Z}_{it} : \gamma)$	$f(\mathbf{X}_{it} : \beta)$	$h(\mathbf{Z}_{it} : \gamma)$
Constant	-12.3257*** (0.6375)	5.5807*** (0.1766)	-9.8887*** (0.8880)	-1.7170*** (0.1080)

1) Standard errors in parentheses

2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3) Temperature, Temperature², Rainfall, and Rainfall² are calculated as 30-year averages (1989~2018). Averages are obtained after excluding the months October and November when the dependent variable is rice yield.

3) Group 1: Red River Delta, Group 2: Northeast/Northwest, Group 3: North Central Coast/South Central Coast, Group 4: Central Highlands/Southeast, Group 5: Mekong Delta (base = Group 5)

The climate variable parameters are estimated to have a significant effect on both the expected value f and variability h in both the rice productivity model and the profitability model. In the average productivity section of the rice productivity model, the linear term for temperature is estimated to be significantly positive, while the quadratic term is estimated to be significantly negative. This result indicates that the relationship between temperature and the expected rice productivity is inverted U-shaped: up to a certain point, an increase in temperature increases the average productivity, but further temperature increase beyond that point reduces productivity. For rainfall, the linear term is estimated to be negative, and the quadratic term is positive, indicating that rainfall has a U-shaped relationship with rice productivity. However, in the typical rainfall range of 1,000 to 2,300 mm, an increase in rainfall decreases the expected rice productivity. An increase in rainfall has a positive effect on expected productivity only if it exceeds 3,710 mm, which is unrealistically high and unlikely to occur even in future climates. In other words, although rainfall is estimated to have a non-linear impact on expected rice productivity, an increase in rainfall reduces expected productivity in realistic rainfall ranges. Additionally, compared to the effect of temperature, the size of rainfall impact on expected productivity is smaller, indicating that rainfall has a smaller effect on productivity than temperature.

When analyzing the impact of climate variables on the variability of productivity/profitability (h), the linear term of climate variables is taken into account. In the first model analyzing rice productivity, rising temperatures reduce the variability of productivity, while increases in rainfall increase variability. In the second model analyzing agricultural income (profitability), both temperature and rainfall parameters are estimated to be positive, indicating that both increased temperature and rainfall increase the variability of productivity, i.e., uncertainty.

The extreme weather dummy is estimated to decrease average rice productivity and increase the uncertainty of rice productivity. However, the estimate of the extreme weather dummy in the variability part of productivity is statistically significant at the 10% level but not at the 5% level, which has a somewhat low statistical significance.

The impacts of regional dummies and time trends on rice productivity are all estimated to be statistically significant at the 5% level. Compared to Group 5 (Mekong Delta), Groups 1 (Red River Delta), 2 (Northeast/Northwest), and 3 (North Central Coast/South Central Coast) have higher average productivity, while Group 4 (Central Highlands/Southeast) has lower average productivity. In <Table 2-3>, Groups 1 and 2 are part of the northern provinces where rice is grown in double cropping, and this result suggests that the productivity per cultivated area in the northern provinces is generally higher than in the southern provinces (Groups 3, 4, 5), which practice triple cropping. The year variable (t) represents the positive and linear time trend of rice productivity in Group 5 (Mekong Delta). 'Group 4 $\times t$ ' is estimated to be positive, while the interaction between the other regional dummies and year (t) are estimated to be negative. This implies that the expected productivity in Group 4 will increase relative to Group 5 with the progress of time, while the expected productivity in Groups 1, 2, and 3 will decrease. In terms of the variability of productivity, the group and year (t) parameters are estimated to be negative, except for 'Group 1 $\times t$ '. This suggests that Groups 1-4 have relatively lower uncertainty in rice productivity compared to Group 5, and all groups except Group 1 show a decrease in yield uncertainty over time.

In the second model, which analyzes agricultural income (profitability), the average profitability part shows that both temperature and rainfall are estimated to be positive in the linear part and negative in the quadratic term. This confirms the inverted U-shaped relationship where extreme climate conditions worsen average profitability. But even in this case, the impact of temperature has a higher magnitude than that of rainfall as in the case of rice productivity.

In the variability part (h), the parameters for Groups 1-3 are all estimated to be significantly negative, confirming that there is lower uncertainty in profitability compared to Group 5 (Mekong Delta). In contrast, the parameter estimate for Group 4 is positive, indicating that the uncertainty of profitability is greater than the Mekong Delta. The year (t) parameter is estimated to be significantly positive, so farmers in the Mekong Delta experience increasing uncertainty in agricultural income over time. The interaction terms between Groups 2-4 and year (t) are estimated to be significantly negative, implying that while uncertainty increases over time in these groups, it remains lower than in the Mekong Delta. For instance, in Group 2, if time increases by 1, the value of the linear term inside the exponential function $h(\mathbf{Z} : \boldsymbol{\gamma}) = \exp(\mathbf{Z}_{it}' \boldsymbol{\gamma})$ increases by $0.0397 + 0.0580 = 0.0183$, causing the uncertainty h to increase as well. The estimate of 'Group 1 $\times$ t ' parameter is positive, but not statistically significant.

When the dependent variable is agricultural income, the extreme weather dummy is estimated to be positive for mean productivity and negative for variability. This suggests that extreme weather conditions, which deviate significantly from typical climate levels, tend to increase expected profitability but decrease uncertainty, which may seem counterintuitive. However, the estimate in the average productivity part is only significant at the 10% level, while the parameter in the variability part is not even significant at the 10% level.

The statistical significance of the regional dummies and the year variable in the agricultural income analysis are somewhat lower than in the rice productivity analysis. In the average profitability analysis, all regional dummies are estimated

to be positive, indicating that farmers in other regions have higher average agricultural income than farmers in Group 5 (Mekong Delta), but the parameter of Group 3 is not statistically significant. Year (t) is estimated to be significantly negative, showing that as time progresses, average profitability in Group 5 (Mekong Delta) decreases. In the case of interaction between regional dummies and year, Groups 1, 2, and 3 also show a decrease in profitability compared to the Mekong Delta (Group 5), with profitability decreasing more rapidly over time. However, the estimation of the 'Group 2 $\times$ t ' parameter is not statistically significant. The 'Group 4 $\times$ t ' parameter is estimated to be positive, but it is not statistically significant as well.

To conclude, 'Analysis 1' analyzed the effects of climate variables on productivity/profitability and estimated models that reflect the uncertainties of productivity and profitability as well as the stochastic impact of weather shocks. However, a limitation of this model is that it does not account for farmers' adaptation. In this context, the following analyses will emphasize adaptation measures, analyzing how farmers' decision-making in response to climate change helps mitigate the adverse effects of climate change.

2.4.2. The Impact of Climate on Farms' Decision-Making (Analysis 2)

Now this sub-study includes the effect of farms' adaptation measures along with the pure impact of climate variables, while also analyzing the effect of observable adaptation (e.g., proportion of crop types, agricultural machinery expenditure) on farmers' productivity or profitability. For this purpose, 'Analysis 2' will first analyze how the proportion of crop types (crop shares) and agricultural machinery expenditure are affected by climate change.

1) Estimation result: crop selection

In analyzing the crop selection behavior of individual farmers, the dependent variables, crop shares, represent the share of each crop type's cultivation area

relative to the total cultivated area in a given year. The crop types are divided into four categories: (1) rice, (2) other food crops and vegetables, (3) industrial crops, and (4) fruit. The vector of farm i 's characteristic variables, X_i , consists of climate variables, regional and farm-specific characteristics, regional dummies, and time trends. The climate variables reflect the impact of temperature and rainfall, using the same specification as in Moore and Lobell (2014). Specifically, the climate variables include the 30-year (1989–2018) average annual temperature, the 30-year average annual rainfall, the squared values of both averages, and the squared deviation between the average temperature/annual rainfall of each year and their respective 30-year averages which reflect the difference between the short-term and long-term effect of climate change. For the regional and farm characteristics variables, the age of the household head, the final education level of the household head, whether the household's commune was classified as a poor one, whether the household head belongs to an ethnic minority group, and the area of the household's commune are used. The regional dummies and time trends include the time variable t ($t=1$ for 2004, $t=2$ for 2006, ..., $t=8$ for 2018), regional dummies based on the regional classification in <Table 2-7>, and the interaction term between t and the regional dummies.

The estimation results for the crop selection behavior of individual farms are shown in <Table 2-12>. In the estimation, the parameter for rice was fixed at 0, so the estimated parameters for the other crops should be understood as relative differences compared to rice. Since the analysis model is nonlinear and not an ordinary least squares (OLS) model, the marginal effects of each variable do not match the parameter estimates and must be recalculated using the estimation results.

We first analyze the effects of climate variables and regional variables. For other food crops and vegetables, the temperature and rainfall variables as well as their squared terms, did not achieve statistical significance. For the squared deviation term, only temperature was estimated to be negative and statistically significant,

meaning that when the annual average temperature deviates from the long-term average, farmers decrease the share of other food crops and vegetables compared to rice. For the regional dummies, the parameters for all regions were statistically significant, with Group 1 estimated as negative, and the coefficients for Groups 2, 3, and 4 were estimated as positive. This implies that, relative to Group 5, Group 1 farms select a smaller area of other food crops and vegetables compared to rice, while the opposite effect occurs in the other groups. The year variable was positive and statistically significant at the 1% level, indicating that in Group 5, the proportion of other food crops and vegetables relative to rice increases over time. For the other regions, the interaction term with the year variable was estimated to be negative, meaning that over time, the proportion of other food crops and vegetables relative to rice decreases. Also, the interaction term for Group 1 and year was not statistically significant.

For industrial crops, temperature and rainfall were estimated to be positive and their squared terms were estimated to be negative, all of which were statistically significant. Therefore, as temperature and rainfall increase up to a certain point, farmers increase the proportion of industrial crops relative to rice. However, after a certain point, the proportion decreases, showing the reverse effect. For the squared deviation term, both temperature and rainfall were estimated as negative and statistically significant, meaning that when the temperature and rainfall deviate from their long-term averages, farmers reduce the proportion of industrial crops relative to rice. The regional dummies were statistically significant for all regions, with negative estimates except for Group 4, meaning that, compared to Group 5, farmers in the majority of regions tend to reduce the area of industrial crops relative to rice. The year variable was estimated with a positive significant value, and the interaction terms between the year and regional dummies were all negative, suggesting a similar effect as other food crops and vegetables. However, the interaction term between Group 4 and year (t) was not statistically significant.

For fruit, temperature was estimated as negative, and its squared term was estimated as positive and both were statistically significant. This means that up

to a certain level, an increase in temperature reduces the proportion of fruit relative to rice, but after a certain point, temperature increases result in a higher proportion of fruit relative to rice. In the case of squared deviations, the temperature deviation was estimated as negative and statistically significant, indicating that when the temperature deviates from the long-term average, farmers reduce the proportion of fruit crops relative to rice. The effects of rainfall, including its linear and squared terms, as well as its squared deviation, were not statistically significant. For the regional dummies, statistically significant effects were found only in Groups 1 and 3. Relative to Group 5, Groups 1, 2, and 3 tend to choose less land for fruit, while Group 4 tends to select more. The year variable and regional-year interaction terms were not statistically significant.

Regarding household and regional characteristics, the age of the household head had a statistically significant and positive effect on all crop groups, meaning that as the household head gets older, the relative area of all crop groups compared to rice increases. The final educational level of the household head is represented by dummy variables where the base variable is 'no degree'. Results show that higher educational levels lead to increased selection of crops other than rice, with the exception of some variables in other food crops and vegetables ('Primary school', 'Secondary school') as well as all 'Others' variables. This suggests that farmers with higher education choose crops that require more complex production technologies and offer higher income potential. The poverty dummy variable was estimated as positive and statistically significant for other food crops and vegetables, meaning that farmers in poorer regions tend to increase the proportion of this group relative to rice. For industrial crops and fruit crops, the effects were negative, with fruit crops not being statistically significant. The ethnic minority dummy was negatively significant for industrial crops and fruit, suggesting that households with an ethnic minority head tend to reduce the proportion of industrial crops and fruits compared to rice. The commune area was negatively significant only for other food crops and vegetables, indicating that farms in larger communes tend to reduce the proportion of these crops relative to rice.

〈Table 2-12〉 Estimation results – the effect of climate on crop share selection

Variable		Other food crops and vegetables			Industrial crops			Fruit		
		Estimate	Std. err.		Estimate	Std. err.		Estimate	Std. err.	
Temperature		-0.4686	0.5520		2.4312	0.7538	***	-2.6786	1.1556	**
Temperature ²		0.0042	0.0111		-0.0540	0.0151	***	0.0556	0.0228	**
Rainfall		0.0007	0.0007		0.0033	0.0009	***	-0.0023	0.0017	
Rainfall ²		-2.15E-07	1.68E-07		-7.19E-07	2.17E-07	***	4.14E-07	4.92E-07	
Sq. Dev.	Temperature	-0.3232	0.0717	***	-0.1654	0.0931	*	-0.4088	0.1605	**
	Rainfall	5.58E-10	7.28E-08		-4.71E-07	1.31E-07	***	1.75E-08	2.18E-07	
Group 1		-0.7196	0.1937	***	-2.1732	0.2901	***	-1.4491	0.3502	***
Group 2		0.4316	0.1855	**	-0.8826	0.2650	***	-0.4063	0.3726	
Group 3		0.3734	0.1642	**	-0.6975	0.2347	***	-1.8215	0.2895	***
Group 4		1.3760	0.1944	***	1.4867	0.2298	***	0.0563	0.3069	
Group 1 × Year(<i>t</i>)		-0.0203	0.0276		-0.1658	0.0445	***	0.0559	0.0457	
Group 2 × Year(<i>t</i>)		-0.0669	0.0251	***	-0.0881	0.0388	**	-0.0005	0.0502	
Group 3 × Year(<i>t</i>)		-0.0768	0.0266	***	-0.0710	0.0397	*	0.0424	0.0489	
Group 4 × Year(<i>t</i>)		-0.0792	0.0345	**	-0.0100	0.0404		0.0634	0.0552	
Year(<i>t</i>)		0.0904	0.0228	***	0.0864	0.0323	***	0.0396	0.0259	
Age of household head		0.0070	0.0012	***	0.0065	0.0016	***	0.0163	0.0024	***
Edu.	Primary school	-0.0763	0.0371	**	0.1546	0.0567	***	0.1667	0.0721	**
	Secondary school	-0.1411	0.0384	***	0.1917	0.0592	***	0.3066	0.0818	***
	Elementary vocational school	0.2809	0.0644	***	0.4530	0.0915	***	0.3265	0.1459	**
	Intermediate vocational school or Vocational college	0.3829	0.0736	***	0.2957	0.1035	***	0.8433	0.1319	***
	College and above	0.9489	0.1056	***	0.7934	0.1467	***	1.2035	0.1749	***
	Others	0.5023	0.4130		-0.0487	0.3406		-1.5707	0.9231	*
Poverty		0.1491	0.0360	***	-0.2857	0.0621	***	-0.1601	0.0999	
Ethnic minority		0.0669	0.0632		-0.5570	0.0956	***	-0.7625	0.1456	***
Commune area		0.0017	0.0007	**	0.0010	0.0009		-0.0016	0.0018	
Constant		6.6990	6.8615		-31.7500	9.3763	***	31.5755	14.0639	**

1) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

2) Temperature, Temperature², Rainfall, and Rainfall² are calculated as 30-year averages (1989~2018).

3) Group 1: Red River Delta, Group 2: Northeast/Northwest, Group 3: North Central Coast/South Central Coast, Group 4: Central Highlands/Southeast, Group 5: Mekong Delta (base = Group 5)

4) 'Edu' refers to the highest level of education received by the household head.

Now, using the estimated parameters and climate variables of future climate scenarios, we can forecast future crop shares. The predictions use only the observed values from 2018, and all variables except for the climate variables are fixed at their 2018 levels, which applies to all other future climate simulations of this sub-study. Therefore, the projections derived from this sub-study can be interpreted as the expected effects of future climate change if it occurs at the current (2018) time point.

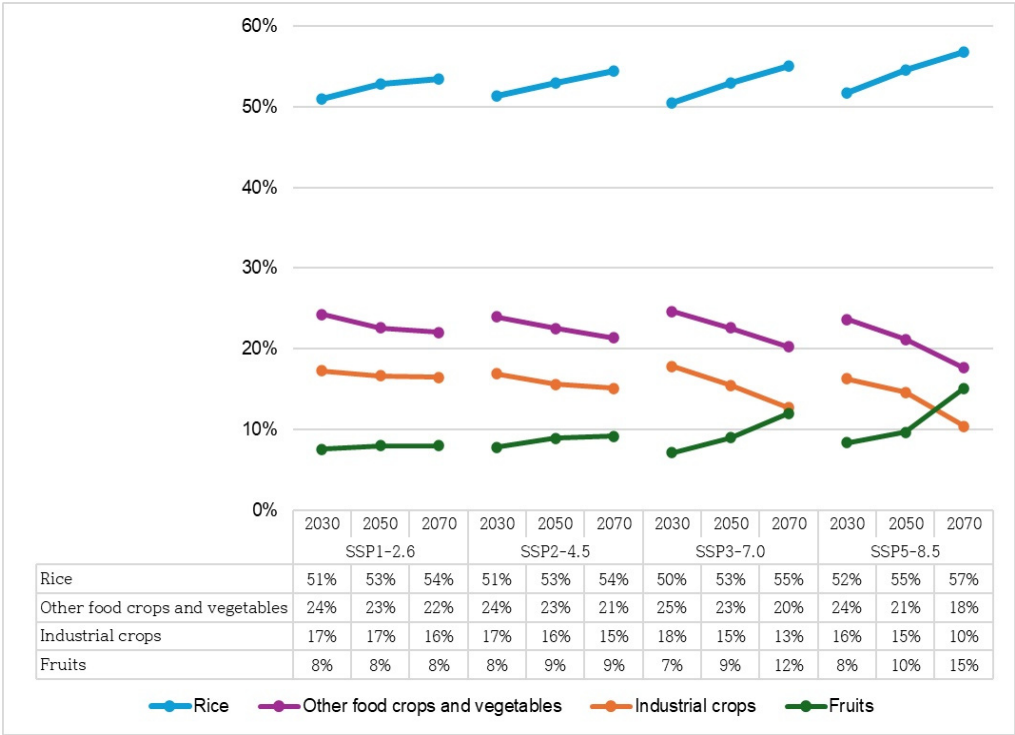
All climate variables for the future climate scenarios are provided only as average values for the forecast periods of 2021-2040, 2041-2060, and 2061-2080. In other words, since there are no values for the weather of a given year, it is not possible to calculate the squared difference between the short-term weather of that year and long-term climate. Consequently, the influence of the squared deviation parameters cannot be reflected in future projections. However, this data limitation does not pose a problem in this analysis, which interprets the predictions as the farmers' adaptation behavior to climate change following the model settings of Moore and Lobell (2014) and Mérel and Gammans (2021). The squared deviation parameters only act as a penalty for short-term decisions when farmers have not fully adapted to climate change. In other words, when farmers fully adapt to the climate and choose adaptation measures accordingly, the squared difference between the weather in the given year and the long-term climate will always be 0. Therefore, all future projections in 'Analysis 2' are derived assuming that farms completely adapt to climate change effect of the long-term and short-term deviation parameter to be 0¹⁸).

The projected changes in the area share for each crop group under the SSP scenarios are shown in <Figure 2-3>. These are the average values of the projected crop shares. In all scenarios, the area share for rice (blue marker) and fruits (green marker) increases over time, while the area share for other food crops and vegetables

18) In 'Analysis 3,' due to this limitation of future climate data, the effect of the (Squared deviation) * (future climate variance – current climate variance) term is not reflected in future projections.

(purple marker) and industrial crops (orange marker) consistently decreases. The magnitude of the increase/decrease is more pronounced when the projections are based on scenarios with less adaptation to climate change. This suggests that rice, which has sustained Vietnamese farmers for a long time, is less negatively affected by climate change. Additionally, the share of fruits increases more rapidly than rice under the SSP3-7.0 and SSP5-8.5 scenarios, where less effort is made toward climate change adaptation. This indicates that focusing on fruit production could be a good adaptation measure for farmers in future climate change scenarios.

[Figure 2-3] Projected crop shares for each SSP Scenario



2) Estimation result: rice share selection

Now, the focus shifts to the share of rice cultivation area instead of multivariate data on crop shares. This approach contrasts with the previous multivariate fractional data analysis, which used four dependent variables. According to the rice production characteristics of Vietnam of <Table 2-7>, rice production does

not occur in any region during October and November. Therefore, the climate variables used for rice productivity analysis are the average temperature and total rainfall obtained after excluding October and November. The estimated parameters are summarized in <Table 2-13>. Regarding climate variables, temperature and rainfall (30-year averages) have a statistically significant U-shaped relationship with rice cultivation area. That is, increases in temperature and rainfall reduce the rice share up to a certain point, after which they start to increase rice share. Among the squared deviation variables, only temperature is significantly positive, meaning that a larger difference between the current year's weather and long-term climate leads to an increased share of rice cultivation. Regional dummy variables are all estimated to have negative values, indicating that all regions have a lower share of rice cultivation compared to Group 5 (Mekong Delta), the largest rice-producing region in Vietnam. Regarding the interactions between year (t) and regional dummies, all interactions show positive values, with the estimates of 'Group 1 $\times t$ ', 'Group 2 $\times t$ ', and 'Group 3 $\times t$ ' being statistically significant.

<Table 2-13> Estimation results – the effect of climate on rice share selection

Variable		Estimate	Standard error	
Temperature		-1.6735	0.3695	***
Temperature ²		0.0384	0.0075	***
Rainfall		-0.0016	0.0004	***
Rainfall ²		5.67E-07	1.31E-07	***
Sq. Dev.	Temperature	0.7563	0.0345	***
	Rainfall	8.59E-08	1.07E-07	
Group 1		-0.3441	0.1750	**
Group 2		-1.2503	0.1676	***
Group 3		-1.3875	0.1511	***
Group 4		-1.7062	0.1585	***
Group 1 $\times$ Year(t)		0.1055	0.0279	***
Group 2 $\times$ Year(t)		0.0850	0.0253	***
Group 3 $\times$ Year(t)		0.0873	0.0270	***
Group 4 $\times$ Year(t)		0.0215	0.0303	
Year(t)		0.0025	0.0236	
Age of household head		0.0019	0.0008	**

Variable		Estimate	Standard error	
Highest level of education received by household head	Primary school	-0.0156	0.0286	
	Secondary school	0.0158	0.0309	
	Elementary vocational school	0.1417	0.0550	***
	Intermediate vocational school or Vocational college	0.1709	0.0572	***
	College and above	0.2934	0.1119	***
	Others	-0.2785	0.2721	
Poverty		0.0547	0.0269	**
Ethnic minority		-0.4293	0.0516	***
Commune area		-0.0018	0.0006	***
Constant		20.6070	4.4139	***

1) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

2) Temperature, Temperature², Rainfall, and Rainfall² are calculated as 30-year averages (1989~2018). Averages are obtained after excluding the months October and November.

3) Group 1: Red River Delta, Group 2: Northeast/Northwest, Group 3: North Central Coast/South Central Coast, Group 4: Central Highlands/Southeast, Group 5: Mekong Delta (base = Group 5)

For household and regional characteristics, farms with older household heads or those located in a poverty-stricken region tend to have a higher share of rice. Regarding the education level of the household head, having graduated from a primary school or higher increases the relative share of rice, which is also statistically significant. Moreover, if the household head belongs to an ethnic minority or if the area of the household's commune is large, the household is likely to reduce the share of rice cultivation, which are statistically significant.

As with the multivariate fractional data, future projections of rice cultivation share can be derived using the predicted future climate variables. The results of the rice share predictions by period and climate scenario are presented in <Table 2-14>. Comparing these predictions with the average rice cultivation share from <Table 2-6>, it is evident that the share of rice cultivation is projected to increase in all periods and scenarios compared to 2018 levels. The amount of increase is larger in future periods and scenarios with fewer carbon reduction efforts.

This suggests that while rice, which has long supported Vietnamese farmers, may

continue to hold its ground, other commodities such as fruits, livestock, and industrial crops may be more adversely affected by climate change although they could have higher market value. Therefore, unless other factors such as market conditions change, it is projected that Vietnamese farmers will choose an increased share of rice cultivation in response to climate change, with the degree of increase becoming more prominent as the forecast period moves further into the future, especially under more pessimistic scenarios. This conclusion is consistent with the results of <Figure 2-3>, which examines future outcomes for other crop groups.

<Table 2-14> Projected rice share for each period/SSP Scenario

SSP Scenario	Period	Mean	Std. dev.	Min.	Max.
SSP1-2.6	2021-2040	0.798	0.140	0.221	0.982
	2041-2060	0.810	0.139	0.223	0.985
	2061-2080	0.814	0.139	0.225	0.984
SSP2-4.5	2021-2040	0.800	0.141	0.221	0.982
	2041-2060	0.812	0.139	0.225	0.983
	2061-2080	0.825	0.136	0.230	0.987
SSP3-7.0	2021-2040	0.792	0.141	0.219	0.982
	2041-2060	0.812	0.140	0.224	0.986
	2061-2080	0.836	0.138	0.235	0.988
SSP5-8.5	2021-2040	0.803	0.141	0.223	0.985
	2041-2060	0.826	0.138	0.232	0.989
	2061-2080	0.863	0.131	0.240	0.992

3) Estimation result: agricultural machinery expenditure

In the analysis of machinery expenditure behavior, a Tobit model is used to estimate the censored data. The explanatory variables are the same as previous crop share analyses. The dependent variables are either the unit area annual machinery cost spent on total crop production or spent specifically on rice production. These two dependent variables are analyzed separately, and the results are presented in <Table 2-15>.

**〈Table 2–15〉 Estimation results – the effect of climate on
agricultural machinery expenditure selection**

Variable		Machinery (total)			Machinery (for rice)		
		Estimate	Std. err.		Estimate	Std. err.	
Temperature		0.9339	0.1432	***	0.8955	0.1251	***
Temperature ²		−0.0179	0.0028	***	−0.0168	0.0024	***
Rainfall		0.0004	0.0001	***	−3.87E−05	4.82E−05	
Rainfall ²		−1.13E−07	2.30E−08	***	−4.77E−09	1.68E−08	
Sq. Dev.	Temperature	−0.0740	0.0115	***	−0.1068	0.0051	***
	Rainfall	4.13E−08	9.19E−09	***	1.80E−08	1.62E−08	
Group 1		−0.0258	0.0222		−0.0038	0.0152	
Group 2		−0.1841	0.0278	***	−0.0578	0.0163	***
Group 3		−0.1029	0.0191	***	−0.0967	0.0131	***
Group 4		−0.0476	0.0236	**	−0.0283	0.0128	**
Group 1×Year(<i>t</i>)		0.0196	0.0031	***	0.0172	0.0017	***
Group 2×Year(<i>t</i>)		0.0254	0.0039	***	0.0161	0.0022	***
Group 3×Year(<i>t</i>)		0.0199	0.0030	***	0.0133	0.0017	***
Group 4×Year(<i>t</i>)		0.0040	0.0047		0.0086	0.0025	***
Year(<i>t</i>)		0.0064	0.0024	***	0.0166	0.0010	***
Age of household head		−0.0009	0.0002	***	0.0003	0.0001	***
Highest level of education received by household head	Primary school	0.0001	0.0045		0.0046	0.0030	
	Secondary school	−0.0034	0.0051		0.0061	0.0035	*
	Elementary vocational school	−0.0260	0.0082	***	0.0199	0.0060	***
	Intermediate vocational school or Vocational college	−0.0364	0.0091	***	0.0172	0.0063	***
	College and above	−0.0689	0.0163	***	0.0366	0.0118	***
	Others	−0.0570	0.0423		−0.0465	0.0333	
Poverty		−0.0416	0.0059	***	−0.0243	0.0040	***
Ethnic minority		−0.0529	0.0092	***	−0.0570	0.0072	***
Commune area		−0.0004	0.0001	***	−0.0004	0.0001	***
Constant		−12.3952	1.8543	***	−11.7830	1.5962	***

1) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

2) Temperature, Temperature², Rainfall, and Rainfall² are calculated as 30-year averages (1989~2018). Averages are obtained after excluding the months October and November in the case of machinery for rice production

3) Group 1: Red River Delta, Group 2: Northeast/Northwest, Group 3: North Central Coast/South Central Coast, Group 4: Central Highlands/Southeast, Group 5: Mekong Delta (base = Group 5)

The impact of climate variables, regional dummies, and years on machinery expenditure behavior shows similar patterns for both total machinery expenditure and machinery expenditure for rice production. First, examining the estimation results for total machinery expenditure, it is found that temperature and rainfall have an inverted U-shaped relationship with machinery expenditure. In other words, an increase in temperature and rainfall raises machinery expenditure up to a certain point, after which it starts to decrease. Among the squared deviation variables, temperature is estimated to have a negative value, while rainfall is positive, and both variables are statistically significant. This means that when the current year's temperature deviates from the long-term average, the household reduces machinery expenditure, while in the case of rainfall, the deviation from the long-term average increases machinery expenditure. The regional dummies are estimated to have negative values, indicating that households not located in Group 5 (Mekong Delta) spend less on machinery compared to those in Group 5. However, the parameter estimate for Group 1 (Red River Delta) is not statistically significant. The parameter estimate for year (t) indicates a positive trend for Group 5, and the interaction terms between region and year are all positive, suggesting that every region increases its machinery expenditure compared to Group 5 over time. However, the parameter estimate is not significant for Group 4. In the case of machinery expenditure for rice production, climate/regional/time trend estimates with statistical significance had the same sign as the parameter estimates of total machinery expenditure, which shows that the impact of climate/region/time on machinery expenditure is consistent regardless of if we focus on rice or on the entire agricultural practice. One notable feature is that for machinery expenditure in rice production, rainfall is not statistically significant for the first-order, second-order, and squared deviation terms, indicating that rainfall does not significantly affect machinery expenditure for rice production in any form.

The influence of household and regional characteristic variables on machinery expenditure differs between total agricultural production and rice production. For example, an increase in the household head's age reduces total machinery

expenditure but increases machinery expenditure for rice production. Regarding the household head's final education level, the signs for the primary school graduation dummy and other education dummies are the same in both models, though not statistically significant. Other education dummies are estimated to have a negative effect on total machinery expenditure but a positive effect on machinery expenditure for rice production, with the 'Secondary school' parameter not being significant in analyzing total machinery expenditure. This indicates that while a higher education level leads to increased machinery expenditure per unit area in rice production, it decreases machinery expenditure per unit area in the case of total agricultural production.

Except for household head age and education dummies, the influence of other household and regional characteristics is estimated with the same sign in both models and is statistically significant. Households located in poor regions, larger communes, as well as households with a household head from an ethnic minority, tend to have smaller machinery expenditure for both rice production and total agricultural production.

Using the estimation results from <Table 2-15>, projections for machinery expenditure under future climate scenarios are presented in <Tables 2-16> (total machinery expenditure) and <2-17> (machinery for rice expenditure). The projections show a consistent tendency where machinery expenditure per unit area increases in future periods for all scenarios. However, there are some exceptions where projected values show a slight decrease in more distant future periods, such as the projected payment of total machinery payment in the 2061-2080 period of the SSP5-8.5 scenario.

**〈Table 2-16〉 Projected machinery payment (for rice production) for
each period/SSP Scenario (VND/m²)**

SSP Scenario	Period	Mean	Std. dev.	Min.	Max.
SSP1-2.6	2021-2040	231	94	0	375
	2041-2060	248	96	0	418
	2061-2080	253	97	0	425
SSP2-4.5	2021-2040	235	94	0	388
	2041-2060	243	94	0	411
	2061-2080	250	95	0	429
SSP3-7.0	2021-2040	234	96	0	380
	2041-2060	246	97	0	416
	2061-2080	249	100	0	442
SSP5-8.5	2021-2040	237	94	0	394
	2041-2060	253	98	0	437
	2061-2080	243	106	0	447

**〈Table 2-17〉 Projected machinery payment (for total agricultural production)
for each period/SSP Scenario (VND/m²)**

SSP Scenario	Period	Mean	Std. dev.	Min.	Max.
SSP1-2.6	2021-2040	327	130	0	548
	2041-2060	344	138	0	608
	2061-2080	350	139	0	620
SSP2-4.5	2021-2040	330	132	0	562
	2041-2060	335	139	0	602
	2061-2080	338	144	0	623
SSP3-7.0	2021-2040	333	131	0	549
	2041-2060	335	140	0	604
	2061-2080	322	156	0	626
SSP5-8.5	2021-2040	330	133	0	572
	2041-2060	337	146	0	625
	2061-2080	295	159	0	606

2.4.3. The Impact of Climate on Rice Productivity and the Effectiveness of Adaptation Measures (Analysis 3)

‘Analysis 3’ estimates the Moore and Lobell (2014) model specified as Equation (2-10) using various functional forms and variables, and presents the most stable result as in <Table 2-18>. The dependent variable is the logarithm of the unit area productivity of rice (kg/m²), and there are two weather variables (z_{it}): average temperature and total rainfall. Therefore, the variables corresponding to climate, μ_i , are the long-term (30-year) averages of the temperature and total rainfall. As in ‘Analysis 2’ which analyzed decision-making behaviors of rice production, ‘Analysis 3’ also excludes October and November when calculating climate variables.

The adaptation measures taken by farmers are categorized into two types: the unobserved adaptation measures represented by squared deviations, and the observed adaptation measures. In this analysis, attention is given to the observed adaptation measures, which are the rice cropping area proportion (s_{it}) and the expenditure on agricultural machinery (c_{it}) choices. The values for the observed adaptation variables are based on the predicted values ($\hat{s}_{it}$ and $\hat{c}_{it}$) derived in ‘Analysis 2’ rather than their actual values. This approach resolves endogeneity issues while also reflecting the long-term adaptation to climate in these adaptation measures. In Equation (2-10), $g(\alpha_i, t)$ contain regional dummies, year variables, and the interaction of regional dummies and years, as in ‘Analysis 2’. Thus, the regression equation for ‘Analysis 3’ is specified as Equation (2-15).

$$\begin{aligned}
 (2-15) \quad y_{it} = & \alpha + \beta_1 \overline{Temp}_i + \beta_2 \overline{Temp}_i^2 + \beta_3 \overline{Rain}_i + \beta_4 \overline{Rain}_i^2 \\
 & + \beta_5 (Temp_{it} - \overline{Temp}_i)^2 + \beta_6 (Rain_{it} - \overline{Rain}_i)^2 + \delta_s \hat{s}_{it} + \delta_c \hat{c}_{it} \\
 & + \delta_i t_i + \sum_{r=1}^4 (\delta_r D_{r,i} + \delta_{rt} D_{r,i} \times t) + \epsilon_{it}
 \end{aligned}$$

〈Table 2–18〉 Estimation results – The impact of climate variables on rice productivity

Variable		Estimate	Std. err.		Variable	Estimate	Std. err.	
Temperature		0.5233	0.0639	***	Group 1	0.1895	0.0159	***
Temperature ²		–0.0116	0.0013	***	Group 2	0.2181	0.0238	***
Rainfall*10 ³		0.1142	0.0504	**	Group 3	–0.0632	0.0025	***
Rainfall ² *10 ⁶		–0.1158	0.0173	***	Group 4	–0.0344	0.0026	***
Sq. Dev.	Temperature	–0.0940	0.0176	***	Group 1 × <i>t</i>	–0.0445	0.0027	***
	Rainfall*10 ⁶	–0.1400	0.0255	***	Group 2 × <i>t</i>	–0.0014	0.0039	
Rice share		0.1193	0.0186	***	Group 3 × <i>t</i>	0.0198	0.0024	***
Machinery expenditure per m ²		0.2368	0.0193	***	Group 4 × <i>t</i>	1.1948	0.0789	***
					Year (<i>t</i>)	1.0550	0.1050	***
					Constant	–7.5549	0.7892	***

1) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

2) Standard errors are obtained from 5,000 bootstrap draws

3) Temperature, Temperature², Rainfall, and Rainfall² are calculated as 30-year averages (1989~2018). Averages are obtained after excluding the months October and November

4) Group 1: Red River Delta, Group 2: Northeast/Northwest, Group 3: North Central Coast/South Central Coast, Group 4: Central Highlands/Southeast, Group 5: Mekong Delta (base = Group 5)

The 30-year average of temperature and its squared value are estimated to be statistically significant at the 1% level, with positive and negative signs, respectively. This suggests that temperature increases productivity up to a certain threshold, but decreases productivity after that threshold, forming an inverted U-shaped relationship. A similar inverted U-shaped relationship is statistically significant for the long-term average of rainfall as well.

As explained in Section 2.2.3, there are three types of adaptation measures that farmers can take in response to climate change. The first type corresponds to implicit adaptation measures, and their effects are identified by the squared deviation between the long-term climate and short-term weather. Both squared deviation parameters for temperature and rainfall are estimated to be statistically significant and negative. These estimates indicate the differences in responses between the long term and the short term. Since the estimates are negative, the analysis concludes that the long-term response curve with respect to climate is

an upper envelope of the short-term response curve as shown in <Figure 2-2>.

The second and third adaptation measures involve the proportion of rice cultivation area and the expenditure on agricultural machinery per unit area of rice cultivation. These two variables reflect farmers' long-term adaptation behavior as discussed in 'Analysis 2'. Both adaptation variables are estimated to have positive and significant values, indicating that increasing the share of rice and increasing expenditure on agricultural machinery lead to enhanced yields. Specifically, the positive estimation for the rice share parameter suggests that farms with larger rice cultivation areas benefit from economies of scale or specialization. Furthermore, future simulations of 'Analysis 2' revealed that farmers tend to increase rice share and machinery expenditure in response to climate change. This implies that changing crop shares and increasing capital investment are valid adaptation measures to reduce the productivity decline of climate change or even enhance productivity.

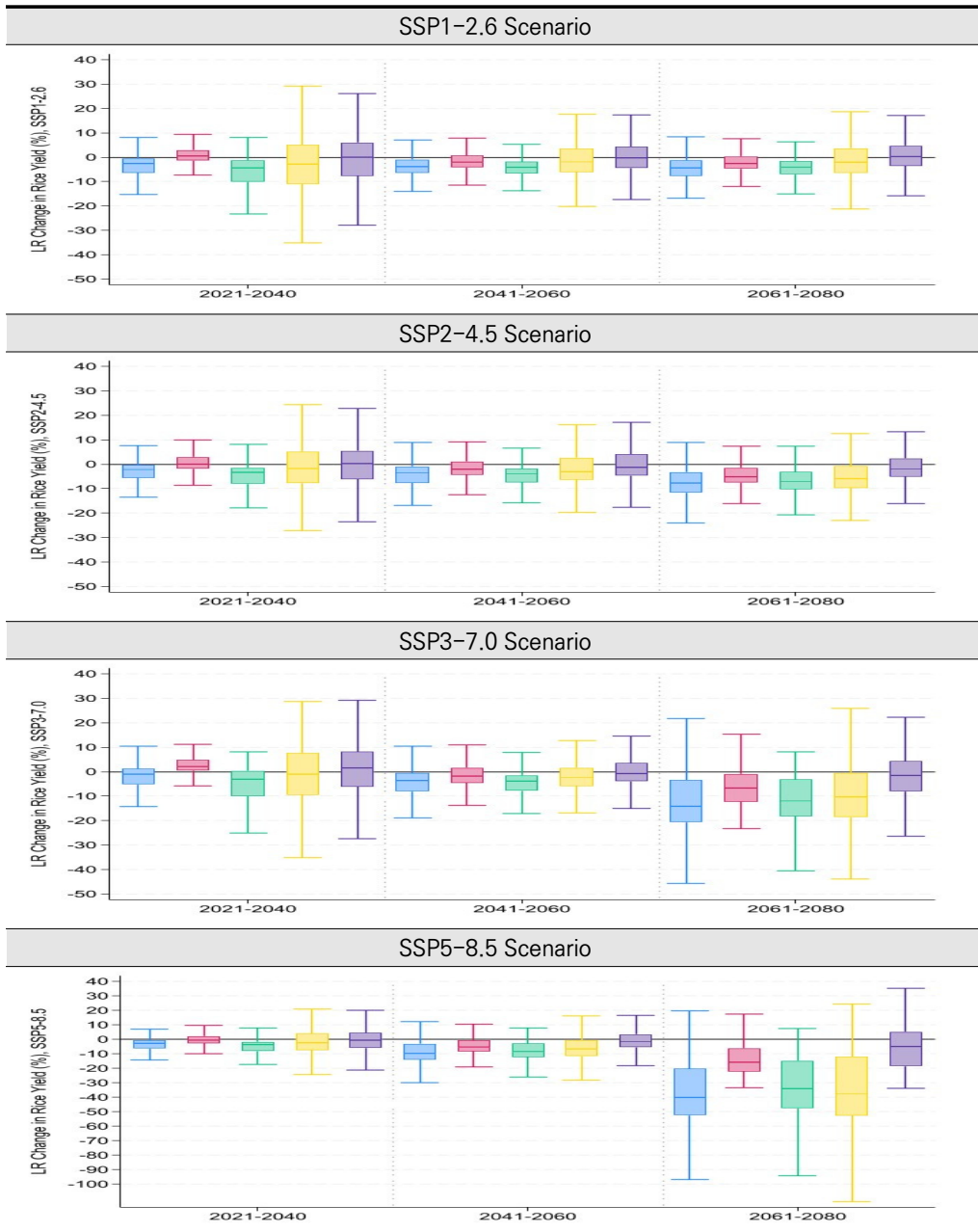
The next step is to simulate the extent to which climate change affects rice productivity using the estimated parameters. This analysis specifies the impacts of climate change on productivity into five scenarios: (1) when no adaptation measures are implemented, (2) when only unobservable farm adaptation behavior is considered, (3) when only changes in the rice share are considered, (4) when only changes in agricultural machinery expenditure for rice cultivation are considered, and (5) when all adaptation measures from (2) to (4) are included. Scenario (1) represents the short-term impact without any adaptation measures, and since the squared deviation parameters from Equation (2-10) are estimated as negative ($\beta_3 < 0$), the projected productivity in the absence of any adaptation measures will always be the lowest. Scenario (2) calculates the productivity change based on the long-term effect, as given in Equation (2-11a). The effects of observable adaptation measures, scenarios (3) and (4), are derived by adding the impact of these measures to the short-term impact in (1). Specifically, the calculation involves adding the changes in rice cultivation area and agricultural machinery expenditure

relative to their 2018 levels, multiplied by their respective estimated parameters. Finally, the productivity change with all adaptation measures (scenario 5) is derived by adding up the unobservable adaptation effects (scenario 2) and the effects of the observable adaptation measures (scenarios 3 and 4).

Simulation results for productivity changes are displayed as boxplots in <Table 2-19>. In aggregating individual farm-level responses, this study first calculates the rice cultivation area share of each regional group and assigns this ratio as a weight to individual predictions. Since rice production is concentrated in Group 5 (Mekong Delta), predictions from this region are given more emphasis. Although there are slight variations depending on the future projection period and scenario, the group weights are approximately 13% (Group 1), 19% (Group 2), 19% (Group 3), 10% (Group 4), and 39% (Group 5). As our study focuses on the climate change impacts in the Mekong Delta, this analysis separates the projection results for farmers in Group 5 (Mekong Delta), as summarized in <Table 2-20>.

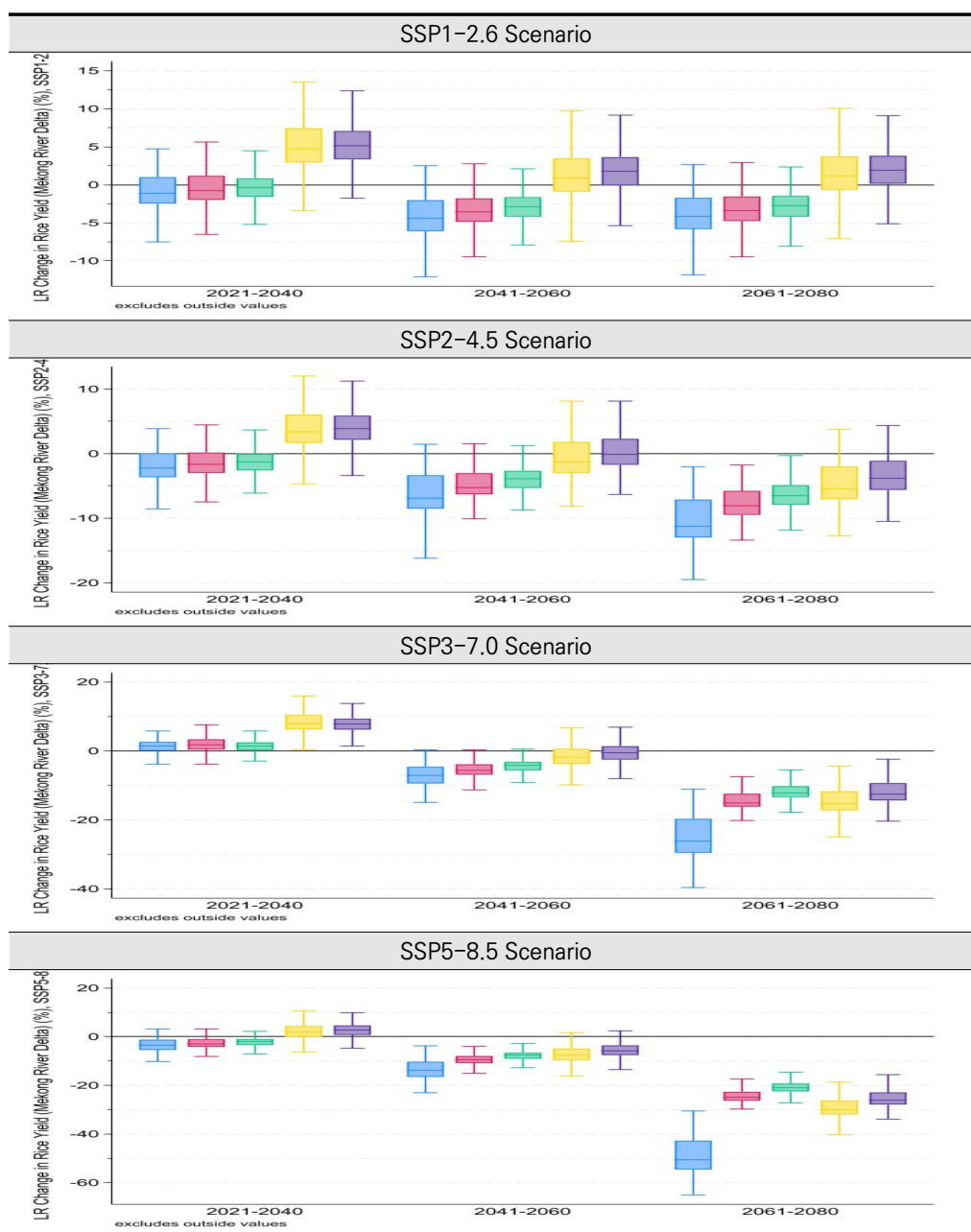
When no adaptation measures are taken into account (blue boxplot), rice productivity shows a steady decline across all future climate scenarios. In the SSP5-8.5 scenario, which assumes the least climate change mitigation efforts, rice productivity is projected to decrease by more than 40% on average during the 2061–2080 period. However, accounting for farms' adaptation, this reduction in rice productivity either becomes smaller or the productivity even increases. For example, in the SSP5-8.5 scenario during the 2061–2080 period, when all forms of adaptation actions are taken into account (purple boxplot), the average decrease in rice productivity is reduced from 40% to about 5%. The impact of adaptation measures is stronger in scenarios with lower mitigation efforts and for more future periods.

〈Table 2-19〉 Future rice yield simulation results – National



- 1) The vertical axis is in percentages (%)
- 2) Adaptation measures are distinguished into five colors. From left to right, the colors in the simulation results represent: no adaptation (blue), unobserved adaptation only (red), crop selection only (green), machinery expenditure only (yellow), and all adaptation measures (purple).
- 3) Each boxplot group consists of four units, representing, the scenario results for 2021-2040, 2041-2060, and 2061-2080 (from left to right).

〈Table 2-20〉 Future rice yield simulation results – Mekong Delta



- 1) The vertical axis is in percentages (%)
- 2) Adaptation measures are distinguished into five colors. From left to right, the colors in the simulation results represent: no adaptation (blue), unobserved adaptation only (red), crop selection only (green), machinery expenditure only (yellow), and all adaptation measures (purple).
- 3) Each boxplot group consists of four units, representing, the scenario results for 2021-2040, 2041-2060, and 2061-2080 (from left to right).

The impact of each adaptation measure can be examined separately, as the red boxplot (impact of unobserved adaptation measures), the green boxplot (impact of crop selection), and the yellow boxplot (impact of machinery expenditure selection). By comparing the extent to which each adaptation measure mitigates productivity reduction, unobserved farm adaptation has the greatest impact on reducing productivity loss. The adaptation effect of adjusting rice share and machinery payment in response to climate change is relatively small.

Simulation results for the Mekong Delta region, as summarized in <Table 2-20>, show that this region is more vulnerable to climate change compared to the national average. For example, in the SSP5-8.5 scenario, when no adaptation measures are applied, productivity is projected to decrease by about 50% on average, which is a more negative outlook than the national average of a 40% decrease. Farms' adaptation helps mitigate such productivity loss in the Mekong Delta as in the national case. Notably, in all projection periods of the SSP1-2.6 scenario, as well as in the 2021-2040 period of the SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios, average productivity is projected to increase by accounting for every type of adaptation measure.

2.4.4. The Impact of Climate on Agricultural Income and Analysis of Neighborhood Effects (Analysis 4)

The estimation results of 'Analysis 4,' which analyzes the impact of climate variables on agricultural income taking into account neighborhood effects, are presented in <Table 2-21>. In this analysis, which examines the profitability of all crop groups without limiting the analysis to a specific crop group, the nonlinear effects of climate and long-term variations could not be reliably estimated due to the heterogeneity of production technologies and growth conditions across different crops. Therefore, 'Analysis 4' simplifies the impact of climate variables to linear effects and instead focuses on neighborhood effects. In this case, the estimation equation from Equation (2-14) is specified as Equation (2-16).

$$(2-16) \quad y_{it} = \frac{\alpha_0}{1-\beta} + \sum_{h=2}^4 \alpha_h \hat{s}_{it}^h + \alpha_c \hat{c}_{it} + \sum_{h=2}^4 \frac{\beta}{1-\beta} \alpha_h \tilde{s}_{it}^h \\ + \frac{\theta_{temp}}{1-\beta} \overline{Temp}_i + \frac{\theta_{rain}}{1-\beta} \overline{Rain}_i + \frac{\theta_t}{1-\beta} t_i + \sum_{r=1}^4 \left(\frac{\theta_r}{1-\beta} D_{r,i} + \frac{\theta_{rt}}{1-\beta} D_{r,i} \times t \right) + \epsilon_{it}$$

$\tilde{s}_{it}^h$ = the average share of crop h in year t in district $v(i)$, excluding farm i

〈Table 2-21〉 Estimation results – The impact of climate on agricultural income and analysis of neighborhood effects

Variable	Estimate	Standard error		Variable	Estimate	Standard error	
α_0	0.3355	0.2105		θ_t	0.5764	0.0474	***
β	0.2188	0.0144	***	θ_1	0.3684	0.0390	***
α_2	-0.4470	0.1094	***	θ_2	0.3864	0.0372	***
α_3	1.6557	0.1209	***	θ_3	-0.1448	0.0490	***
α_4	2.9948	0.1989	***	θ_4	-0.0323	0.0058	***
α_c	0.4211	0.3216		θ_{1t}	0.0003	0.0073	
θ_{temp}	-0.0096	0.0079		θ_{2t}	0.0214	0.0066	***
θ_{rain}	-0.0001	0.0000	***	θ_{3t}	-0.0129	0.0068	*
				θ_{4t}	0.0143	0.0078	*

1) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

2) Temperature and Rainfall are calculated as 30-year averages (1989~2018)

3) Group 1: Red River Delta, Group 2: Northeast/Northwest, Group 3: North Central Coast/South Central Coast, Group 4: Central Highlands/Southeast, Group 5: Mekong Delta (base = Group 5)

The climate variable parameters, θ_{temp} and θ_{rain} , are estimated to be negative, indicating that increases in temperature and rainfall negatively impact profitability. However, θ_{temp} is not statistically significant. Among the regional and year(t) parameters, all but θ_{1t} (the interaction between Group 1 and t) are statistically significant at the 10% level. Compared to Group 5 (the Mekong Delta), Groups 1 and 2 generally have higher profitability, whereas Groups 3 and 4 show lower average profitability. The positive estimate for θ_t suggests that profitability in the Mekong Delta region tends to increase over time. Time trends in profitability are also positive for other regions. For instance, in Group 3, although θ_{3t} is negative, the net effect of an increase in t is $0.5764 - 0.0129 = 0.5635 > 0$, thus increasing profitability.

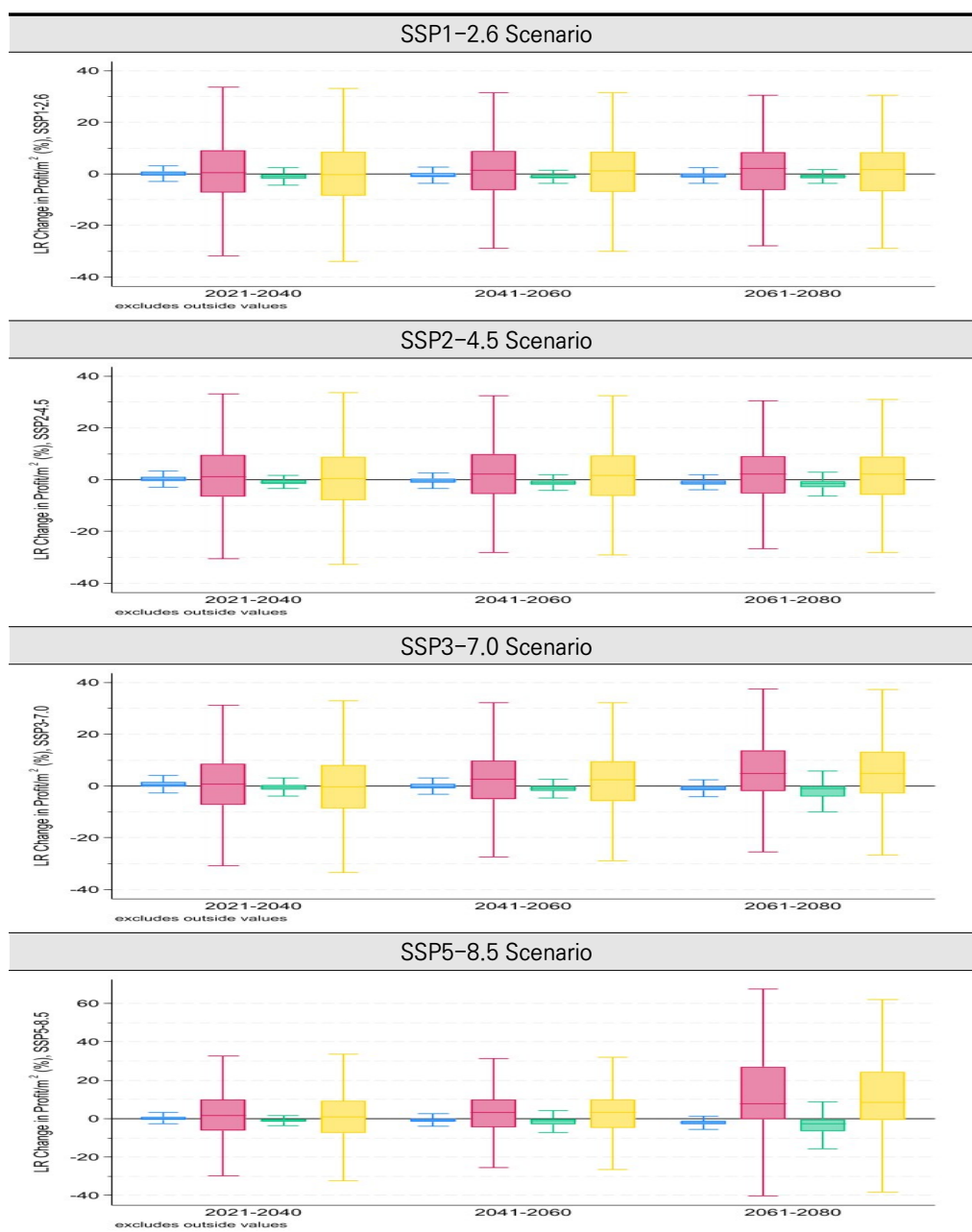
Among the adaptation-related parameters, α_2 , α_3 , α_4 represent the effects of crop shares for other food crops and vegetables, industrial crops, and fruit, respectively, relative to the share for rice. Increasing the land ratio for other food crops and vegetables decreases profitability, while increasing the ratios for industrial crops and fruit trees enhances profitability. The parameter α_c , which reflects the effect of agricultural machinery expenditure, is also positive, indicating that increasing machinery expenditures boosts profitability.

The main difference between the model in Equation (2-16) and the rice productivity model in Section 2.4.3 is that Equation (2-16) is designed to capture the spillover or neighborhood effects of climate change on neighboring farms including their adaptation decisions. This spillover effect, represented by the parameter β , is estimated to be 0.2188. Since this value is statistically significant and falls between 0 and 1, it confirms the existence of a neighborhood effect. For example, when rainfall increases by 1 mm, the profitability of a specific farm i would decrease by -0.01% as $\theta_{rain} = -0.0001$. However, neighboring farms within the same district also experience the rainfall increase, which then influences farm i 's profitability through feedback effects. Consequently, the overall change in farm i 's profitability after accounting for these neighborhood interactions is adjusted as follows.

$$(\theta_{rain} + \beta\theta_{rain} + \beta^2\theta_{rain} + \dots) \times 100 = \frac{\theta_{rain}}{1-\beta} \times 100 = \frac{-0.0001}{1-0.2188} \times 100 \approx -0.13\%$$

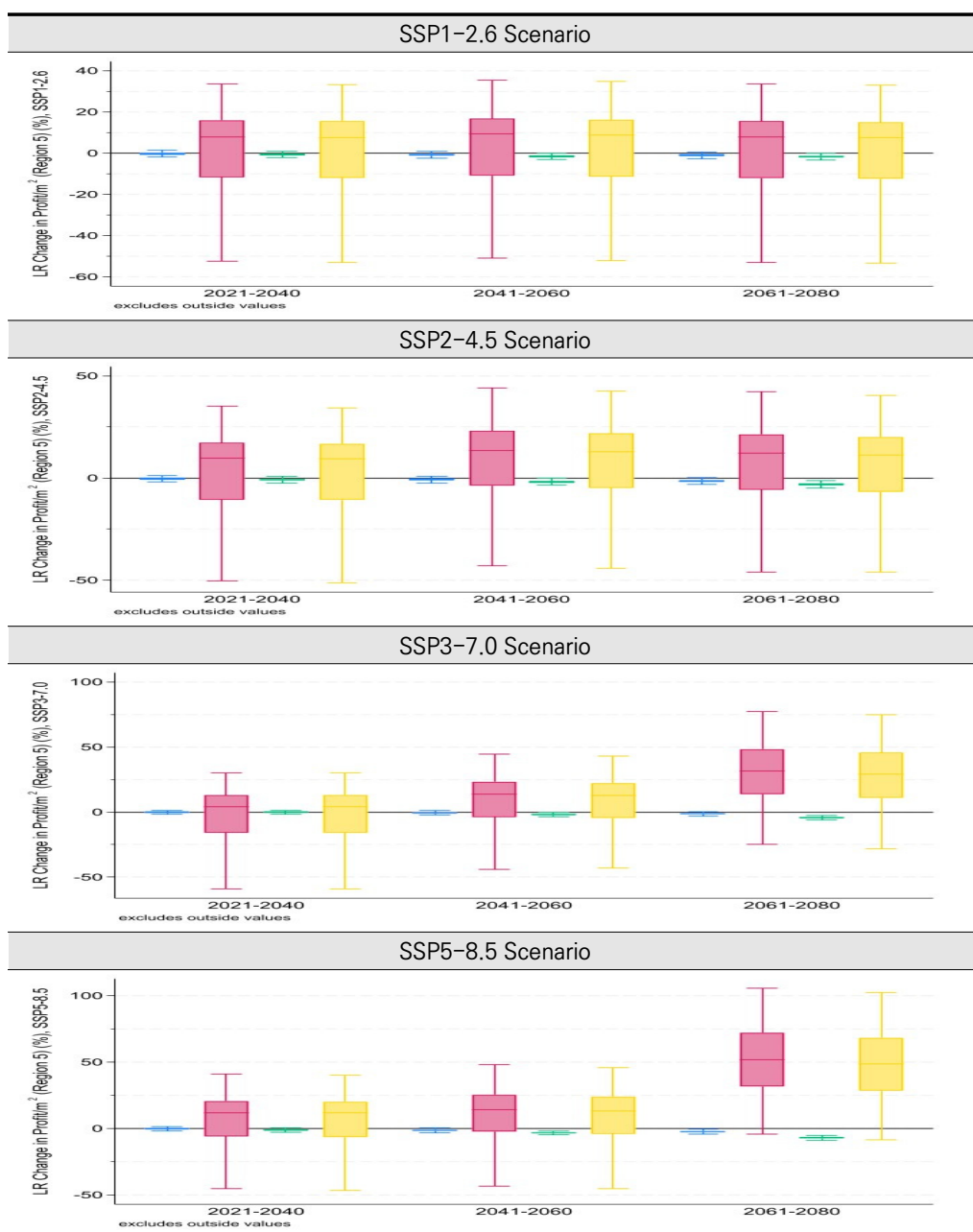
That is, the multiplier effect of shift in a regional characteristic variable is $\frac{1}{1-\beta} \approx 1.28$. The multiplier effect of shifting crop share is $\frac{\beta}{1-\beta} \approx 0.28$. For example, if in farm i 's district, the average share of fruit in farms other than farm i increases by 0.1, then the profitability of farm i increases by $0.1 \times \alpha_4 \times \frac{\beta}{1-\beta} \times 100 = 0.1 \times 2.9948 \times 0.28 \times 100 = \text{¥} 8.4\%$, even if the fruit share of farm i itself remains unchanged.

⟨Table 2–22⟩ Future profitability (agricultural income) simulation results – National



- 1) The vertical axis is in percentages (%)
- 2) Adaptation measures are distinguished into four colors. From left to right, they represent simulation results for no adaptation measures (blue), crop selection only (red), machinery expenditure only (green), and all adaptation measures (yellow).
- 3) Each boxplot group consists of four units, representing, the scenario results for 2021-2040, 2041-2060, and 2061-2080 (from left to right).

〈Table 2-23〉 Future profitability (agricultural income) simulation results – Mekong Delta



- 1) The vertical axis is in percentages (%)
- 2) Adaptation measures are distinguished into four colors. From left to right, they represent simulation results for no adaptation measures (blue), crop selection only (red), machinery expenditure only (green), and all adaptation measures (yellow).
- 3) Each boxplot group consists of four units, representing, the scenario results for 2021-2040, 2041-2060, and 2061-2080 (from left to right).

The simulation results of profitability changes under future climate conditions while accounting for neighborhood effects, are presented in <Table 2-22>. Similar to the rice productivity simulation, this analysis applies weights based on farmland area, assigning each farm a weight that is proportionate to the total farmland area of the regional group that farm belongs to. As a result, Group 5 (Mekong Delta) results are emphasized. In the case of adaptation, there are three types: allowing for only crop share adjustments, allowing for only changes in machinery expenditure, and allowing for both types of adaptations. <Table 2-23> summarizes these simulations with results from Group 5 (Mekong Delta) only.

In <Table 2-22>, which summarizes national effects, profitability shows a small yet steady decline when adaptation measures are not accounted for (blue boxplot). For instance, under the SSP5-8.5 scenario, the projected average profitability change rates for 2021–2040, 2041–2060, and 2061–2080 are approximately 5%, -0.3%, and -1%, respectively. The profitability decrease without adaptation is relatively small in size compared to the rice productivity simulation results in <Table 2-19> and <Table 2-20> ('Analysis 3'). This is likely due to the inclusion of diverse crop groups in the profitability analysis, leading to a mixture of varied responses to climate change. Furthermore, unlike 'Analysis 3,' which simulates yield (weight (kg) per unit area), this analysis simulates income per unit area, potentially incorporating market price effects. In other words, as agricultural productivity decreases due to climate change, rising market prices may conceal the true negative effects. Nonetheless, even when accounting for crop heterogeneity and price effects, climate change continues to detriment farm profitability.

In short-term projections, average changes in profitability are similar whether or not they account for adaptation, indicating that farmers' adaptation efforts do not significantly impact short-term profitability. However, in future periods, profitability losses are mitigated by taking adaptation into account, and profitability even increases in some cases. For example, under the SSP5-8.5 scenario for 2061–2080, the projection shows that average profitability rises by about 9% with all adaptation measures applied (yellow boxplot). When comparing the effects of the

two types of adaptation measures (red and green boxplots), changes in crop shares have a more substantial impact on profitability than adjustments in machinery expenditure. In some scenarios, increased machinery spending even slightly reduces profitability.

In <Table 2-23>, which focuses on simulation results for farms in the Mekong Delta, the positive impact of adjusting crop shares is marked, with profitability increasing by approximately 5% to 50% when all adaptation measures are applied.

2.5. Conclusions

To conclude, Sub-study 1 first examines how climate change affects rice productivity or agricultural income in the Mekong Delta region, considering both unobserved adaptive actions and specific observable adaptation measures, such as crop selection and spending on agricultural machinery.

By using the Just-Pope production to estimate how climate change impacts the expected values and variability of productivity and profitability, temperature significantly influences the expected values of these outcome variables. After a certain threshold, an increase in temperature reduces expected productivity and profitability. In the case of variability (uncertainty) of rice productivity, rising temperatures tend to decrease variability while increased rainfall tends to increase it. Regarding variability of income, however, increases in both temperature and rainfall increase variability. Additionally, under extreme weather conditions, the expected rice productivity declines and variability rises, revealing the negative impacts of random climate fluctuations.

This sub-study also investigates how adaptive measures of farms are affected by climate variables, analyzing how decisions on crop selection and machinery investment respond to climate change. The results indicate that climate variables generally have a statistically significant impact on these decisions. Moreover, a simulation of future climate scenarios suggests that farms will increase the share of rice and fruit crops while reducing other food crops and vegetables, and specialty crops, alongside an increase in machinery expenditure.

In analyzing rice productivity and agricultural income while taking adaptation measures into account, results reveal an inverted U-shaped relationship between productivity and climate variables (temperature and rainfall), where an increase of such variables beyond a certain threshold negatively impacts productivity. In the case of profitability analysis, the effect of climate variables is reflected only on a linear scale and puts more emphasis on neighborhood effects. Profitability

analysis results reveal that temperature and rainfall increases have negative yet relatively small effects on profitability. The neighborhood effect analysis indicates that farms within the same district do influence each other's decisions.

Simulating future scenarios with adaptation measures suggests that the negative impact of climate change on productivity and profitability may be mitigated, and may even lead to improvements in some cases. In addition, the profitability analysis confirms the existence of significant neighborhood effects among farms within the same district, indicating some sort of social influence.

These findings offer several key insights. First, without appropriate adaptation measures, rice productivity is expected to decline substantially, particularly in the Mekong Delta. Given the central role of rice in this region, measures to safeguard productivity—such as drought/flood management, crop improvement, and disaster response—are essential. Individual measures, such as adjusting crop combinations and mechanization, are also necessary. This sub-study demonstrates that appropriate adaptation measures can substantially reduce potential yield declines, underscoring the need for public investment as well as financial and educational support for individual adaptation efforts.

Second, the impact of climate change on overall crop income is relatively smaller than on rice, which is due to the diversification effect across crop types and the focus on income (monetary variable) rather than yield per area (kg). Nonetheless, climate change consistently reduces profitability as in the case of rice yield. As farms adjust crop combinations and machinery investment, total crop income could potentially increase, highlighting the importance of financial and educational support for crop diversification and capital investment.

Third, the sub-study identifies significant neighborhood effects in crop selection, suggesting potential benefits from localized training and crop specialization initiatives. This implies that training programs related to crop selection could yield positive externalities and that regional-level programs could achieve substantial outcomes.

3. Factors Influencing Farmers' Decision-Making in Adopting Climate Change Adaptation Measures in the Mekong River Basin

3.1. Climate Change Vulnerability and Impacts in the Mekong Basin Countries

3.1.1. Climate Change Vulnerability in the Mekong Basin Countries

Climate change is the phenomenon of human-induced changes in climate, which the UNFCCC (1992) defines as changes in climate caused by direct and indirect human activities, including natural climate variability. The IPCC (2021) projects that the global average temperature will increase by 1.5°C above pre-industrial levels before 2040, earlier than originally projected. Climate change is accompanied by rising temperatures and increased precipitation variability, which manifests itself in the form of climate shocks, such as droughts and floods, that negatively impact economic activity and human quality of life.

LMICs are more vulnerable to climate change than high-income countries at higher latitudes, with LMICs in Asia experiencing an increase in the frequency and intensity of climate shocks, including droughts, floods, heat waves, and sea level rise, as temperatures rise by 1.5°C to 2°C (IPCC, 2022). This is contributing to a growing food security crisis, and climate change is expected to hit LMICs particularly hard by significantly reducing agricultural productivity, as the economies of most LMICs are heavily dependent on the agricultural sector (Rosenzweig et al., 2014). In addition, rising global average temperatures are causing a decline in agricultural land. According to the IPCC (2021), about 8% of the world's agricultural land will become unsuitable for agriculture at a 1.5°C increase in temperature, which will disproportionately harm agriculture in LMICs through a variety of pathways, including salt intrusion from sea level rise, desertification from drought, and increased crop stress.

In addition to direct economic losses in LMICs, such as reduced agricultural productivity, climate change causes a range of other problems across the spectrum of human life, including increased (1) tropical diseases, (2) increased mortality, (3) loss of labor, (4) climate refugees due to sea level rise, and (5) increased impacts on the poor. Among LMICs, the Mekong River Basin is one of the most vulnerable regions to climate change in terms of temperature and precipitation. The region is located in the monsoon climate zone, where precipitation is concentrated in the summer, resulting in high variability in precipitation throughout the year. Due to climate change, rainfall variability in the rainy season is expected to increase from -16% to +17% in the future (Mekong River Commission, 2017). The Lower Mekong Basin (LMB) in particular is one of the most vulnerable regions in the world to climate change, with 2021 experiencing the lowest rainfall in 100 years.

About 30% of households in the region have experienced floods and droughts in the past year, and GDP in the LMB is projected to decline under all climate change scenarios, leading to rural-urban migration and international migration of farmers (Mekong River Commission, 2017). Declining agricultural productivity due to climate change is also leading to a decrease in food intake, which negatively impacts health (WHO, 2023). In addition, Mekong Basin countries are projected to experience an increase in the number of heat wave days with temperatures above 35°C under all climate change scenarios, and heat-related mortality is expected to continue to rise due to urbanization and the heat island effect (World Bank, 2021). Globally, many people rely heavily on rice grown in the Mekong River Delta, and rising temperatures due to climate change will severely impact agricultural productivity in the region (Caitlin et al., 2019).

According to a 2018 survey by Social Impact Monitoring and Vulnerability Assessment (SIMVA), the largest socio-economic survey of households in the Mekong River Basin, including Vietnam, Laos, Cambodia, and Thailand, about 46% of households in the region rely on agriculture as their main source of livelihood. Specifically, the GDP contribution of the agriculture and fisheries sector to Vietnam's economy was 12.0% (as of 2023), accounting for 33.6% of total

employment (as of 2022). In Lao PDR, the GDP contribution of agriculture and forestry was 16.1% (in 2023) and the contribution of agriculture and forestry employment was 69.6% (in 2022). As you can see, agriculture still plays an important role in the economies of Vietnam and Laos. However, climate change adaptation and resilience policies in these countries are still weak, and the lack of capital and infrastructure in the Mekong River Basin makes it difficult to respond to climate change (USAID, 2022).

3.1.2. Climate Change Impacts and Effects in the Mekong River Basin Countries

Climate change damages in the Mekong River Basin directly affect agriculture and food security in several neighboring countries. Droughts and floods are expected to destabilize agricultural water supplies, increasing crop yield variability and causing significant declines in rice production, the main staple crop in the Mekong River Delta. In the Mekong Delta region of Vietnam, average annual temperatures are projected to increase by 1.7°C to 1.9°C and precipitation is expected to increase by 5% to 15% by the end of the 21st century (UNDP, 2022). As a result, agricultural production is expected to decline by 5.6% to 6.2% by 2030 and by 7.6% to 10.6% by 2050 (World Bank, 2021). Among other climate change phenomena, drought and salinity are expected to pose the greatest threat to the agricultural sector in the region. In Laos, rice yields are projected to decline by 5-20% by the 2040s due to climate change-induced rainfall irregularities, heat waves, and increased nighttime temperatures (World Bank, 2021).

Rice produced in the Mekong River Delta accounts for about 55% of Vietnam's total rice production (Tan Yen et al., 2019; Xiao et al., 2021), so the damaging effects of climate change in the region pose a significant threat to Vietnam's economy and food security. In 2016, the Mekong River Delta experienced the most severe drought in its history, with 1.8 million hectares of agricultural land exposed to drought and salinity intrusion (Smajgl et al., 2015). Paddy fields account for 48% of the total agricultural land in the region, with 3.9 million hectares as of 2021, accounting for about 54% of Vietnam's total paddy area, but since 2005, an average

of 300 hectares of farmland has been lost annually due to climate change (Dinh et al., 2017).

Vietnam's Ministry of Natural Resources and Environment (MONRE, 2009, 2011) and the National Institute of Meteorology, Hydrology and Environment (IMHEN, 2009, 2011) estimate that the Mekong River will rise by 0.65 to 1 meter by 2050, submerging 13% to 39% of the Mekong Delta in sea water. In 2007, the International Center for Environment Management also reported that for every 1 meter of sea level rise, 38% of the Mekong Delta would be underwater because the Mekong Delta is 5 meters below sea level (Mackay et al., 2011). The damages caused by sea level rise will directly affect the agriculture and livelihoods of the approximately 17 million farmers living in and around the Mekong Delta.

In the Mekong Delta region, rice is cultivated three times per year, primarily during the winter-spring season (November-February), summer-autumn season (April-July), and fall-winter season (August-November). Salinity inputs mainly occur during the winter-spring season in 10 provinces in the Mekong Delta region (Province, Long An, Vinh Long, Ca Mau, Bac Lieu, Tien Giang, Hau Giang, Soc Trang, Tra Vinh, Kien Giang, Ben Tre). Flooding also occurs frequently in nine of these provinces (Long An, Dong Thap, Ca Mau, Can Tho, Tien Giang, An Giang, Vinh Long, Hau Giang and Kien Giang), mainly during the fall-winter season, and six of these provinces are exposed to the risk of both salinity and flooding every year. Compared to the average rice production from 2005-2016, the projected yields for the winter-spring season in 2020-2050 are estimated to decrease by an average of 0.72 million tons per year under the RCP 4.5¹⁹⁾ scenario, and by an average of 1.17 million tons per year under the RCP 8.5²⁰⁾ scenario, assuming average salinity and flooding. It is also predicted that climate change will reduce rice yields in Laos by about 14.5% by the 2050s under the RCP 8.5 scenario (Li et al, 2017, Chun J.A. et al, 2021).

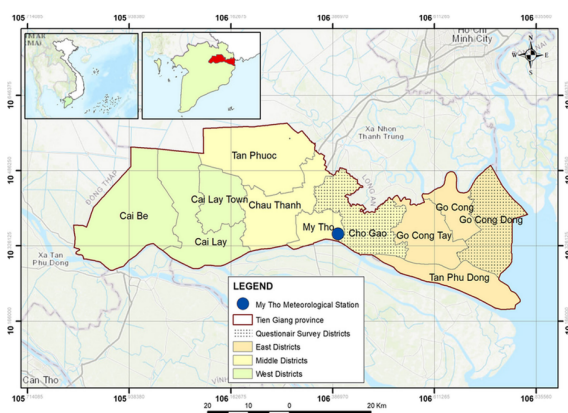
19) RCP 4.5 (Representative Concentration Pathway 4.5) is one of the four greenhouse gas concentration scenarios adopted in the IPCC's Fifth Assessment Report (AR5)

20) The RCP 8.5 scenario is one of the Representative Concentration Pathways (RCP) used in climate change research, representing the highest greenhouse gas emission pathway.

[Figure 3-1] Map of Vientiane Province, Laos



[Figure 3-2] Map of Tien Giang Province, Vietnam



3.2. Climate Change Adaptation Measures of Farmers in the Mekong Basin

3.2.1. Types of Climate Change Adaptation by Farmers in the Mekong Basin

Actions to respond to climate change in agriculture can be broadly categorized into adaptation and mitigation (Wreford, Moran, and Adger, 2010). **Climate change adaptation** is defined as strategies to minimize the negative impacts of climate change and take advantage of new opportunities, and is an adaptation process that takes into account expected changes in climate and its impacts (IPCC, 2014). **Climate change mitigation** measures, on the other hand, seek to reduce the intensity and speed of climate change by reducing the greenhouse gas emissions that cause climate change. High-income countries focus primarily on climate change mitigation measures, such as GHG emission reductions, while LMICs are responding to climate change primarily through adaptation measures (Wreford, Moran, and Adger, 2010).

Climate change adaptation in agriculture occurs at multiple levels, including (1) individual, (2) household, (3) community, (4) national, and (5) international cooperation (Adger et al., 2005). To respond to the multidimensional impacts of climate change, national climate change adaptation policies and internationally coordinated development cooperation programs are important at the macro level, but individual farmers' adaptation decisions are also important at the micro level. However, rural communities in the Mekong Basin often lack the financial and institutional resources for formal climate change adaptation planning (Evers et al., 2018).

Recent studies have shown that farmers in the Mekong Basin are responding to climate change on an individual, small-scale, and spontaneous basis due to low capital mobilization and uncertainty about the risks posed by climate change (Christoplos et al., 2017; Malik, Qin, and Smith, 2010; Stern, 2007). This means that farmers' responses to climate change are mainly individual, reactive, and

short-term rather than organized, proactive, and long-term. In practice, farmers in the Mekong River Basin are primarily using adaptation measures such as (1) Changing seed variety, (2) Adjusting planting calendar, (3) Crop diversification, (4) Enhancing land endowments, (5) Livestock diversification, (6) improving irrigation, and (7) Utilizing forest resources to cope with climate change risks such as flooding, drought, sea level rise, and saltwater intrusion (Son and Kingsbury, 2020; Vo, Mizunoya, and Nguyen, 2021). In the absence of appropriate climate change adaptation measures in the agricultural sector, climate change is expected to reduce the yield of several crops, including rice (Challinor et al., 2014). Therefore, farmers in the Mekong River Basin need to adopt appropriate adaptation measures to avoid the negative impacts of climate change on the agricultural sector and maintain agricultural productivity and food security.

Climate change adaptation measures play an important role in maintaining stable agricultural productivity and thus enhancing food security (Dow et al., 2013). Iglesias et al. (2007) categorize climate change adaptation measures into three types: (1) management, (2) technology and tools, and (3) infrastructure. Although differences exist depending on the geography and climatic conditions of individual countries, climate change adaptation measures commonly adopted by smallholder farmers in Southeast Asia include the following (CGIAR, 2011; ADB, 2009)

- Change in crop varieties
- Changes in cropping patterns and cropping calendar
- Improved farm management
- Use of climate-resilient crop varieties

3.2.2. Types of Climate Change Adaptation Measures for Farmers in the Mekong Basin

Climate change adaptation measures in the agricultural sector need to be adapted to the characteristics of agricultural land and environmental conditions in each region. Southeast Asian countries are particularly vulnerable to climate change impacts due to their (1) long coastlines, (2) concentration of population and

economic activities in coastal areas, (3) rapidly growing populations, natural hazards such as droughts, heavy rains, and floods, and (4) dependence on agriculture (ADB, 2009). Therefore, farmers have been utilizing climate change adaptation measures such as using more drought and heavy rainfall tolerant seeds and shifting planting schedules to avoid droughts, taking into account local agricultural conditions (ADB, 2009). In particular, crop diversification and changing seed varieties are among the most common climate change adaptation measures used by Vietnamese farmers due to their low cost and simplicity (Hoang Ha Vo, 2021). Farmers may use these adaptation measures individually, or they may use multiple adaptation measures simultaneously to mitigate the impacts of climate change (Adger et al., 2005; Locatelli et al., 2008).

3.2.2.1. Adjusting Planting Calendar

Adjusting Planting Calendar is a climate change adaptation measure that can be taken at the farm level, which refers to **changing the timing of farmers' cultivation activities**, such as sowing and harvesting, and **shortening the growing season**. In upland farms in Pantabangan, Nueva Ecija, Philippines, farmers adapt to the earlier onset of the rainy season by cultivating their upland farms earlier to increase agricultural production and enhance household income from agricultural activities (Lasco and Boer, 2006; Lasco et al., 2011). Adjusting Planting Calendar plays an important role not only in increasing agricultural production but also in balanced water use (Wang et al., 2020).

3.2.2.2. Crop Diversification

Crop diversification refers to farmers shifting their farming practices from growing a single crop to **growing multiple diverse crops**. **Crop rotation**, the periodic rotation of different types of crops on the same land, is also a form of crop diversification. Crop diversification can increase yields as well as diversify the risk of agricultural production in the face of uncertain climate change (Lasco et al., 2011).

3.2.2.3. Changing Seed Variety

Changing seed variety refers to changing the seed variety of a cultivated crop to a **climate change-resistant variety** instead of a climate change-vulnerable variety. For example, in the Mekong River Delta, rice varieties with shorter growing cycles allow farmers to harvest rice twice during the rainy season. Seed variety change is highly dependent on the accuracy of climate forecasts, access to climate-tolerant varieties, and market acceptance of the resulting produce, and in practice, many farmers in Vietnam adopt and grow climate-tolerant rice varieties (Snidvongs, 2008; Lasco et al., 2011).

3.2.2.4. Field Preparation

Field preparation is the process of preparing agricultural fields and waterways for crop cultivation, such as clearing the fields and waterways and removing weeds **to create an environment where crops can grow well**. In particular, it is a climate change adaptation measure in the form of creating an environment suitable for the growth of the crops to be grown in response to climate change.

3.2.2.5. Adjusting Planting Techniques

Adjusting planting techniques refers to **changes and adjustments in the use of various forms of technology for growing crops**, such as the timing and method of irrigation, use of fertilizers and pesticides/herbicides, and use of labor, and includes **crop management** for climate change adaptation (Le Dang et al., 2014). Cultivation technology adjustment is a widely used measure in climate change adaptation in Southeast Asia, including Vietnam, Laos, and Cambodia. For example, rice farmers in Kandal province, Cambodia, prepare for uncertain climate change (precipitation) by dividing their paddy fields into two parts and using different cultivation techniques. One half of the paddy field uses conventional wet rice cultivation techniques that can withstand heavy rainfall, while the other half uses the System of Rice Intensification (SRI), a drought-resistant and low-water-

consumption cultivation technique (Resurreccion et al., 2009; Lasco et al., 2011). This method helps to ensure stable rice productivity in the face of extreme rainfall and variable and uncertain water access.

3.2.2.6. Private Water Use Management

Water use management refers to **individual changes in practices to conserve water**, such as water recycling and water filtration. Individual and community water use management is important for adapting to the impacts of climate change, such as water scarcity and flooding. To conserve water, individual farmers can adopt technologies to efficiently use, store, and recycle water or take steps through water filtration technologies. They can also build public water facilities or improve existing ones.

3.2.2.7. Improve Private and Communal Water Facilities

Improving water facilities refers to **the construction or improvement of water facilities** such as private and public water storage. In 2002, rice farmers in the Dulac region of the Philippines adopted Alternative Wetting and Drying (AWD) or controlled irrigation. With multiple farmers sharing a single deep well pump and threats of diminishing water availability, farmers practicing AWD were able to reduce water use by 25%. In addition, AWD is less labor intensive, reducing management costs by 20-25% and increasing farm incomes (Lasco et al., 2011).

3.2.2.8. Income Diversification

Income diversification is a response to the volatility of farm income due to climate change that allows farmers to engage in **non-farm activities** or **to shift from cropping to livestock rearing** to ensure a stable income in the event of adverse climatic conditions. In the Vientiane Plain and Savannakhet province of Lao PDR, it is a common practice for farmers to diversify their income by raising livestock as well as crops and utilizing natural resources in the surrounding area to compensate for losses in agricultural income due to climate stress (Snidvongs,

2008; Lasco et al., 2011).

3.2.2.9. Buying Insurance

Farmers can respond to climate change risks by **purchasing different forms of insurance to cover different risks that may occur to their human assets, physical assets, livestock or crops**. For example, farmers who recognize the health risks of climate change as high may purchase health insurance. This purchase or investment in insurance is a reflection of how farmers perceive the risks of climate change (Le Dang et al., 2014).

3.2.2.10. Using Agro-Climate Information

Using agro-climatic information is a form of climate change adaptation that utilizes **climate information relevant to crop cultivation and management** to help farmers better understand and manage climatic conditions. According to Lasco et al. (2011), the use of accurate climate information by farmers can maximize the effectiveness of improved species adoption by allowing farmers to appropriately adjust planting and harvesting schedules of improved species and implement variety management tailored to individual climatic conditions.

3.3. International Support for Enhancing Farmers' Climate Change Adaptation Capacity in the Mekong Basin

To strengthen farmers' capacity to adapt to climate change, collaboration and engagement with organizations that deal with weather and climate information is essential (Wood et al., 2014). Lack of weather and climate information is one of the main barriers to effective climate change adaptation (Muema et al., 2018), and access to timely and accurate climate information services is critical for effective climate change adaptation, especially in the agricultural sector (Jones et al., 2000).

Weather information provided by national and institutional organizations can have a significant impact on large numbers of farmers at relatively low cost. Advances in information and communication technology (ICT) have facilitated the collection and dissemination of information, creating an environment in which information on climate change and its response can be quickly communicated and disseminated to rural areas. In Vietnam, climate information services are mainly provided by government agencies, international organizations, research institutions, and non-governmental organizations (Christoplos et al., 2017). The Ministry of Natural Resources and Environment (MONRE), the ministry responsible for managing the impacts of climate change, works with the Ministry of Agriculture and Rural Development (MARD) to create climate change scenarios and develop national climate change target programs. These ministries operate climate change units at the local, provincial, and national levels, and provide the meteorological information needed for climate risk management planning at each level. In addition to government-led provision of climate information services, international support and collaboration with international organizations are also strengthening the adaptive capacity of farmers in the Mekong Basin.

3.3.1. DeRisk South East Asia

DeRisk South East Asia is a project designed to manage climate risk in the agricultural sector in Southeast Asia and is a multilateral collaboration (2018–2023) between the World Meteorological Organization (WMO, Switzerland), the University of Southern Queensland (USQ, Australia), and the International Centre for Tropical Agriculture (CIAT, Vietnam). The target countries are Vietnam, Laos, Cambodia, and Myanmar in the Mekong River Basin, a region with high vulnerability to climate change.

DeRisk project uses climate forecasting programs to manage multiple risks associated with climate change and increase adaptive capacity in the agricultural sector. In particular, one of the main objectives of DeRisk's work is the **development and distribution of the Agro-Climatic Bulletin (ACB)**. The ACB provides farmers with climate information and weather forecasts relevant to agricultural production to inform decision-making related to agricultural production. Weather information such as precipitation, temperature, and humidity is used by farmers to determine harvest schedules and fertilizer and pesticide usage.

From 2020 to 2024, DeRisk partnered with the Department of Crop Production of Vietnam's Ministry of Agriculture and Rural Development to develop agrometeorological information sheets to benefit more than 220,000 farmers in 13 provinces, 52 districts, and 521 communes in the Mekong Delta region. Farmers were provided with climate information through village bulletin boards, village loudspeaker broadcasts, and local messenger applications (Zalo). For example, in Tien Giang province, we distributed three ACBs – seasonal, monthly, and 10-day – to help farmers make agricultural production decisions. A survey of 202 farmers in Tien Giang province found that the introduction of ACBs was associated with increased rice yields, with farmers who utilized agrometeorological information reporting an average increase in rice yield of 266 kg per hectare and an increase in revenue of approximately \$78 per hectare, and 39.6% of farmers reported a decrease in pesticide costs (Swaans. C. & Le. T. T., 2024).

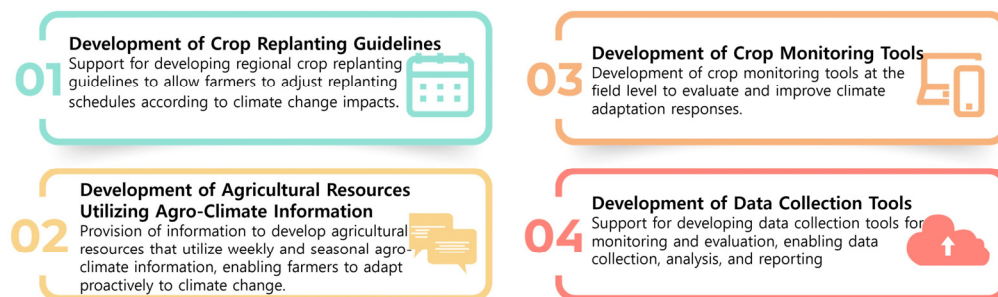
Based on these results, the Ministry of Agriculture and Rural Development (MARD) in Vietnam recognized the ACB development and deployment process as a useful technology and expanded it to all 13 Mekong Delta provinces, becoming part of Vietnamese government policy with an annual government budget of approximately \$17,000 to contribute to national crop management and climate change adaptation measures. With strong government support and contributions from Technical Working Groups (TWGs) in 13 Mekong Delta provinces, ACB has been successfully implemented and scaled up in Vietnam. In addition, Local Technical Agroclimatic Committees (LTACs) have facilitated dialogue among diverse stakeholders, provided advice on responses to climate variability, and informed agricultural planning and decision-making. In doing so, DeRisk's work is credited with helping farmers in the Mekong Delta improve their agricultural productivity and strengthen their resilience to climate change.

3.3.2. SAMIS (Strengthening agro-climatic monitoring and information systems)

SAMIS is a project implemented by the Food and Agriculture Organization (FAO) from 2018 to 2021 designed **to support agricultural policy and climate change adaptation by monitoring and analyzing agro-climatic data and strengthening communication at the national and provincial levels** in Lao PDR. SAMIS works closely with the Lao Ministry of Agriculture (MAF) and Ministry of Natural Resources and Environment (MoNRE) to provide climate information for agricultural planning and decision-making at the national, regional, and village levels.

Farmers in Laos are using agro-climatic information and advice to **select crop varieties** and **improve agricultural practices**, such as water and fertilizer usage. These advisories have been integrated into the LaCSA system and have reached more than 100,000 farmers through farmer field schools, broadcasts, and social media (WhatsApp, Facebook, etc.). SAMIS partnered with DeRisk to provide technical inputs to the LaCSA system, contributing to the development of the Lao climate information service system. The collaboration began with DeRisk supporting specific activities for SAMIS and has expanded into several areas. The main areas

of collaboration are as follows:



SAMIS adopted the tools and approaches introduced by DeRisk and integrated them into the LaCSA system. As a result, more than 80 percent of the more than 100,000 Lao farmers received agro-meteorological information and agricultural advice through village loudspeakers to improve their existing farming practices. Specifically, they utilized (1) crop variety selection, (2) planting timing, and (3) water management strategies. As a result of adjusting farming practices based on information from LaCSA, average crop yields increased by 17%, average gross income increased by 33%, and production costs increased by 8% due to increased use of fertilizers and pesticides, but losses from pests decreased by 77.4% (Swaans. C. & Kim. K. H., 2023).

3.3.3. LaCSA (The Laos Climate Service for Agriculture)

LaCSA provides agriculture-related climate information services, including agro-climatological information in Laos, to help agricultural producers, service providers such as agricultural extension services, and agricultural policy makers predict crop growing seasons and respond appropriately to climate change. In partnership with the Lao Statistics Bureau (LSB), LaCSA consolidates data from all weather stations in Laos into one database to provide farmers with short- and medium-term weather forecasts, as well as seasonal forecasts and advisory information for specific crops. LaCSA also provides agro-climatic information services, such as soil, crop, and pest data, which are also useful to relevant stakeholders. For example, it provides

management recommendations for the most commonly grown crops (rice, cassava, maize, coffee, banana, and cabbage), informs how to best manage pests and diseases, or provides yield forecasts or specific crop indicators such as planting numbers and Growing Degree Days (GDD). This information is summarized in a farmer-friendly format and provided free of charge in the form of weekly or monthly information sheets.

3.3.4. Mekong River Commission(MRC)

The MRC was established in 1995 as an internationally coordinated organization of Vietnam, Cambodia, Laos, and Thailand to coordinate water resources development in the Mekong River Basin. The MRC has developed and operated flood management and drought forecasting and warning systems and established climate information systems in the Mekong River Basin, and has supported farmers and fishers in their adaptation to climate change through policy instruments such as the Mekong River Commission's Climate Change and Adaptation Initiative (CCAI), a policy organization that supports farmers and fishers in their adaptation to climate change. Despite these efforts, however, there are a number of technical and policy challenges to establishing practical and effective flood and drought management regimes. The main challenges are as follows:

01 Lack of Predictive Accuracy
It is important to improve predictive accuracy in climate change-related prediction and warning systems, but policy outcomes can be insufficient due to technical limitations

02 Lack of Collaboration among Members
MRC requires close collaboration among members, but challenges exist, such as insufficient resources, practical collaboration, and discrepancies in national policy interests

03 Lack of High-Resolution Data
There is a shortage of high-resolution data needed for predictive models, making it difficult to establish efficient management systems

04 Difficulty in Proposing Practical Prediction and Warning Measures
Methods for proposing realistic predictions and warnings that transcend the limits of individual countries are necessary, but technical and policy challenges make this difficult

International cooperation is essential for sustainable development and climate change adaptation in the Mekong River Basin. International support is playing an important role in enhancing the Mekong Basin's capacity to respond to climate change and improving the quality of life of local people. However, technical and policy challenges still exist, and careful impact evaluation is needed to maximize the benefits of the projects and identify alternatives to compensate for the shortcomings. Therefore, this study (sub-study 2) aims to analyze the factors that influence the decision to adopt agricultural climate information services to enhance farmers' adaptive capacity to climate change and draw policy implications to promote farmers' utilization of climate change adaptation measures.

3.4. Rationale and Need for the Study

This study aims to **analyze the decision-making factors behind the adoption of climate change adaptation measures**, which are the main strategies that individual farmers can choose to respond to climate change. To this end, this study aims to provide an in-depth look at farmers' utilization of climate change adaptation measures based on data collected through household surveys in the Mekong River Basin in Vietnam and Lao PDR. It also analyzes the factors that influence farmers' decision to adopt climate change adaptation measures by comprehensively considering various factors such as demographic characteristics, socio-economic variables, access to climate change information, experience of climate change-related damages, and cognitive and non-cognitive abilities. From this analysis, we draw **policy implications for promoting and supporting farmers' adoption of climate change adaptation measures** in the future.

In LMICs, agriculture accounts for a large share of the economy and is particularly vulnerable to extreme climatic conditions caused by climate change. As a result, they face challenges such as declining agricultural productivity, food shortages, and income insecurity, which negatively impact farmers' livelihoods and quality of life. In particular, the Mekong River Basin is vulnerable to climate risks and requires practical and systematic adaptation measures to respond to climate change.

In this context, it is important to understand which adaptation measures farmers choose to respond to climate change and how they make adoption decisions. This is essential to address the practical challenges faced by farmers and to develop more effective climate change adaptation policies and farmer support programs. In particular, farmers in LMICs have limited access to resources and information and need technical and financial support, training, and appropriate information from governments and international organizations to strengthen their capacity to respond effectively to climate change. Therefore, this study analyzes the main factors that influence farmers' decisions to adopt climate change adaptation

measures, which will contribute to prioritizing support and suggesting more effective support measures.

The study also aims to contribute to the development of climate change adaptation strategies that are applicable not only in the Mekong River Basin, but also in LMICs and regions with similar environments and conditions. This is based on an in-depth understanding of what climate change adaptation measures farmers actually perceive and choose as effective. In particular, it aims to contribute to strengthening climate resilience at the community and national levels by providing information that can be used to develop customized climate change adaptation strategies that take into account local characteristics and climate change risks.

Therefore, this study aims to contribute to the improvement and development of policies that can promote farmers' climate change adaptation by improving the understanding of farmers' use of climate change adaptation measures in the Mekong River Basin and the determinants of their adoption. In doing so, it also aims to improve farmers' capacity to respond to climate change, thereby contributing to the goals of increasing agricultural productivity, securing food security, and poverty alleviation, and ultimately contributing to sustainable agriculture and rural development.

3.5. Literature Review

Climate change adaptation measures at the farm level refer to a range of agricultural and non-agricultural technical responses that farmers adopt to mitigate the negative impacts of climate change. The adoption of these adaptation measures is a complex process in which farmers adjust their current behaviors in anticipation of future uncertain climate conditions and is dependent on a variety of factors. Key decision-making factors include demographic and (1) socio-economic factors such as age, education, income and asset levels, access to credit, and (2) climate outlook, (3) cognitive and non-cognitive skills, (4) social connections, (5) access to climate change information, and (6) awareness of climate change adaptation measures. These factors can be important decision variables that influence farmers' adoption of climate change adaptation measures.

Analyzing the factors that influence farmers' decisions to adopt climate change adaptation measures has important implications for the development and implementation of policies to strengthen farmers' capacity to cope with climate change. Previous studies have conducted various analyses in this context and found that economic resources, technical support, and socio-cultural background, as well as demographic factors, are key variables in farmers' decision to adopt adaptation measures. Specifically, Dang et al. (2019) reviewed the literature on climate change adaptation measures and found that existing studies have focused on demographic factors, economic factors, resource and technical factors, institutional and political factors, social and cultural factors, and cognitive and psychological factors as determinants of farmers' decision to adopt climate change adaptation measures. However, they emphasized the relative lack of research on social and cultural factors and cognitive and psychological factors.

Much of the literature has focused on the importance of farmers' access to credit and resource utilization in the adoption of climate change adaptation measures. This is based on the logic that the better access farmers have to finance and resources, the more proactive they will be in adopting adaptation measures in

response to climate change. However, recent research has expanded attention to more psychological and social factors, such as access to climate change information, social connections, self-efficacy, and risk preferences, as factors that influence farmers' adoption of climate change adaptation measures.

In particular, research on climate change information access has focused on whether farmers acquire climate information through traditional media such as TV and radio or through interactions with neighbors. More recently, with the development of Internet and Communication Technology (ICT), studies are also analyzing the effectiveness of providing climate information through mobile applications or social media, and of combining agricultural extension services with ICT to support farmers. For example, Djido et al. (2021) found that in Ghana, climate information delivered through mobile devices significantly influenced farmers' adoption of various climate change adaptation measures, including water management, adoption of improved varieties, and multiple-cropping. In addition, studies by KOICA (2022) and CGIAR (2022) in the Mekong River Basin analyzed farmers' decisions to adopt climate change adaptation measures and their effects on agricultural productivity among farmers participating in the DeRisk project, and both studies found that access to climate change information had a positive impact on farmers' level of climate change adaptation.

In addition, social networks have been recognized as an important factor in farmers' adoption of technology and climate change adaptation measures. Di Falco (2019) and Paul (2016) found that smallholder farmers are influenced by the adoption of climate change adaptation measures by neighboring farmers. These studies emphasized that the more interaction between farmers, especially within social networks, is an important factor in promoting farmer adoption of adaptation measures. Non-cognitive factors also influence farmers' adoption of climate change adaptation measures. Several studies have highlighted how farmers' risk preferences and self-efficacy play a role in their decision to adopt adaptation measures. In particular, Kreft (2021) highlights that non-cognitive capabilities explain farmers' behavior better than common demographic variables or resource

utilization, and are an important predictor of how farmers will respond in the face of climate change.

Therefore, this study comprehensively analyzes the factors that influence farmers' adoption of climate change adaptation measures, including not only **demographic and socio-economic factors**, but also access to **agro-climate information services** such as weather forecasting and agricultural extension services provided in the study area, **social connections**, and **non-cognitive abilities**. In doing so, we aim to provide practical and multidimensional policy implications for strengthening the climate change adaptive capacity of farmers in the Mekong Basin.

3.6. Analytical Framework

This study analyzes the determinants of farmers' decision to adopt climate change adaptation measures based on self-collected household survey data from Vietnam and Laos in the Mekong River Basin. The main dependent variable is the number of climate change adaptation measures adopted by farmers in the Mekong River Basin countries. In addition to individual climate change adaptation measures, we consider the unique characteristics of individual climate change adaptation measures and categorize them by similar characteristics to estimate the climate change adaptation measure index, which indicates the overall propensity to utilize climate change adaptation measures.

The classification of climate change adaptation measures according to similar characteristics is as follows: (1) Variety/Crop Diversification (Crop Diversification, Changing Seed Varieties), (2) Adjusting farming practices (Adjusting Planting Calendar, Adjusting Planting Techniques), (3) Water use management/infrastructure improvements (Water Use Management, Private/Communal Water Facility Improvement), (4) Climate information utilization, (5) Income Diversification, and (6) Insurance purchase. However, in Lao PDR, we excluded insurance as a climate change adaptation measure from our analysis because no households responded to climate change through insurance.

To measure the overall use of climate change adaptation measures by farmers, we estimated a climate change adaptation measure index using principal component analysis (PCA). Principal component analysis is a statistical technique for finding common major patterns in multivariate data consisting of several interrelated variables by reducing the data while preserving as much of the variation represented by these variables as possible, based on the correlations between the variables (Jolliffe, 2002). Since principal component analysis considers the correlations between multiple variables to identify key patterns and combines variables with weights that reflect them, it automatically estimates the optimal weights to produce an index without the need for subjective weighting.

Crop Diversification	Variety/crop diversification	Climate Change Adaptation Index
Changing Seed Variety		
Adjusting Planting Calendar	Adjusting farming practices	
Adjusting Planting Techniques		
Private Water Use Management	Water use management/ infrastructure improvements	
Improve Private Water Facilities		
Improve Communal Water Facilities		
Income Diversification	Income Diversification	
Using Agro–Climate Information	Climate information utilization	
Buying Insurance	Insurance purchase	

This study uses principal component analysis to set weights that take into account the correlation between individual climate change adaptation measures variables to summarize and combine the common information shared by each variable to create a composite index. The individual climate change adaptation measures variable(X_i)s a dummy variable that takes the value of 1 if the farmer has adopted climate change adaptation measures and 0 if not.

$$X_i = \begin{cases} 1 & \text{if a farm has implemented climate change adaption on measure } i \\ 0 & \text{if a farm has not implemented climate change adaption on measure } i \end{cases}$$

After standardizing the individual climate change adaptation measure variables, the covariance matrix is calculated using these values to determine the eigenvectors, which are the weights of the variables that constitute each principal component, and the eigenvalues, which indicate the variance explained by each principal component. Let X_i represent a climate change adaptation measure i , μ_i represent the mean of adaptation measure i and σ_i represent the standard deviation of adaptation measure i . Then, the standardized value of adaptation measure i (denoted as $X_{i, std}$) and the principal component(C) calculated using the vector of standardized adaptation measure variables(X_{std}) are as follows:

$$X_{i, std} = \frac{X_i - \mu_i}{\sigma_i}$$

$$C = \frac{1}{N} X_{std}^T X_{std}$$

$$CV_i = \lambda_i V_i$$

where V_i represents the eigenvector, and λ_i represents the eigenvalue.

Using the first principal component, which best explains the variability in the data among multiple principal components, the Climate Change Adaptation Measure Index is calculated as follows. The first principal component is expressed as a linear combination of each variable, and the weight assigned to each variable indicates the extent to which the variable contributes to the index. Here, p represents the number of individual climate change adaptation measures used to estimate the index.

$$\text{Climate Change Adaptation index} = v_1 X_1 + v_2 X_2 + \dots + v_p X_p$$

The main explanatory variables include demographic variables, socio-economic variables, information access variables, resource and technical factor variables, and various factors that may influence farmers' decision to adopt climate change adaptation measures, such as awareness of climate change, experience of climate change impacts, awareness of climate change adaptation measures, respondents' non-cognitive skills, and social connections. Demographic factors include farmers' age, gender, education level, total number of household members, and number of adults in the household, while socio-economic information includes an asset index estimated using PCA based on the household's ownership of individual assets, the size of farmland held, and whether the household head's main occupation is agriculture. Resource and technical factors included years of farming experience, access to finance, and access to agricultural extension services to acquire information and skills related to farming. We also considered farmers' non-cognitive capabilities, such as self-efficacy, which is a subjective perception of whether farmers believe they can solve difficulties or problems on their own, and social connectedness, which is measured by considering opportunities to get help in times of need or the presence of neighbors with whom they can share

agriculture-related information, as key explanatory variables. Farmers' awareness of climate change (awareness of climate change in general, awareness of drought, and awareness of flooding), past experience with climate change damage (severity of agricultural damage due to flooding or drought), and awareness of climate change adaptation measures were also considered as key explanatory variables. Climate information accessibility²¹⁾, which refers to the availability of climate information from various sources, was also considered as an important factor in the adoption of climate change adaptation measures.

In the analysis with the climate change adaptation measures index as the dependent variable, Multiple Ordinary Least Squares (Multiple OLS) regression was used to estimate the decision-making factors that explain farmers' propensity to adopt climate change adaptation measures, as follows To mitigate endogeneity issues by controlling for differences in geographic heterogeneity, the factors affecting climate change adaptation decisions were analyzed by controlling for village-level fixed effects.

$$(3-1) \quad y_i = \alpha + \beta_1 access_i + X_i \beta_2 + u_i^{22})$$

y_i : Climate Change Adaptation Measure Index

$access_i$: Climate Information Accessibility

X_i : Explanatory Variable Vector (Factors Influencing Decision-Making on Climate Change Adaptation Measures)

u_i : Error Term

In cases where the dependent variable is a dummy variable, such as the adoption of individual climate change adaptation measures and the adoption of climate change adaptation measures categorized by characteristics, logistic regression or logit analysis was used in addition to linear probability model (LPM) using linear

21) For climate change information uptake, the analysis is broken down by information received (weather forecasts, agricultural advice, etc.), source of information (radio, village-level bulletin boards, mobile applications, etc.), and project (DeRisk, LaCSA, local government agricultural maps).

22) This model and all subsequent models use heteroscedasticity robust standard errors.

regression analysis to estimate the decision-making factors of farmers' adoption of climate change adaptation measures as follows.²³⁾

$$(3-2a) \quad y_i^* = \alpha + \beta_1 advise_i + X_i \beta_2 + u_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases}$$

$$(3-2b) \quad P(y_i = 1) = \frac{\exp(\alpha + \beta_1 advise_i + X_i \beta_2 + u_i)}{1 + \exp(\alpha + \beta_1 advise_i + X_i \beta_2 + u_i)}$$

In addition, we utilize the Seemingly Unrelated Regression (SUR) estimator (β_{SUR}) proposed by Zellner (1962) because the efficiency of the least squares estimation method for each individual climate change adaptation measure and the use of climate change adaptation measures in a category may be impaired due to the correlation between the error terms of the dependent variable.

$$\beta_{SUR} = [X'(\Sigma^{-1} \otimes I_3)X]^{-1} X'(\Sigma^{-1} \otimes I_3)Y$$

For the actual estimation, we use the variance-covariance matrix estimated from the OLS analysis for each dependent variable to jointly derive the Generalized Least Squares (GLS) estimates ($\beta_{\widehat{SUR}}$). In subsequent models, when multiple dependent variables are used that are correlated, we use a model that takes into account the correlation between the error terms.

In addition, we conducted ordered logistic regression analysis to estimate the intensity of climate change adaptation and future adoption intentions for each climate change adaptation measure, as farmers may have different adoption propensities depending on their knowledge of the adaptation measure and their willingness to adopt or continue to utilize the measure in the future. Previous studies have mainly used ordinary logit or probit models with the dependent variable being whether or not adaptation measures have been implemented, but in this study, in addition to logit analysis, an ordered logit model was used to analyze

23) For convenience, the same symbols as before will be used for variables and variable coefficients. However, it should be noted that each represents a different estimated value in practice.

the intensity of climate change adaptation measures (Long, 1997). The intensity of implementation of each climate change adaptation measure was tested by estimating whether the effect of the explanatory variables on the categorical dependent variable composed of the ordinal scale is significant by dividing the five categories of climate change adaptation measures into five ordinal scales, considering whether they are aware of the measure, whether they know how to implement the measure, whether they are currently implementing the measure, and whether they intend to implement the measure in the future.

$$(3-3) \quad P(y_i > j) = \frac{\exp(X_i' \beta - \tau_j)}{1 + \exp(X_i' \beta - \tau_j)} \quad j = 1, 2, 3, 4, 5$$

$y_i = 1$: Unaware of adaptation measures

$y_i = 1$: Aware of adaptation measures but do not know how to implement them

$y_i = 2$: Know how to implement adaptation measures but have not implemented them in the past year

$y_i = 3$: Implemented adaptation measures in the past year but have no intention to continue in the future

$y_i = 5$: Implemented adaptation measures in the past year and intend to continue in the future

3.7. Data

3.7.1. Household Survey Data

We conducted farmer surveys in Vietnam and Laos in collaboration with local partner organizations. In Vietnam, we surveyed farmers in Tien Giang province who participated in a survey conducted by our research team in 2022 to build panel data. Panel data is data collected from the same people at multiple points in time, centered on the same survey questions, and has the following advantages. First, you can observe how a particular topic changes over time, and second, you can obtain time series data as well as cross-sectional data for the information you need. This has the advantage of providing multi-dimensional information.

In the case of Vietnam, the survey was conducted in two communes within each of the five districts in Tien Giang province where the 2022 survey was conducted, and two villages within each commune. The districts, communes, and villages were randomly selected for the 2022 survey. The survey was conducted from September 5 to September 19, 2024 (surveyor training and pre-survey period: September 5 to September 8, 2024), and the number of respondents per village was approximately 16 households, with a minimum of 11 and a maximum of 20 households responding, depending on the number of traceable households that participated in the 2022 survey.

In Laos, three districts within Vientiane province were selected for the survey, and two villages were randomly selected from each district, for a total of 308 households in six villages in three districts, and the survey was conducted from June 17 to June 28, 2024 (surveyor training and pre-survey period: June 17 to June 21, 2024). The survey was designed to include at least 47 households in each village, and care was taken to identify respondents so that the number of respondents did not vary across counties and villages.

The questionnaire consisted of questions measuring (1) household demographics,

(2) agricultural resource and asset status, (3) agricultural productivity and agricultural income by major crops, (4) awareness and attitudes toward climate change, (5) implementation of climate change adaptation measures, (6) access to climate change information, (7) self-efficacy and social relationships, and (8) subjective well-being. The survey has similar modules to the survey conducted in Vietnam, but the questions are tailored to the Lao farmers' context, measuring variables such as crops grown and climate information provided.

3.7.2. Summary Statistics of Surveyed Households

The number of surveyed households in each village in Laos and Vietnam is shown in <Table 3-1> and <Table 3-2>.

<Table 3-1> Distribution of surveys by village in Laos

District	Village	Number of completed surveys
Phônông	N00 T00	54 (17.5%)
	A00 X00	47 (15.3%)
Thoulakham	N00 P00	58 (18.8%)
	B00 P00	47 (15.3%)
Thoulakham	N00	48 (15.6%)
	P00 T00	54 (17.5%)
Total		308 (100%)

<Table 3-2> Distribution of surveys by village in Vietnam

District	Commune	Village	Number of completed surveys
Go Cong Dong	T000 H000	T00 N00	16 (5.0%)
		X00 G00	16 (5.0%)
	T000 T000	A00	16 (5.0%)
		A00	16 (5.0%)
Tan Phu Dong	T000 T000	T00 H00	16 (5.0%)
		T00 B00	16 (5.0%)
	P000 D000	L00 Q00	16 (5.0%)
		B00 T00	16 (5.0%)

District	Commune	Village	Number of completed surveys
Go Cong Tay	LOOO B000	K00 N00	16 (5.0%)
		L00 H00	16 (5.0%)
	D000 S000	T00 T00	16 (5.0%)
		K00 T00	16 (5.0%)
Go Cong Town	LOOO H000	H00 H00	16 (5.0%)
		H00 P00	16 (5.0%)
	B000 X000	T00 N00	16 (5.0%)
		A00	16 (5.0%)
Cho Gao	H000 D000	A00 C00	16 (5.0%)
		N00 H00	16 (5.0%)
	P000 K000	P00 L00	11 (3.4%)
		P00 K00	20 (6.3%)
Total			319 (100%)

The characteristics of the households that completed the survey include the following In terms of the gender distribution of household heads among households that completed the survey in Vietnam and Laos, the percentage of households headed by men was more than three times higher than the percentage of households headed by women in both Vietnam and Laos. In Vietnam, 240 (75.2%) of the 319 total households were headed by men and 79 (24.8%) were headed by women. Laos had 243 (78.9%) male-headed households and 65 (21.1%) female-headed households out of 308 total households. Vietnam had 243 (78.9%) male-headed households and 65 (21.1%) female-headed households.

〈Table 3–3〉 Household Characteristics by Country Survey

Household Characteristics		Vietnam		Laos	
Household Head Gender	Male	240 (75.2%)		243 (78.9%)	
	Female	79 (24.8%)		65 (21.1%)	
Household Head Age	20s	0 (0.00%)	Average age: 58.8 years (SD: 9.5 years)	3 (1.0%)	Average age: 55.1 years (SD: 11.3 years)
	30s	9 (2.8%)		34 (11.0%)	
	40s	43 (13.5%)		71 (23.1%)	
	50s	121 (37.9%)		96 (31.2%)	
	60s	103 (32.3%)		79 (25.7%)	
	70s and above	43 (13.5%)		25 (8.1%)	
Highest level of education received by household head	No degree	17 (5.3%)		16 (5.2%)	
	Primary school	134 (42.0%)		93 (30.2%)	
	Secondary school	117 (36.7%)		83 (27.0%)	
	Elementary vocational school	42 (13.2%)		59 (19.2%)	
	Intermediate vocational school or Vocational college	0 (0.0%)		46 (14.9%)	
	College	4 (1.3%)		11 (3.6%)	
Household Head Engaged in Agriculture		268 (84.01%)		240 (87.9%)	
Number of Household Members	Total Household Members	Avg: 3.9 (SD: 1.8)		Avg: 5.3 (SD: 2.1)	
	Adult Household Members	Avg: 3.9 (SD: 1.8)		Avg: 3.9 (SD: 1.4)	
	Minor Household Members	Avg: 0 (SD: 0)		Avg: 1.3 (SD: 1.4)	
Total Household Income ²⁴⁾	Total Household Income	113million VND		75.7million LAK	
	Income per Household Member	29million VND		16.1million LAK	
Financial Accessibility	None	220 (69.0%)		181 (58.8%)	
	Past Usage Experience	13 (4.0%)		85 (27.6%)	
	Currently Using	86 (27.0%)		42 (13.6%)	
Total		319 (100%)		308 (100%)	

24) As of 2023, the GDP per capita in Vietnam was 103 million VND, and in Laos, the GDP per capita was 36.7 million LAK. (Source: World Bank)

In terms of the age of the head of household, the average age of the head of household was 58.8 years old in Vietnam and 55.1 years old in Laos. In terms of the education level of the head of household, Vietnam had the majority of households with a head with primary or secondary education (78%). In Lao PDR, about 57% of households had primary or secondary education, and about 19% had a two- or four-year university education. In Vietnam, 268 out of 319 households (84.0%) and in Laos, 240 out of 308 households (87.9%) reported that the main occupation of the household head was agriculture. Even when the main occupation of the household head is not agriculture, the majority of households are involved in agricultural production activities. The average number of household members is 3.9 in Vietnam (3.9 adults and 0 children) and 5.3 in Lao PDR (3.9 adults and 1.3 children).

In terms of average annual household income, the average total annual household income in Vietnam is VND113 million, and the average income per household member is VND29 million. About 69% of all households in Vietnam have never used financial services such as loans or savings, while about 4% have used financial services in the past but are not currently using them, and about 27% are currently using financial services. The average annual gross household income in Laos is approximately 75.7 million Lao Kip (LAK), and the average income per household member is 16.1 million LAK. Approximately 59% of all respondent households in Laos have never used financial services such as loans or savings, while 28% have used financial services in the past but are not currently using them, and 14% are currently using financial services.

3.8. Key Findings

Farmers in Vietnam and Lao PDR perceived that climate change was occurring and had experienced impacts from actual climate change. Many farmers also expected climate shocks such as droughts and floods to occur in the future due to climate change.

Of the 308 total households surveyed in Laos, 275 (89.3%) strongly agreed or agreed that temperatures have increased in the past five years, and 233 (75.6%) strongly agreed or agreed that rainfall patterns have become unpredictable in the past five years. In fact, nearly 60% (185 households) of households surveyed in Laos have experienced drought in the past three years, and more than half (109 households) of those who have experienced drought have experienced severe drought. About 51% (157 households) of farmers expect droughts to occur in the next three years, and about 53% (163 households) believe that climate change will make droughts more frequent and severe. In addition, about 29% (89 households) of households will be affected by flooding in the next three years, with 44% (39 households) of those affected experiencing severe flooding. However, in contrast to perceptions of the future threat of drought, only 16% (48 households) expected flooding to occur in the next three years, and only 19% (59 households) expected flooding to occur more frequently and more severely due to climate change.

Of the 319 households surveyed in Vietnam, 156 (48.9%) reported experiencing damage from drought since the 2022 survey, and 144 (45.1%) reported experiencing severe damage from drought. Along with drought, 134 households (42.0%) experienced saltwater intrusion, a common climate disaster in the Mekong Delta region of Vietnam, and 128 households (40.1%) experienced severe damage due to saltwater intrusion. In contrast, only 36 households (11.3%) experienced damage from flooding after 2022 and 29 households (9.1%) experienced severe damage.

In order to respond to climate change and climate shocks caused by climate change, we investigated what climate change adaptation measures farmers in Vietnam and

Laos are adopting and how they perceive climate change adaptation measures. The number of households surveyed that are aware of how each adaptation measure can be used to respond to climate change, the number of households that have actually implemented each adaptation measure in the past year, and the number of households that are willing to implement each adaptation measure in the future are shown in the table below. In Vietnam, farmers have adopted and implemented the following climate change adaptation measures in the following order: **(1) field preparation, (2) adjusting planting techniques, (3) using Agro-climate information, (4) private water use management, and (5) private water use management.** In Lao PDR, farmers adopted and implemented climate change adaptation measures in the following order: **(1) changing seed variety, (2) adjusting planting techniques, (3) adjusting planting calendar, (4) using Agro-climate information, and (5) crop Diversification.** In Vietnam, the adoption rate of climate change adaptation measures through water use management and individual water facility improvement was higher, while in Lao PDR, the adoption rate was lower. This suggests that Lao PDR has fewer resources and capacity to manage water use and improve water facilities at the household level than Vietnam. In addition, in both countries, many farmers are responding to climate change by adjusting farming techniques and utilizing agro-meteorological information.

〈Table 3-4〉 Knowledge and Implementation of Climate Change Adaptation Measures by Country

Climate Change Adaptation Measures	Vietnam			Laos		
	Knowledge	Implementa-tion	Willingness to act	Knowledge	Implementa-tion	Willingness to act
Adjusting Planting Calendar	144 (45.1%)	68 (21.3%)	84 (26.3%)	105 (34.1%)	104 (33.8%)	105 (34.1%)
Crop Diversification	86 (27.0%)	46 (14.4%)	59 (18.5%)	95 (30.8%)	94 (30.5%)	96 (31.2%)
Changing Seed Variety	117 (36.7%)	60 (18.8%)	84 (26.3%)	113 (36.7%)	111 (36.0%)	113 (36.7%)
Field Preparation	202 (63.3%)	170 (53.3%)	184 (57.7%)	46 (14.9%)	46 (14.9%)	43 (14.0%)
Adjusting Planting Techniques	176 (60.5%)	148 (46.4%)	164 (51.4%)	109 (35.4%)	105 (34.1%)	100 (32.5%)

Climate Change Adaptation Measures	Vietnam			Laos		
	Knowledge	Implementation	Willingness to act	Knowledge	Implementation	Willingness to act
Private Water Use Management	119 (37.3%)	103 (32.3%)	119 (37.3%)	7 (2.3%)	7 (2.3%)	9 (2.9%)
Improving Private Water Facilities	182 (57.1%)	120 (37.6%)	143 (44.8%)	12 (3.9%)	12 (3.9%)	10 (3.3%)
Improving Communal Water Facilities	24 (7.5%)	17 (5.3%)	27 (8.5%)	5 (1.6%)	5 (1.6%)	5 (1.6%)
Income Diversification	101 (31.7%)	81 (25.4%)	91 (28.5%)	29 (9.4%)	28 (9.1%)	25 (8.1%)
Buying Insurance	48 (15.0%)	26 (8.2%)	43 (13.5%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Using Agro-Climate Information	142 (44.5%)	133 (41.7%)	135 (42.3%)	99 (32.1%)	95 (30.8%)	81 (26.3%)
Total	319 (100%)			308 (100%)		

The majority of households perceive climate change adaptation measures positively. In Vietnam, 63% of respondents (201 households) perceived that climate change adaptation measures are effective in increasing agricultural productivity, and 60.2% (192 households) perceived that people believe it is important to implement climate change adaptation measures. In Lao PDR, 66% of respondents (203 households) perceived that climate change adaptation measures are effective in increasing agricultural productivity, and 67% (206) perceived that people believe it is important to implement climate change adaptation measures.

Agricultural extension services train farmers on new farming techniques, varieties, equipment, and pest management methods, and provide essential information about agriculture, such as weather and market information. Especially in LMICs, they are an important means for farmers to gain the information and empowerment they need to respond to climate change and increase agricultural productivity. In Vietnam, 110 households (34.5%) reported having participated in agricultural extension services since 2022, of which 85 participated in a public agricultural extension services provided by the government and 52 participated in a private agricultural extension services. In Vietnam, households that have participated

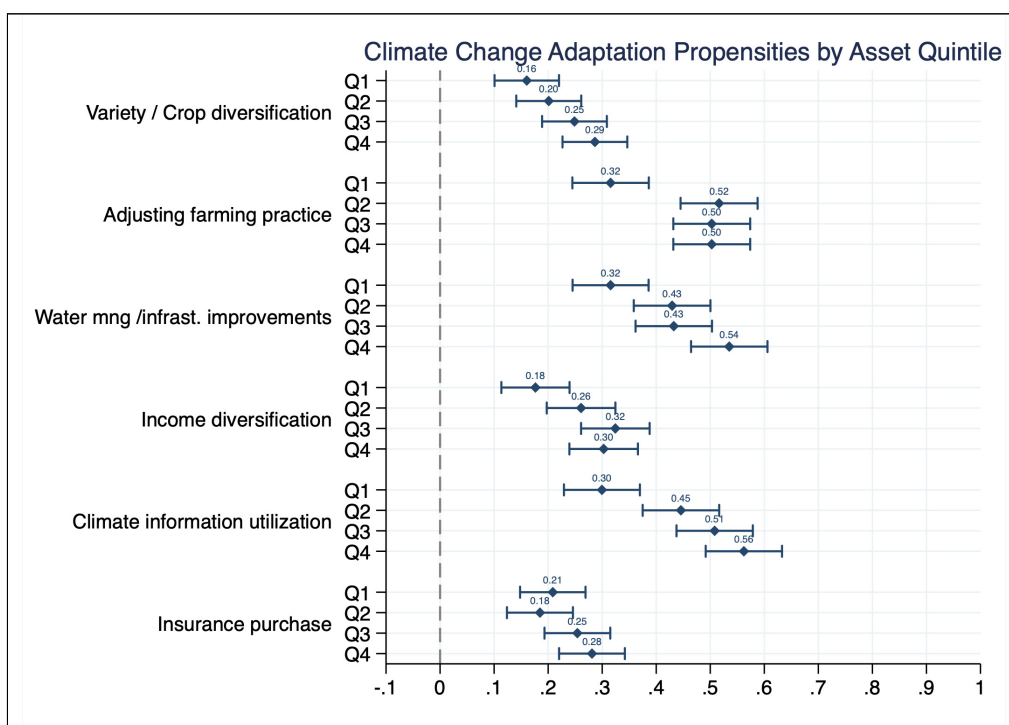
in agricultural extension services have received an average of 1.6 trainings. In Lao PDR, 105 households (34.1%) had participated in agricultural extension services in the past three years. Of these, 86 households participated in agricultural extension services provided by the government, while 50 households participated in agricultural extension services provided by NGOs and other private organizations. In particular, 33 households (10.7%) had received training on how to use the LaCSA application through agricultural extension services, with an average of two trainings.

Regarding access to climate information in the surveyed areas, in Vietnam, 74.6% (238 households) of the surveyed households have access to climate information from DeRisk, such as weather forecasts beyond 2022, climate-related agricultural advice, and DeRisk. Only 23 households (7.2%) have access to climate information provided by DeRisk through village bulletin boards, which is likely due to the fact that the DeRisk program has been terminated and is not providing ongoing information. Other than DeRisk, 236 households (74.0%) have access to weather forecasting information and 111 households (34.8%) have access to agricultural extension services. In Lao PDR, 63% (193 households) of surveyed farmers have access to climate information, including post-2021 weather forecasts, climate-related agricultural advice, and LaCSA. Of these, 122 households (39.6%) had access to LaCSA, 85 households (27.6%) had access to weather forecasting information other than LaCSA, and 26 households (8.4%) had access to agricultural advisory services. However, only 95 households reported actually utilizing agro-meteorological information for climate change adaptation measures, indicating that despite the majority of households having access to climate information, not many farmers are using and applying this information to respond to climate change.

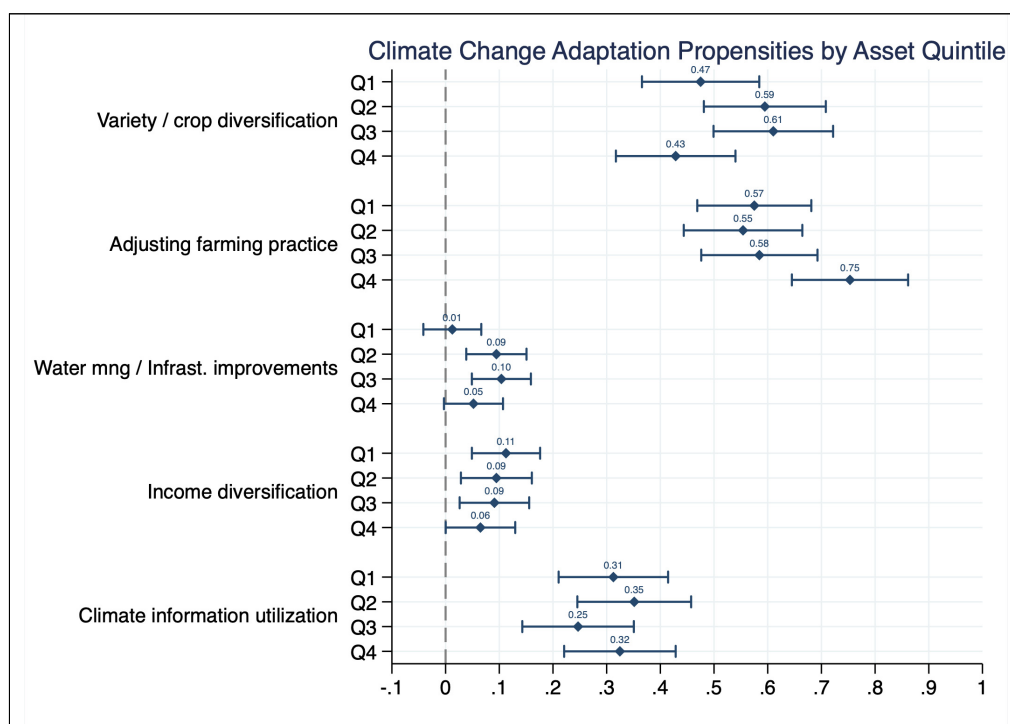
To analyze the factors that influence farmers' decisions to implement climate change adaptation measures, this study estimates an index of farmers' climate change adaptation measures and categorizes individual climate change adaptation measures into climate change adaptation measures with similar characteristics as follows: (1) variety/crop diversification (crop diversification, changing seed

varieties), (2) adjusting farming practices (adjusting planting calendar, adjusting planting techniques), (3) water use management/infrastructure improvements (water use management, private/communal water facility improvement), (4) climate information utilization, (5) income diversification, and (6) insurance purchase. However, in the case of Lao PDR, we excluded insurance as a climate change adaptation measure from our analysis because no households had purchased insurance.

[Figure 3–3] Climate Change Adaptation Propensity by Asset Quintile in Vietnam



[Figure 3–4] Climate Change Adaptation Propensity by Asset Quintile in Laos



First, we examine the impact of factors such as assets and land size on farmers' adoption of adaptation measures and find that these individual factors do not explain farmers' adaptation decisions. While we can identify some rough relationships, such as low-cost adaptation measures such as climate information utilization are adopted more actively by the lowest asset group, and water management and facility improvements are adopted more actively by the middle and higher asset groups, these relationships do not capture the effects of farmers' individual characteristics and institutional support, so in the following analysis, we analyze the determinants of farmers' decision to adopt climate change adaptation measures using multiple regression analysis.

The results of multiple linear regression analysis using the least-squares method, considering several control variables, on the climate change adaptation measures index calculated through principal component analysis (PCA) are summarized in <Table 3-5a> and <Table 3-5b>

In Lao PDR (Table 3-5a), **access to climate information** significantly explains farmers' climate change adaptation decisions. We also find that awareness of climate change in general is negatively related to the propensity to adapt, while non-cognitive capabilities such as **self-efficacy** are important determinants of the adoption of climate change adaptation measures. This suggests that simply being aware that climate change is real is not enough to change farmers' behavior to actively adopt and implement adaptation measures in response to climate change. However, self-efficacy, a non-cognitive ability to believe that one can solve a problem through one's own efforts when faced with a problem, was found to have a positive effect on the adoption of climate change adaptation measures, suggesting that farmers' adoption and implementation of climate change adaptation measures can be promoted through education or campaigns that can increase their self-efficacy to solve/mitigate problems in response to climate change through the adoption of climate change adaptation measures with the awareness that climate change is real. As existing studies on climate change adaptation measures lack consideration of non-cognitive capabilities such as self-efficacy, we use the control variables from model (3) in the table below in the subsequent analysis.

In the case of Vietnam (Table 3-5b), we used a panel fixed effects model to take advantage of panel data, and to compare the results, we examined the results of pooled OLS considering data from both time points and multiple regression analysis using data from each time point. Similar to the results in Laos, **access to climate information** and **self-efficacy** were positively correlated with the climate change adaptation action index in Vietnam. Panel fixed effects models were used to analyze the impact of changes in climate information access and self-efficacy between the two time points on the change in the climate change adaptation action index, suggesting that households with increased climate information access and self-efficacy increased their climate change adaptation action index. In addition, we found that the experience of drought damage is positively correlated with the climate change adaptation action index in Vietnam. This suggests that, depending on the local environment and conditions, **the**

experience of drought damage may affect farmers' decisions to adopt climate change adaptation measures differently.

In both Lao PDR and Vietnam, farmers with higher levels of climate information access and self-efficacy had higher levels of climate change adaptation measures, indicating a higher level of overall climate change adaptation measure utilization or activeness.

〈Table 3–5a〉 Factor Analysis of Climate Change Adaptation Measures Index in Laos

Laos	(1)	(2)	(3)
	Climate Change Adaptation Index	Climate Change Adaptation Index	Climate Change Adaptation Index
Gender (Female=1)	–0.009 (0.187)	0.069 (0.190)	0.121 (0.193)
Age (years)	0.020 (0.053)	0.015 (0.055)	0.012 (0.051)
Age Squared Term	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)
Education Level (years)	0.015 (0.020)	0.018 (0.020)	0.011 (0.020)
Agricultural Engagement	–0.029 (0.271)	0.025 (0.269)	0.085 (0.258)
Farming Experience (years)	0.002 (0.007)	0.002 (0.007)	–0.001 (0.007)
Number of Household Members	0.050 (0.040)	0.045 (0.045)	0.033 (0.040)
Number of Adults in Household	0.003 (0.080)	0.002 (0.082)	–0.008 (0.077)
Asset Index	–0.032 (0.057)	–0.030 (0.056)	–0.055 (0.054)
Size of Agricultural Land (Ha)	0.001 (0.018)	–0.003 (0.015)	–0.003 (0.013)
Access to Finance	–0.004 (0.103)	–0.035 (0.106)	–0.060 (0.105)
Number of Agricultural Extension Services	–0.011 (0.030)	0.004 (0.032)	–0.003 (0.031)
Access to Climate Information	0.569*** (0.159)	0.586*** (0.160)	0.552*** (0.155)
Awareness of Climate Change (Normalized to a 0–1 Index)	–	–0.791** (0.345)	–0.782** (0.345)
Awareness of Drought Risk (Normalized to a 0–1 Index)	–	–0.293 (0.311)	0.043 (0.326)

Laos	(1)	(2)	(3)
	Climate Change Adaptation Index	Climate Change Adaptation Index	Climate Change Adaptation Index
Awareness of Flood Risk (Normalized to a 0–1 Index)	–	0.307 (0.289)	0.403 (0.289)
Experience with Drought (Normalized to a 0–1 Index)	–	–0.093 (0.228)	–0.154 (0.223)
Experience with Flood (Normalized to a 0–1 Index)	–	–0.135 (0.232)	0.059 (0.232)
Social Network (Normalized to a 0–1 Index)	–	–	–0.454 (0.497)
Self-Efficacy (Normalized to a 0–1 Index)	–	–	1.788*** (0.421)
Constant	–1.426 (1.429)	–0.634 (1.516)	–1.578 (1.483)
Observations	273	273	273

Village fixed effects are included. Heteroscedasticity robust standard errors in parentheses.

* p < 0.10, ** p < 0.05, *** p < 0.01

〈Table 3–5b〉 Factor Analysis of Climate Change Adaptation Measures Index in Vietnam

Vietnam	Climate Change Adaptation Measures Index			
	(1) Panel Fixed Effects Model (1st and 2nd Survey)	(2) Pooled OLS (1st and 2nd Survey)	(3) Multiple Regression Analysis (1st Survey)	(4) Multiple Regression Analysis (2nd Survey)
Gender (Female=1)	–	0.030 (0.084)	0.014 (0.106)	0.107 (0.173)
Age (years)	0.122 (0.119)	0.076* (0.042)	0.098* (0.053)	0.036 (0.097)
Age Squared Term	–0.001 (0.001)	–0.001* (0.000)	–0.001* (0.000)	–0.000 (0.001)
Education Level (years)	0.165 (0.101)	0.051* (0.025)	0.046* (0.024)	0.049 (0.040)
Agricultural Engagement	–0.348* (0.210)	0.166 (0.136)	0.108 (0.165)	0.077 (0.382)
Number of Household Members	0.052 (0.088)	0.031 (0.029)	0.029 (0.030)	0.010 (0.052)
Asset Index	0.397* (0.219)	0.154 (0.090)	0.021 (0.113)	0.293** (0.129)
Size of Agricultural Land (Ha)	–1.92e–06 (4.87e–06)	4.56e–06 (3.20e–06)	4.45e–06* (2.56e–06)	9.64e–06 (0.0000186)
Access to Finance	–0.182 (0.292)	0.050 (0.123)	0.071 (0.134)	–0.012 (0.286)

Vietnam	Climate Change Adaptation Measures Index			
	(1) Panel Fixed Effects Model (1st and 2nd Survey)	(2) Pooled OLS (1st and 2nd Survey)	(3) Multiple Regression Analysis (1st Survey)	(4) Multiple Regression Analysis (2nd Survey)
Number of Agricultural Extension Services	0.203 (0.223)	0.303** (0.136)	0.435** (0.169)	0.308 (0.195)
Access to Climate Information	0.599*** (0.199)	0.802*** (0.154)	0.979*** (0.175)	0.649*** (0.224)
Experience with Saltwater Intrusion (Normalized to a 0–1 Index)	0.057 (0.218)	–0.121 (0.150)	–0.104 (0.208)	–0.006 (0.272)
Experience with Drought (Normalized to a 0–1 Index)	0.533** (0.224)	0.639*** (0.125)	0.664*** (0.185)	0.487** (0.201)
Experience with Flood (Normalized to a 0–1 Index)	–0.067 (0.309)	0.172 (0.188)	0.828 (0.623)	0.049 (0.261)
Social Network (Normalized to a 0–1 Index)	1.282 (1.029)	0.594 (0.676)	0.642 (0.942)	0.062 (1.069)
Self-Efficacy (Normalized to a 0–1 Index)	1.447** (0.639)	1.358*** (0.300)	1.720*** (0.544)	1.451*** (0.435)
Time Fixed Effect (Second Survey = 1)	–0.787*** (0.288)	–0.624** (0.249)	–	–
Constant	–7.363* (4.125)	–3.790** (1.339)	–5.317*** (1.588)	–3.376 (2.732)
Observations	654	654	384	270

Heteroscedasticity robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results of the analysis of the factors influencing the implementation of each climate change adaptation measure ((1) Variety/crop diversification, (2) Adjusting farming practice, (3) Water use management/infrastructure improvements, (4) Income diversification, (5) Climate information utilization, and (6) Insurance purchase) categorized by similar characteristics are shown in Table 3-6a and Table 3-6b. In the case of Lao PDR (Table 3-6a), we analyzed the decision-making factors for the adoption of five types of climate change adaptation measures,

excluding the utilization of climate change adaptation measures through the purchase of insurance because no farmers purchased insurance. In Lao PDR, we did not find any common factors affecting the adoption of all climate change adaptation measures, but we can see that **agricultural extension services, access to climate information, and self-efficacy** are positively related to the adoption and implementation of some adaptation measures. In the case of Vietnam (Table 3-6b)), we categorized climate change adaptation measures into six types and analyzed the decision-making factors for adopting each type of adaptation measure using panel fixed effects models and pooled OLS. The results show that different influencing factors are identified for each type of adaptation measure. As in the case of Lao PDR, we did not find any common factors affecting the adoption of all climate change adaptation measures. However, similar to the Lao analysis, **agricultural extension services, access to climate information, and self-efficacy** were found to have a significant impact on the adoption and implementation of some adaptation measures. The fact that no common factors were found to influence the decision to adopt all climate change adaptation measures in both Lao PDR and Vietnam suggests that different factors may influence farmers' decisions depending on the type and nature of each adaptation measure. This suggests that policies to promote the adoption of climate change adaptation measures need to be tailored in different ways, taking into account the type and nature of the adaptation measures being targeted, when formulating policies and implementing them on the ground.

In the case of Lao PDR, the proactivity of implementing climate change adaptation measures, which considers farmers' decision-making processes such as knowledge, implementation, and future intention to implement adaptation measures, as well as whether or not they have adopted climate change adaptation measures, was made into an ordinal variable, and factor analysis of climate change adaptation measure adoption was conducted through ordinal logit analysis, and the coefficients were presented as odds ratios (Table 3-7)). In Lao PDR, **agricultural extension services** are positively correlated with income diversification and climate information

utilization. In addition, **access to climate information** promotes adjustment of varieties/crops and farming methods, but is negatively associated with climate information utilization. This confirms that access to climate information alone does not necessarily lead to active uptake of climate information. **Self-efficacy** is also positively correlated with variety/crop and farming practice adjustments, but negatively correlated with climate information utilization. Therefore, it is worth considering the possibility that the belief in one's own ability to solve problems may be a factor that leads to more active adoption of other climate change adaptation measures, such as variety/crop diversification or farming practice adjustments, rather than the use of external information (climate information). Awareness of climate change in general has also been shown to inhibit response, suggesting that awareness of climate change can lead to fatalism. However, awareness of specific events, such as awareness of specific extreme weather events (e.g., flooding), may facilitate climate change action.

〈Table 3–6a〉 Analysis of Decision–Making Factors for the Adoption of Climate Change Adaptation Measures by Category in Laos

Laos	(1) Variety/crop diversification	(2) Adjusting farming practice	(3) Water use management/ infrastructure improvements	(4) Income diversification	(5) Climate information utilization
Gender (Female=1)	0.002 (0.074)	0.107 (0.080)	0.101* (0.052)	–0.030 (0.047)	–0.084 (0.072)
Age (years)	0.012 (0.023)	0.019 (0.023)	0.008 (0.011)	0.011 (0.012)	0.017 (0.018)
Age Squared Term	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)
Education Level (years)	–0.008 (0.009)	0.015* (0.008)	–0.003 (0.004)	0.002 (0.005)	0.003 (0.007)
Agricultural Engagement	0.097 (0.120)	0.201* (0.110)	0.003 (0.058)	–0.158** (0.065)	0.112 (0.106)
Farming Experience (years)	–0.004 (0.003)	–0.002 (0.003)	0.001 (0.002)	0.004** (0.002)	–0.003 (0.003)
Number of Household Members	0.012 (0.029)	–0.012 (0.020)	–0.013 (0.010)	0.003 (0.011)	–0.017 (0.016)
Number of Adults in Household	0.010 (0.037)	0.021 (0.031)	0.018 (0.015)	–0.023 (0.019)	0.007 (0.030)

Laos	(1)	(2)	(3)	(4)	(5)
	Variety/crop diversification	Adjusting farming practice	Water use management/ infrastructure improvements	Income diversification	Climate information utilization
Asset Index	-0.042* (0.025)	0.010 (0.022)	-0.001 (0.011)	-0.018 (0.018)	0.015 (0.021)
Size of Agricultural Land (Ha)	0.004 (0.009)	-0.001 (0.005)	0.007 (0.006)	-0.001 (0.004)	-0.002 (0.005)
Access to Finance	0.002 (0.041)	0.009 (0.046)	0.033 (0.023)	-0.035 (0.025)	0.014 (0.038)
Number of Agricultural Extension Services	0.018 (0.012)	0.004 (0.011)	0.005 (0.007)	0.027*** (0.009)	0.028*** (0.008)
Access to Climate Information	0.222*** (0.067)	0.141** (0.065)	0.014 (0.036)	0.041 (0.033)	-0.134** (0.058)
Awareness of Climate Change (Normalized to a 0–1 Index)	-0.143 (0.156)	-0.346** (0.147)	0.031 (0.070)	0.070 (0.079)	0.190 (0.134)
Awareness of Drought Risk(Normalized to a 0–1 Index)	0.238* (0.143)	0.040 (0.134)	-0.004 (0.065)	-0.050 (0.063)	0.145 (0.122)
Awareness of Flood Risk(Normalized to a 0–1 Index)	0.349*** (0.117)	0.029 (0.124)	-0.019 (0.059)	0.118* (0.065)	0.026 (0.122)
Experience with Drought(Normalized to a 0–1 Index)	-0.074 (0.091)	-0.031 (0.092)	0.056 (0.055)	-0.016 (0.053)	-0.013 (0.082)
Experience with Flood (Normalized to a 0–1 Index)	-0.193* (0.105)	0.075 (0.102)	0.028 (0.057)	0.015 (0.059)	-0.122 (0.097)
Social Network (Normalized to a 0–1 Index)	-0.090 (0.220)	-0.073 (0.197)	-0.045 (0.102)	0.015 (0.059)	0.219 (0.203)
Self-Efficacy (Normalized to a 0–1 Index)	0.541*** (0.172)	0.480** (0.185)	-0.081 (0.113)	0.041 (0.093)	-0.478*** (0.181)
Constant	-0.435 (0.690)	-0.453 (0.661)	-0.143 (0.285)	-0.204 (0.312)	-0.116 (0.544)
Observations	273	273	273	273	273

Village fixed effects are included. Heteroscedasticity robust standard errors in parentheses. Linear Probability Model(LPM) is used for (1)~(5).

* p < 0.10, ** p < 0.05, *** p < 0.01

<Table 3–6b> Analysis of Decision-Making Factors for the Adoption of Climate Change Adaptation Measures by Category in Vietnam

Vietnam	Variety/crop diversification		Adjusting farming practice		Water use management/ infrastructure improvements		Income diversification		Climate information utilization		Insurance purchase	
	(1) Panel FE	(2) Pooled OLS	(1) Panel FE	(2) Pooled OLS	(1) Panel FE	(2) Pooled OLS	(1) Panel FE	(2) Pooled OLS	(1) Panel FE	(2) Pooled OLS	(1) Panel FE	(2) Pooled OLS
Gender (Female=1)	–	0.050* (0.026)	–	–0.004 (0.039)	–	0.052 (0.047)	–	–0.033 (0.033)	–	–0.045 (0.033)	–	0.016 (0.031)
Age (years)	0.014 (0.039)	0.005 (0.009)	0.055 (0.036)	0.029** (0.013)	–0.039 (0.026)	0.011 (0.014)	0.069** (0.032)	0.004 (0.012)	0.038 (0.037)	0.031** (0.013)	–0.010 (0.025)	0.001 (0.008)
Age Squared Term	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000** (0.000)	0.000 (0.000)	–0.000 (0.000)	–0.001** (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000* (0.000)	0.000 (0.000)	0.000 (0.000)
Education Level (years)	0.047 (0.042)	0.011** (0.005)	0.040* (0.024)	0.014** (0.006)	0.008 (0.027)	0.006 (0.009)	0.041 (0.036)	0.003 (0.007)	0.040 (0.030)	0.015** (0.005)	0.003 (0.021)	0.007* (0.004)
Agricultural Engagement	–0.045 (0.076)	0.044 (0.039)	0.023 (0.079)	0.088* (0.044)	–0.002 (0.068)	0.029 (0.042)	–0.196*** (0.074)	–0.032 (0.046)	–0.152** (0.075)	0.039 (0.036)	–0.027 (0.078)	0.004 (0.049)
Number of Household Members	0.013 (0.024)	0.008 (0.011)	0.007 (0.034)	0.013 (0.010)	0.078*** (0.026)	–0.008 (0.010)	–0.021 (0.026)	–0.003 (0.010)	–0.005 (0.026)	0.014** (0.007)	–0.020 (0.026)	0.008 (0.008)
Asset Index	0.017 (0.059)	0.038 (0.025)	0.093 (0.077)	–0.041 (0.028)	–0.055 (0.067)	0.070** (0.027)	0.185** (0.083)	0.061** (0.025)	0.158** (0.072)	0.042 (0.033)	0.056 (0.062)	0.007 (0.026)
Size of Agricultural Land (Ha)	0.000 (0.000)	–0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)	–0.000*** (0.000)	–0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)	–0.000** (0.000)	–0.000 (0.000)
Access to Finance	–0.009 (0.092)	0.015 (0.035)	0.003 (0.080)	0.028 (0.041)	–0.130 (0.086)	–0.012 (0.041)	0.034 (0.092)	0.023 (0.043)	–0.106 (0.072)	–0.029 (0.030)	0.012 (0.077)	0.043 (0.033)
Number of Agricultural Extension Services	0.083 (0.068)	0.093** (0.042)	0.027 (0.080)	0.059 (0.046)	0.047 (0.076)	0.095** (0.039)	0.015 (0.067)	0.027 (0.045)	0.120** (0.059)	0.091** (0.041)	–0.120* (0.066)	–0.060 (0.041)
Access to Climate Information	0.064 (0.061)	0.107** (0.041)	0.249*** (0.070)	0.224*** (0.046)	0.203*** (0.072)	0.194*** (0.034)	0.009 (0.065)	0.057 (0.042)	0.126** (0.059)	0.221*** (0.049)	–0.001 (0.058)	0.099** (0.047)

Vietnam	Variety/crop diversification		Adjusting farming practice		Water use management/ infrastructure improvements		Income diversification		Climate information utilization		Insurance purchase	
	(1) Panel FE	(2) Pooled OLS	(1) Panel FE	(2) Pooled OLS	(1) Panel FE	(2) Pooled OLS	(1) Panel FE	(2) Pooled OLS	(1) Panel FE	(2) Pooled OLS	(1) Panel FE	(2) Pooled OLS
Experience with Saltwater Intrusion (Normalized to a 0–1 Index)	–0.042 (0.071)	–0.061 (0.041)	0.072 (0.077)	0.052 (0.048)	0.047 (0.074)	–0.036 (0.039)	–0.100 (0.074)	–0.066 (0.054)	0.064 (0.068)	–0.043 (0.059)	0.021 (0.059)	0.028 (0.039)
Experience with Drought (Normalized to a 0–1 Index)	0.096 (0.069)	0.143*** (0.044)	0.202*** (0.077)	0.206*** (0.056)	0.037 (0.069)	0.049 (0.052)	0.068 (0.072)	0.129*** (0.032)	0.120** (0.059)	0.150*** (0.030)	0.070 (0.062)	0.013 (0.045)
Experience with Flood (Normalized to a 0–1 Index)	–0.139 (0.113)	0.040 (0.081)	–0.109 (0.127)	–0.035 (0.072)	–0.080 (0.119)	0.054 (0.061)	0.309*** (0.105)	0.124 (0.094)	0.008 (0.087)	0.046 (0.072)	–0.028 (0.104)	–0.043 (0.055)
Social Network (Normalized to a 0–1 Index)	0.355 (0.318)	0.170 (0.185)	0.298 (0.397)	–0.085 (0.204)	0.298 (0.357)	0.417* (0.211)	–0.102 (0.338)	0.122 (0.156)	0.440 (0.335)	–0.055 (0.224)	0.087 (0.271)	0.171 (0.167)
Self-Efficacy (Normalized to a 0–1 Index)	0.138 (0.177)	0.222** (0.096)	0.393** (0.200)	0.373*** (0.122)	0.452** (0.177)	0.462*** (0.119)	0.493*** (0.180)	0.296*** (0.082)	0.033 (0.171)	0.128 (0.090)	0.196 (0.151)	0.042 (0.094)
Time Fixed Effect (Second Survey = 1)	–0.093 (0.089)	–0.083 (0.062)	–0.127 (0.108)	0.007 (0.072)	–0.027 (0.096)	–0.109 (0.074)	–0.075 (0.098)	–0.115 (0.077)	–0.303*** (0.084)	–0.161** (0.075)	–0.325*** (0.075)	–0.341*** (0.064)
Constant	–1.139 (1.277)	–0.353 (0.292)	–2.249* (1.145)	–1.056** (0.408)	0.808 (0.840)	–0.391 (0.442)	–2.138* (1.112)	0.162 (0.356)	–1.493 (0.990)	–0.697* (0.380)	0.404 (0.716)	0.405 (0.285)
Observations	654	654	654	654	654	654	654	654	654	654	654	654

Village fixed effects are included. Heteroscedasticity robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

〈Table 3-7〉 Analysis of Factors Influencing Proactiveness in Implementing Climate Change Adaptation Measures in Laos

Laos	(1) Variety/crop diversification	(2) Adjusting farming practice	(3) Water use management/ infrastructure improvements	(4) Income diversification	(5) Climate information utilization
Gender (Female=1)	1.132 (0.400)	1.697 (0.627)	4.080** (2.372)	0.802 (0.579)	0.550 (0.251)
Age (years)	1.034 (0.116)	1.082 (0.098)	1.083 (0.229)	1.403 (0.537)	1.158 (0.131)
Age Squared Term	1.000 (0.001)	0.999 (0.001)	0.999 (0.002)	0.997 (0.003)	0.999 (0.001)
Education Level (years)	0.960 (0.039)	1.046 (0.038)	0.972 (0.087)	1.029 (0.061)	1.001 (0.046)
Agricultural Engagement	1.291 (0.747)	2.220* (0.967)	1.663 (2.443)	0.086** (0.085)	2.103 (1.280)
Farming Experience (years)	0.984 (0.013)	1.002 (0.013)	1.018 (0.028)	1.072*** (0.028)	0.969** (0.014)
Number of Household Members	1.022 (0.133)	0.929 (0.080)	0.802 (0.159)	0.930 (0.119)	0.967 (0.096)
Number of Adults in Household	1.122 (0.197)	1.056 (0.141)	1.297 (0.377)	0.992 (0.246)	0.929 (0.163)
Asset Index	0.826 (0.098)	1.079 (0.107)	1.032 (0.238)	0.865 (0.177)	1.155 (0.147)
Size of Agricultural Land (Ha)	1.007 (0.031)	0.989 (0.026)	1.059 (0.046)	0.971 (0.039)	0.980 (0.032)
Access to Finance	1.004 (0.194)	1.015 (0.199)	1.930 (0.789)	0.562 (0.204)	0.954 (0.217)
Number of Agricultural Extension Services	1.137 (0.102)	1.040 (0.056)	1.091 (0.134)	1.196*** (0.060)	1.204*** (0.067)
Access to Climate Information	2.975*** (0.926)	1.976** (0.556)	1.867 (1.188)	1.644 (0.718)	0.401*** (0.133)
Awareness of Climate Change (Normalized to a 0–1 Index)	0.563 (0.430)	0.199** (0.133)	2.184 (2.911)	1.174 (1.213)	3.912 (3.578)
Awareness of Drought Risk(Normalized to a 0–1 Index)	2.914 (2.029)	1.633 (1.009)	0.702 (0.967)	0.576 (0.453)	3.040 (2.355)
Awareness of Flood Risk (Normalized to a 0–1 Index)	5.095*** (3.115)	1.291 (0.697)	0.550 (0.712)	2.730 (1.908)	1.086 (0.741)
Experience with Drought (Normalized to a 0–1 Index)	0.762 (0.315)	0.831 (0.356)	2.707 (3.567)	1.178 (0.836)	0.777 (0.374)
Experience with Flood (Normalized to a 0–1 Index)	0.342** (0.171)	1.485 (0.705)	1.794 (2.222)	1.730 (1.282)	0.658 (0.396)
Social Network (Normalized to a 0–1 Index)	0.590 (0.620)	1.054 (0.898)	0.230 (0.361)	0.841 (1.269)	2.144 (2.337)
Self-Efficacy (Normalized to a 0–1 Index)	10.648*** (9.135)	5.540** (4.113)	0.312 (0.754)	0.743 (0.738)	0.063*** (0.060)
Observations	273	273	273	273	273

Village fixed effects are included. Heteroscedasticity robust standard errors in parentheses.

* p < 0.10, ** p < 0.05, *** p < 0.01

3.9. Conclusions

Based on data collected through farmer surveys in Vietnam (Mekong River Delta) and Laos (Mekong River Basin), this study provides an in-depth look at **the uptake and utilization of climate change adaptation measures**, which are the main strategies that farmers can choose to adapt to climate change at the individual farm level, and analyzes **which factors influence farmers' decisions to adopt climate change adaptation measures**.

To do so, we examined the distribution of farmers' knowledge of, adoption of, and willingness to adopt and implement individual climate change adaptation measures in the study areas of Vietnam and Lao PDR. In Vietnam, the following climate change adaptation measures were adopted and practiced by farmers in the following order: **(1) field preparation, (2) adjusting planting techniques, (3) using Agro-climate information, (4) private water use improvements, and (5) water use management**. In Laos, farmers adopted and implemented climate change adaptation measures in the following order: **(1) changing seed variety, (2) adjusting planting techniques, (3) adjusting planting calendar, (4) using Agro-climate information, and (5) crop diversification**. In the case of knowledge of how to implement each adaptation measure, since knowing how to implement the measure enables households to actually adopt and implement the measure, we found that some of the households with knowledge actually adopted and implemented the measure, and the proportion of households with knowledge of adaptation measures and the proportion of households that actually adopted and implemented the measure were similar in both countries. However, the gap is wider in Vietnam than in Laos, indicating that Vietnamese farmers' knowledge of climate change adaptation measures is not as high as the rate at which they are implementing them. Therefore, it is important to consider **how to move beyond simply communicating knowledge about climate change adaptation measures to facilitating and supporting farmers to actually adopt and implement them**.

To analyze the determinants of the adoption of climate change adaptation measures, we used (1) **individual climate change adaptation measure adoption**, (2) **climate change adaptation measure adoption categorized by similar characteristics**, and (3) **climate change adaptation measure index** as dependent variables. Individual climate change adaptation measures were categorized by adaptation measures with similar characteristics, and a total of six climate change adaptation measure classifications were utilized: (1) Variety/crop diversification, (2) Adjusting farming practice, (3) Water use management/infrastructure improvements, (4) Income diversification, (5) Climate information utilization, and (6) Insurance purchase. In the case of Laos, we excluded households from the analysis because there were no households that responded to climate change by purchasing insurance. The climate change adaptation measures index was estimated using the principal component analysis method to measure the overall level of utilization or activeness of climate change adaptation measures by farmers, and the index was calculated using a weighted average method that linearly combines the variables with optimal weights, taking into account the correlation between each climate change adaptation measure adoption variable.

The main decision-making factors used as explanatory variables in the analysis include (1) **demographic variables** (age, gender, education level, number of household members, number of adult household members), (2) **socio-economic variables** (asset index, size of farmland held, whether the household head is a farmer), (3) **resource and technical factor variables** (years of farming experience, access to finance, access to agricultural extension services), as well as various aspects such as (4) **climate change awareness** (awareness of climate change, awareness of climate change adaptation measures), (5) **experience** (experience of damage caused by climate change), (6) **self-efficacy**, and (7) **social network** (social relationships). This provides a multifaceted and comprehensive analysis of the factors that influence farmers' decisions to adopt climate change adaptation measures.

Many farmers in Vietnam and Laos perceived that climate change was occurring and had experienced impacts such as floods and droughts due to actual climate change. Many farmers also expected climate shocks such as droughts and floods to occur in the future due to climate change. In addition, while the majority of households perceive climate change adaptation measures positively, relatively few farmers actually use and apply climate information to adopt climate change adaptation measures. Therefore, in addition to efforts **to improve awareness of climate change adaptation measures, policy support is needed to provide incentives and remove barriers to actually adopting and implementing positive adaptation measures.**

The analysis of household surveys in Laos and Vietnam also found that **access to climate information** significantly explains farmers' propensity to make general climate change adaptation decisions. In the case of Laos, perceptions of climate change in general were found to be a barrier to adaptation, while non-cognitive capabilities such as **self-efficacy** were found to be a factor in the adoption of adaptation measures. This suggests that awareness of the existence of climate change alone is not enough to lead to behavioral change to actively adopt and implement adaptation measures to respond to climate change, but must be accompanied by improvements in non-cognitive aspects such as self-efficacy.

In addition, we analyzed the factors affecting the adoption of each adaptation measure (1) variety/crop diversification, (2) adjusting farming practice, (3) water use management/infrastructure improvements, (4) income diversification, (5) climate information utilization, and (6) insurance purchase), and found that while we did not find a strong common influence on the adoption of all adaptation measures, we did find that **agricultural extension services, access to climate information, and self-efficacy** were positively associated with the adoption and implementation of some adaptation measures. However, in the case of Laos, we also found that when we analyzed the uptake of individual adaptation measures, we found that agricultural extension services were positively correlated with income diversification and climate information utilization. In addition, in Laos,

climate information access and self-efficacy were negatively correlated with climate information utilization, even though they facilitated variety/crop and farming method adjustments. This suggests that high access to climate information or high self-efficacy alone may not necessarily lead to active adoption of climate information. Therefore, to promote the use of climate information as an adaptation measure, **policy efforts are needed to provide and support programs that empower farmers to actively use climate information to adapt to climate change, not simply by increasing access to climate information or increasing self-efficacy**, but by providing appropriate ways to use climate information and apply it in practice. This is consistent with our findings that access to and use of agricultural extension services increases the adoption of adaptation measures through the use of climate information.

Taken together, these results suggest that access to information about climate change is not enough to increase the adoption of climate change adaptation measures, but must be accompanied by awareness of the specific situation of individual farmers, confidence in solving problems (self-efficacy), and capacity building through agriculture extension services. This suggests that to promote farmers' adoption of climate change adaptation measures, it is necessary to go beyond the general distribution of climate change-related resources (information, awareness, etc.) to identify and improve individual farmers' characteristics (self-efficacy) to use these resources effectively, and to enhance farmers' capacity to adapt to climate change through appropriate agricultural extension services. Furthermore, policy recommendations can be drawn for policy efforts to provide incentives or identify and remove barriers to farmers' adoption and utilization of climate change adaptation measures through actual behavioral change, using improved information access, awareness, and capacity.

4. The Effects of Climate Change Adaptation Measures on Farmers' Quality of Life

4.1. Study Objectives

The main objective of this study is to analyze the impact of the adoption of climate change adaptation measures on various outcomes of individual farmers. Specifically, the study aims to comprehensively analyze the impact of the adoption of climate change adaptation measures on various aspects of farmers' household income, agricultural income, household consumption expenditure, household food consumption expenditure, agricultural productivity, and subjective quality of life. The research methodology includes least-squares method, panel fixed effects analysis, and endogenous replacement regression analysis using instrumental variable estimation. In particular, in the case of Vietnam, an endogenous replacement regression model is applied to analyze the differences between farmers who adopted climate change adaptation measures and those who did not, in order to reduce the bias caused by endogeneity in assessing the impact of climate change adaptation measures on farmers. This study aims to identify the impact of climate change adaptation measures on farmers' performance and provide useful information and implications that can be utilized in policy formulation to support farmers' adoption of climate change adaptation measures.

4.2. Literature Review

Climate change and resulting climate shocks have complex impacts on various aspects of the lives of farming households and their members. In particular, climate change negatively affects agricultural productivity. Numerous studies have shown that fluctuations in rainfall, rising average temperatures, climate shocks such as floods and droughts, and the occurrence of pests and diseases adversely impact crop growth. Countries in the Mekong River Basin are severely threatened in terms of agricultural productivity and food security due to the combination of climate change impacts and regional vulnerabilities, leading to phenomena such as droughts, floods, and saltwater intrusion. Nguyen Van Tho (2022) reported that droughts and saltwater intrusion in the Mekong region, driven by climate change, have significantly affected the livelihoods and agricultural production of local farmers in recent years, especially in 2016 and 2020, impacting millions of hectares of agricultural land and posing a major threat to food security. Di Falco et al. (2011) and Onyeneke (2021) confirmed that the adoption of climate change adaptation measures by farmers has a positive impact on agricultural productivity.

Changes in agricultural productivity due to climate change also have a negative impact on agricultural labor. For example, in China, which borders the Mekong River countries, a 1°C increase in average temperature was projected to adversely affect crop production, reducing agricultural labor inputs by about 7% (Huang et al., 2020). In addition, Zhang and Shindell (2021) found that climate change will reduce the amount of agricultural labor by about 1 billion hours per year by the 2050s. This reduction in agricultural labor could put a severe strain on rural economies in countries with large numbers of agricultural laborers, such as Vietnam, Laos, and Cambodia.

The impacts of climate change are not limited to the agricultural sector, as it also exacerbates health and nutrition issues. Springmann et al. (2016) analyzed the pathways through which climate change leads to malnutrition and deaths, particularly the effects of poor health due to under nutrition and underweight

caused by a lack of fruits and vegetables in the diet. In addition, health conditions are exacerbated by sustained exposure to higher temperatures, while water scarcity and pollution caused by drought contribute to disease. Countries in the Mekong River Basin are projected to experience a continued increase in mortality associated with heat-related illnesses due to an increase in the number of days with temperatures above 35°C under all climate change scenarios, as well as urbanization and the urban heat island effect (World Bank, 2021). Honda et al. (2014) analyzed that under a specific climate scenario (A1B in CMIP3), the number of heat-related deaths in Southeast Asia is projected to increase by 295% by 2030 and 691% by 2050, while Dang et al. (2019) analyzed that the elderly and those with respiratory diseases will be more severely affected by high temperatures, making the impacts of climate change more severe for health vulnerable populations. In addition, food shortages and rising food prices due to declining agricultural productivity and weakened agricultural value chains can lead to under nutrition, which threatens the health of farming households. Von Braun (2022) found that climate change is likely to disrupt smooth food supply chains, making it more difficult to access nutrient-rich foods, which in turn will lead to health problems associated with under nutrition. These problems are most acute in low-income countries, where climate change resilience is low. Climate change also leads to psychological strain on farm household members, causing high levels of stress and adversely affecting mental health (McMichael and Lindgren, 2011).

As such, climate change-related shocks affect farm households across multiple sectors, including agriculture, labor, and health, ultimately leading to a decline in quality of life. The World Health Organization (WHO, 2004) defines 'quality of life' as 'an individual's perception of his or her own condition in relation to his or her goals, expectations, and interests within the culture and value system in which he or she lives', and it is believed that climate change-related degradation of agriculture, labor, and health can lead to a multidimensional decline in quality of life.

Against this background, this study analyzes the impact of climate change and the adoption of climate change adaptation measures on various aspects of farmers' quality of life, including income, consumption expenditure, subjective life satisfaction, and optimism for the future, based on survey data from farmers in the Mekong River basin in Vietnam and Laos. In particular, the effectiveness of climate change adaptation measures is assessed by comparing the differences in outcomes between farmers who have adopted adaptation measures and those who have not. This analysis will provide a deeper understanding of climate change impacts and responses of farmers in Mekong River Basin countries such as Vietnam and Laos. Therefore, this study will be extended to Mekong River Basin countries to comprehensively analyze the performance of farmers in various aspects of their quality of life as well as agricultural productivity.

4.3. Analytical Framework

This study analyzes the effects of climate change-induced shocks and the adoption of climate change adaptation measures based on survey data collected independently. To do this, the basic model includes whether households have experienced climate shocks (*shock*)²⁵). For climate shocks, the Vietnam household survey examines major climate shocks identified through stakeholder interviews, specifically droughts, floods, and saltwater intrusion, while in the case of Laos, the survey considers droughts and floods. Explanatory variables are selected as appropriate for explaining each outcome variable, and an analysis is conducted using Ordinary Least Squares (OLS) on outcome variables (y), including farm household agricultural production, agricultural income, labor input hours, household members' health status, and subjective quality of life. For example, in analyzing farm productivity (yield per unit of land), explanatory variables may include climate shock experience, as well as input factors (such as seeds, fertilizers, pesticides, and herbicides), irrigation methods, and experience with agricultural extension services from government.

The following model is estimated for the basic analysis.

$$(4-1) \quad y_{ij} = \alpha_j + \beta_1 shock_i + X_{ij}\beta_2 + u_{ij}$$

y_{ij} : Outcome Variables for Farm Households and Members j

$shock_i$: Experience with Climate Shocks

X_{ij} : Explanatory Factors for Outcome Variables j

u_{ij} : Error Term

In addition, we estimate the following model to analyze the impact of the adoption of climate change adaptation measures on individual outcome variables (y_{ij} in equation 4-2) and the extent to which they mitigate the effects of climate shocks

25) In the case of climate shocks, the Vietnam household survey examines major climate shocks identified through stakeholder interviews, specifically droughts, floods, and saltwater intrusion. For Laos, the survey considers droughts and floods

(β_3 in equation 4-3).

$$(4-2) \quad y_{ij} = \alpha_j + \beta_1 adapt_{ik} + \beta_2 X_{ij} + u_{ij}$$

$$(4-3) \quad y_{ij} = \alpha_j + \beta_1 adapt_i + \beta_2 shock_{ik} + \beta_3 shock_i * adapt_{ik} + \beta_4 X_{ij} + u_{ij}$$

$adapt_{ik}$: Adoption of Climate Change Adaptation Measures k

In addition, the cross-sectional nature of these models introduces endogeneity bias, which can lead to inaccurate estimates of coefficients. For example, if farmers with higher technical skills or better access to information actively adopt climate change adaptation measures, the results of the basic model based on cross-sectional data may overestimate the effect of climate change adaptation measures. To mitigate this problem, we use panel fixed effects analysis and instrumental variable estimation of survey data to analyze endogenous replacement regressions.

Instrumental variable estimation is a method of obtaining consistent estimates by securing a kind of exogenous variation by using an instrumental variable that is correlated with the endogenous variable but has a small degree of influence on the dependent variable (i.e., climate change adaptation decisions) without going through the endogenous variable. In the case of this study, we use the distance to sources of climate change information and key facilities (roads, village loudspeakers, village centers) as instrumental variables that are correlated with climate change access but are relatively unrelated to the dependent variable (adoption of climate change adaptation measures) except through climate change information uptake. In a study with a similar objective, Di Falco et al. (2011) use as instrumental variables the availability of information on climate change through agricultural maps and neighbors.

For the analysis with instrumental variables, we estimate the following model using two-stage least squares (2SLS).

$$(4-4) \quad y_{ij} = \alpha_j + \beta_1 adapt_{ik} + X_{ij}\beta_2 + u_{ij},$$

$$(4-5) \quad adapt_{ik} = \alpha_k + Z_i\pi + X_{ik}\xi + v_{ik},$$

For convenience, the estimate obtained using the two-step least-squares method when expressed in terms of $Y = X\beta + u$, $adapt = Z\pi + v$ is

$$(4-6) \quad \widehat{\beta}_{2sls} = [X'Z(Z'Z)^{-1}Z'X]^{-1}X'Z(Z'Z)^{-1}Z'Y$$

The consistency of the above estimates ($\widehat{\beta}_{1:2sls}$) obtained through this method with previous estimates can be checked.

By conducting the above analysis, it is possible to analyze the treatment effects of the introduction of climate change adaptation measures ($adapt_{ik}$) on different areas of the lives of farmers and their members. However, on the other hand, if there are systematic differences in characteristics between farmers adopting and not adopting climate change adaptation measures, the treatment effects of adopting climate change adaptation measures may be heterogeneous between adopters and non-adopters. Analyzing the difference in such treatment effects provides key insights into whether current climate change adaptation measures are being implemented effectively. Specifically, it allows us to predict whether promoting climate change adaptation measures among non-adopting farms would yield results similar to the treatment effects experienced by those that have already adopted them. To extend the literature in this regard, this study aims to explore this heterogeneity in treatment effects using an endogenous switching regression (ESR) analysis (Maddala and Nelson, 1975). Using this method, Di Falco et al. (2011) find that climate change adaptation measures such as water variety switching, soil and water conservation, and the adoption of mixed agroforestry lead to an increase in farmers' food productivity, based on data from Ethiopian farmers. They also find that the expected increase in productivity following the adoption of adaptation measures is larger for farmers who do not adopt adaptation measures than for those who do.

The farmer's choice of climate change adaptation measures is modeled as follows. For simplicity, we assume that there is only one type of climate change adaptation measure($Adapt_i$).²⁶⁾

$$(4-7) \quad Adapt_i^* = Z_i\omega + \eta_i, \text{ with } Adapt_i = 1, \text{ if } Adapt_i > 0 \text{ and } 0 \text{ otherwise}$$

$Adapt_i^*$: Marginal Utility from the Adoption of Climate Change Adaptation Measures

Z_i : Explanatory Factors for the Adoption of Climate Change Adaptation Measures

η_i : Error Term

That is, a farmer adopts a climate change adaptation measure if the marginal utility ($Adapt_i^*$) of adopting the adaptation measure is greater than zero ($Adapt_i = 1$).

When setting up a problem like this, farmers are placed in two different regimes: with and without climate change adaptation measures.

Situation 1: When Adaptation Measures are Adopted

$$(4-8) \quad y_{1i} = \alpha_1 + \beta_1 Adapt_{1i} + X_{1i}\beta_2 + \epsilon_{1i} \text{ if } Adapt_i = 1$$

Situation 2: When Adaptation Measures are Not Adopted

$$(4-9) \quad y_{2i} = \alpha_2 + \beta_3 Adapt_{2i} + X_{2i}\beta_4 + \epsilon_{2i} \text{ if } Adapt_i = 0$$

y_{ni} : Outcome Variable of Farm Household in Situation n ($n = 1$ or 2)

X_{ni} : Explanatory Factors for the Outcome Variable j in Situation n ($n = 1$ or 2)

ϵ_{ni} : Error Term in Situation n ($n = 1$ or 2)

For convenience, we assume that the error term has a trivariate normal distribution with mean zero as follows

$$(\eta \ \epsilon_1 \ \epsilon_2)' \sim N(0, \Sigma) \text{ with } \Sigma = \begin{pmatrix} \sigma_n^2 & \sigma_{n1} & \sigma_{n2} \\ \sigma_{1n} & \sigma_1^2 & . \\ \sigma_{2n} & . & \sigma_2^2 \end{pmatrix}$$

²⁶⁾ The actual analysis considers multiple adaptation measures.

In this situation, the basis of the error term can be expressed as the relationship between the probability density function and the cumulative distribution function.

$$(4-10) \ E[\epsilon_{1i}|Adapt_{ij} = 1] = \sigma_{1\eta} \frac{\phi(Z_i\alpha)}{\Phi(Z_i\alpha)}$$

This can be expressed as $\sigma_{1\eta}\lambda_{1i}$.

$$(4-11) \ E[\epsilon_{2i}|Adapt_{ij} = 0] = -\sigma_{2\eta} \frac{\phi(Z_i\alpha)}{1 - \Phi(Z_i\alpha)}$$

This can be expressed as $\sigma_{2\eta}\lambda_{2i}$.²⁷⁾

For efficient estimation, the Full Information Maximum Likelihood (FIML) method (Lee and Trost, 1978) is applied, which maximizes the following likelihood function.

$$(4-12) \ \ln L_i = \Sigma Adapt_{ij} [\ln \phi(\frac{\epsilon_{1i}}{\sigma_1}) - \ln \sigma_1 + \ln \Phi(\theta_{1i})] \\ + (1 - Adapt_{ij}) [\ln \phi(\frac{\epsilon_{2i}}{\sigma_2}) - \ln \sigma_2 + \ln (1 - \Phi(\theta_{2i}))] \\ \theta_{ki} = \frac{(Z_i\alpha + \rho_j \epsilon_{ji} / \sigma_k)}{\sqrt{1 - \rho_k^2}}$$

Through estimation, the expected values of the outcome variable based on the adoption of adaptation measures can be derived for both the group that adopted the measures and the group that did not.

$$E[y_{1i}|Adapt_{ij} = 1] = X_{1i}\beta_1 + \sigma_{1i}\lambda_{1i}$$

$$E[y_{2i}|Adapt_{ij} = 0] = X_{2i}\beta_2 + \sigma_{2i}\lambda_{2i}$$

$$E[y_{2i}|Adapt_{ij} = 1] = X_{1i}\beta_2 + \sigma_{2i}\lambda_{1i}$$

$$E[y_{1i}|Adapt_{ij} = 0] = X_{2i}\beta_1 + \sigma_{1i}\lambda_{2i}$$

27) If $\widehat{\sigma_{1\eta}}$ and $\widehat{\sigma_{2\eta}}$ are estimated to be statistically significant, this indicates that the adoption of adaptation measures is endogenous to the outcome variable.

The treatment effect of adaptation measures can be derived for both the adoption and non-adoption groups by examining the difference in the expected values of the outcome variable.

	Adoption Decision	Non-Adoption Decision	Treatment Effect
Actual Adopters	$E[y_{1i} Adapt_{ij} = 1]$	$E[y_{2i} Adapt_{ij} = 1]$ (<i>CounterFactual</i>)	TT Treatment Effect for the Adoption Group
Actual Non-Adopters	$E[y_{1i} Adapt_{ij} = 0]$ (<i>CounterFactual</i>)	$E[y_{2i} Adapt_{ij} = 0]$	TU Treatment Effect for the Non-Adoption Group
Marginal Effect	BH_1 Heterogeneity between the Adoption and Non-Adoption Groups	BH_2 Heterogeneity between the Adoption and Non-Adoption Groups	

$$TT = E[y_{1i}|Adapt_{ij} = 1] - E[y_{2i}|Adapt_{ij} = 1] = X_{1i}(\beta_1 - \beta_2) + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{1i}$$

$$TU = E[y_{1i}|Adapt_{ij} = 0] - E[y_{2i}|Adapt_{ij} = 0] = X_{2i}(\beta_1 - \beta_2) + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{2i}$$

$$BH_1 = E[y_{1i}|Adapt_{ij} = 1] - E[y_{1i}|Adapt_{ij} = 0] = (X_{1i} - X_{2i})\beta_{1i} + \sigma_{1\eta}(\lambda_{1i} - \lambda_{2i})$$

$$BH_2 = E[y_{2i}|Adapt_{ij} = 1] - E[y_{2i}|Adapt_{ij} = 0] = (X_{1i} - X_{2i})\beta_{2i} + \sigma_{2\eta}(\lambda_{1i} - \lambda_{2i})$$

Therefore, by using the difference in the expected values, the treatment effect of climate change adaptation measures can be derived for both the adoption and non-adoption groups among farm households in Vietnam and Laos. By comparing these values, the effects of individual adaptation measures can be analyzed, and the focus of adaptation support for the non-adoption group can be determined.

4.4. Key Findings

This study analyzed the impact of climate change shocks and the adoption of climate change adaptation measures on households' well-being and subjective quality of life, and found that in Laos, some climate change adaptation measures are positively correlated with farmers' well-being and quality of life. In <Table 4-1a>, the effects of climate change adaptation measures categorized by type according to the characteristics of individual adaptation measures were analyzed, and it was found that Adjusting farming practice (Adjusting Planting Calendar, Adjusting Planting Technology) had a significant positive correlation with consumption expenditure per household member, and a limited positive correlation with income per household member at the 10% significance level. Income diversification was found to be positively related to per capita income and optimism about future life, but negatively related to satisfaction with current life. Climate information utilization was found to increase income per household member and agricultural income per household member. In terms of subjective quality of life, climate information utilization was negatively associated with satisfaction with current life, but had a limited positive association with optimism about future life.

In the case of per capita income, which is an indicator of the income level of farm households, the amount of per capita income was significantly higher in farms that adopted climate change adaptation measures such as farming method adjustment, income diversification, and climate information utilization, but in the case of agricultural income per capita, which can be directly related to agricultural production, there was only a limited increase in agricultural income per capita in the case of climate information utilization. This suggests that utilizing climate information in agriculture can be an effective climate change adaptation measure to increase agricultural income and household income. The negative coefficient of income diversification, which increases household income but has no significant effect on increasing agricultural income, reaffirms that income

diversification may not increase agricultural income because farmers engage in off-farm income-generating activities, but may be beneficial in terms of overall household income.

In general, household consumption expenditure is widely used as a proxy for household living standards in LMICs where income is difficult to measure. However, consumption expenditure is characterized by the fact that it is not as volatile as income. This is because even if income is highly volatile in the short term, there are basic expenditures that need to be made in order to survive, and households tend **smoothing** their consumption by considering not only current income but also future income when making consumption expenditures. For Lao farm households, the adoption of climate change adaptation measures was not significantly associated with per capita consumption expenditure or per capita food expenditure. Only in the case of agricultural adaptation was there a significant positive correlation with consumption expenditure per household member.

Satisfaction with current life is negatively correlated with diversification of varieties and crops, income diversification, and use of climate information, which can be interpreted as households that have adopted climate change adaptation measures are less satisfied with their current life due to climate change. In contrast, optimism about future life is positively correlated with adaptation measures such as water management, income diversification, and climate information use, suggesting that households that have adopted these adaptation measures tend to be more optimistic about the future, even if they are less satisfied with their current life.

These results suggest that different types of climate change adaptation measures may have different impacts on farm households' well-being and subjective quality of life. The results also suggest that some adaptation measures are more effective than others, such as water resource management, which is expected to be relatively costly, or diversification of varieties and crops, which is associated with higher risks, because they can be undertaken at lower cost and with less risk while

maintaining the broad framework of current farming practices, such as adjustments to farming schedules, more active use of climate information in farming, and income diversification to diversify income risks from climate change. This suggests that climate change adaptation measures that are expected to be relatively low in cost and difficulty to implement, such as adjusting farming practice, climate information utilization, and income diversification, may be cost-effective in terms of improving farmers' well-being and quality of life.

In addition, we found that wealth index and access to finance, which represent the level of household assets, are positively related to household income, agricultural income, consumption expenditure, and food expenditure, as expected, as well as household well-being and satisfaction with current life. This suggests that increasing household assets or access to finance may lead to income-generating opportunities. In addition, from a policy support perspective, access to agricultural extension services is positively correlated with per capita household income and agricultural income, confirming the effectiveness of agricultural extension services in empowering farmers. These results suggest that the transfer of agricultural technology and information through rural maps and agricultural information services such as LaCSA may have contributed to the increase in farmers' productivity. At the same time, self-efficacy and social relationships are less correlated with income and consumption expenditures, which are indicators of well-being, but are associated with higher levels of satisfaction with current life. These results suggest that climate information provision, such as agricultural extension services at the local government level and agro-meteorological services implemented in cooperation with them, can have a positive impact on farmers' well-being. It also suggests that various aspects such as access to finance, self-efficacy, and social connections need to be considered when designing and implementing effective farmer support policies and programs.

〈Table 4-3〉 analyzes the effects of individual climate change adaptation measures ((1) adjusting planting calendar, (2) crop diversification, (3) changing seed varieties, (4) adjusting planting techniques, and (5) climate information utilization) most

actively adopted by Lao farmers on their livelihoods and quality of life, and shows similar results to the effects of climate change adaptation measures by type. Among the adaptation measures, Adjusting Planting Calendar and Adjusting Cultivation Technology showed different effects, with Adjusting Cultivation Technology increasing household income and agricultural income, while Adjusting Planting Calendar showed no significant effect in terms of income.

In the case of Vietnam, panel data were used to analyze the effects of six types of climate change adaptation measures on the quality of life of Vietnamese farmers using panel fixed effects models and pooled OLS (Table 4-1b). Panel fixed-effects models have the advantage of removing the effect of unobserved factors that do not change over time, thus reducing bias and estimating treatment effects that are closer to causal effects. However, it does not remove bias due to unobserved factors that change over time, so if important variables that change over time and affect households' well-being and quality of life are omitted, endogeneity problems may arise and bias estimates cannot be obtained.

The results in Table 4-1b show that for all six types of climate change adaptation measures, neither the change in the decision to adopt between two time points (panel fixed effects model) nor the adoption at each time point (pooled OLS) resulted in significant changes in household income and agricultural income. However, water management was found to increase per capita household consumption expenditure to a limited extent, and the adoption of income diversification measures was positively associated with per capita household consumption expenditure. No climate change adaptation measures were found to have a significant impact on food expenditure per household member or satisfaction with current life. In terms of optimism about future life, households that responded to climate change by purchasing insurance were less optimistic. This may be due to the fact that purchasing insurance is a type of action taken to prepare for future risks due to anxiety about the future.

In order to minimize the endogeneity problems that may arise from pooled OLS

using least squares estimation and panel fixed effects models using panel data, an endogenous logistic regression with two-stage least squares using instrumental variables was used to analyze the Vietnamese data. <Table 4-1c> shows the results of the endogenous regression analysis using instrumental variables (distance to roads, markets, village centers, access to information, etc.) for each type of climate change adaptation measure.

The average treatment effect (ATT) was significant for households that implemented the following measures: (1) variety/crop diversification, (2) adjusting farming practice, (3) water use management/infrastructure improvements, (4) income diversification, (5) climate information utilization, and (6) insurance purchase in terms of household income per household member and farm income. However, in the case of purchasing insurance, which is difficult to directly attribute to an increase in current household income and agricultural income, the ATT is negative, suggesting that the payment of premiums to purchase insurance and the moral hazard of purchasing insurance may cause a decrease in household income and agricultural income.

For consumption expenditures, which are relatively less volatile than income, the ATTs for all types of climate change adaptation measures show an increase in consumption expenditures per household member with each adaptation measure. However, in the case of per capita food expenditure, satisfaction with current life, and optimism about future life, the ATTs were different for each type of climate change adaptation measure. For optimism about future life, insurance purchase has a significant negative ATT, which is consistent with the panel fixed effects analysis.

The ATT results estimated from the endogenous fixed effects regression analysis confirm that the adoption of climate change adaptation measures by farmers, excluding the purchase of insurance, has a consistently positive effect on increasing household income and agricultural income, and may also have a positive effect on household consumption expenditure. However, nutrition intake

(food consumption expenditure) and subjective quality of life (satisfaction with current life and optimism about future life) may have different effects depending on the characteristics of different types of climate change adaptation measures, suggesting that it is necessary to consider the characteristics of the objectives and targets when formulating and implementing policies and projects to support farmers.

〈Table 4-1a〉 (Laos) Analysis of the Effects of Categorized Climate Change Adaptation Measures

Laos	(1)	(2)	(3)	(4)	(5)	(6)
	Income per Person (Log)	Agricultural Income per Individual (Log)	Consumption Expenditure per Head (Log)	Food Expenditure per Person (Log)	Satisfaction with Current Life	Optimism about Future Life
Variety/crop diversification	0.154 (0.108)	0.159 (0.115)	0.039 (0.056)	0.018 (0.030)	-0.073*** (0.022)	0.018 (0.021)
Adjusting farming practice	0.184* (0.105)	0.141 (0.116)	0.113** (0.048)	0.015 (0.031)	0.025 (0.023)	-0.019 (0.020)
Water use management/ infrastructure improvements	-0.180 (0.217)	-0.119 (0.239)	0.010 (0.091)	0.035 (0.084)	0.015 (0.034)	0.053* (0.030)
Income diversification	0.316** (0.144)	-0.261 (0.167)	0.125 (0.081)	0.023 (0.050)	-0.076** (0.030)	0.070** (0.028)
Climate information utilization	0.242** (0.114)	0.229* (0.138)	-0.043 (0.050)	0.049 (0.035)	-0.078*** (0.027)	0.047* (0.025)
Gender (Female=1)	-0.001 (0.124)	-0.015 (0.152)	-0.052 (0.050)	0.020 (0.040)	0.006 (0.026)	-0.002 (0.024)
Age (years)	0.092** (0.037)	0.054 (0.035)	0.033 (0.015)	0.021** (0.009)	0.016*** (0.006)	-0.003 (0.009)
Age Squared Term	-0.001** (0.0001)	-0.0005 (0.0003)	-0.0003** (0.0001)	-0.0002** (0.0001)	-0.0001** (0.0001)	0.00002 (0.0001)
Education Level (years)	0.015 (0.013)	-0.001 (0.015)	0.005 (0.006)	0.005 (0.004)	-0.002 (0.003)	0.001 (0.003)
Agricultural Engagement	0.012 (0.210)	0.295 (0.211)	-0.228** (0.105)	-0.097* (0.049)	0.082** (0.037)	-0.018 (0.040)
Farming Experience (years)	0.007 (0.005)	0.005 (0.005)	0.001 (0.002)	0.001 (0.001)	-0.001 (0.001)	0.000 (0.001)
Number of Household Members	-0.057* (0.033)	-0.046 (0.033)	-0.027* (0.014)	-0.009 (0.009)	-0.001 (0.006)	-0.018** (0.009)
Number of Adults in Household	-0.102* (0.053)	-0.107* (0.056)	-0.038* (0.022)	-0.049*** (0.013)	0.001 (0.010)	0.016 (0.011)

Laos	(1)	(2)	(3)	(4)	(5)	(6)
	Income per Person (Log)	Agricultural Income per Individual (Log)	Consumption Expenditure per Head (Log)	Food Expenditure per Person (Log)	Satisfaction with Current Life	Optimism about Future Life
Asset Index	0.097** (0.043)	0.134*** (0.046)	0.051** (0.021)	0.020* (0.011)	0.033*** (0.009)	-0.007 (0.007)
Size of Agricultural Land (Ha)	0.013 (0.025)	0.016 (0.026)	0.001 (0.006)	-0.001 (0.002)	0.007*** (0.003)	-0.003 (0.002)
Access to Finance	0.127* (0.073)	0.161** (0.081)	0.057 (0.040)	0.004 (0.022)	-0.018 (0.015)	0.013 (0.014)
Number of Agricultural Extension Services	0.041*** (0.016)	0.053*** (0.015)	0.006 (0.009)	0.001 (0.009)	0.005 (0.004)	-0.004 (0.003)
Access to Climate Information	-0.063 (0.120)	-0.008 (0.128)	-0.039 (0.056)	0.044 (0.030)	0.052** (0.024)	-0.073*** (0.020)
Awareness of Climate Change (Normalized to a 0-1 Index)	0.137 (0.220)	0.108 (0.249)	0.002 (0.131)	-0.0001 (0.066)	-0.080 (0.056)	0.105** (0.051)
Awareness of Drought Risk(Normalized to a 0-1 Index)	0.293 (0.210)	0.057 (0.238)	-0.005 (0.103)	-0.015 (0.063)	0.018 (0.050)	-0.056 (0.043)
Awareness of Flood Risk (Normalized to a 0-1 Index)	-0.247 (0.189)	-0.065 (0.190)	0.090 (0.090)	0.025 (0.065)	0.052 (0.039)	-0.038 (0.037)
Experience with Drought (Normalized to a 0-1 Index)	-0.269* (0.156)	-0.155 (0.175)	-0.080 (0.069)	-0.044 (0.046)	-0.027 (0.033)	0.029 (0.027)
Experience with Flood (Normalized to a 0-1 Index)	-0.023 (0.161)	-0.014 (0.170)	-0.115 (0.075)	-0.034 (0.042)	0.015 (0.035)	0.034 (0.034)
Social Network (Normalized to a 0-1 Index)	-0.348 (0.322)	-0.292 (0.332)	-0.243 (0.208)	-0.036 (0.091)	0.271*** (0.075)	-0.198*** (0.055)
Self-Efficacy (Normalized to a 0-1 Index)	-0.300 (0.296)	0.030 (0.307)	-0.138 (0.132)	-0.040 (0.091)	0.150** (0.067)	0.097* (0.051)
Constant	-0.052 (1.096)	0.398 (1.015)	0.501 (0.401)	0.091 (0.264)	-0.221 (0.166)	0.803*** (0.268)
Observations	273	273	273	273	273	273

Village fixed effects are included. Heteroscedasticity robust standard errors in parentheses.

* p < 0.10, ** p < 0.05, *** p < 0.01

〈Table 4-1b〉 (Vietnam) Analysis of the Effects of Categorized Climate Change Adaptation Measures

Vietnam	Income per Person (Log)		Agricultural Income per Individual (Log)		Consumption Expenditure per Head (Log)		Food Expenditure per Person (Log)		Satisfaction with Current Life		Optimism about Future Life	
	(1) Panel FE	(2) Pooled OLS	(1) Panel FE	(2) Pooled OLS	(1) Panel FE	(2) Pooled OLS	(1) Panel FE	(2) Pooled OLS	(1) Panel FE	(2) Pooled OLS	(1) Panel FE	(2) Pooled OLS
Variety/crop diversification	-0.108 (0.138)	0.009 (0.105)	-0.049 (0.119)	0.114 (0.100)	-0.064 (0.076)	0.025 (0.055)	-0.009 (0.098)	0.094 (0.077)	0.013 (0.030)	0.014 (0.029)	0.014 (0.020)	0.015 (0.013)
Adjusting farming practice	0.093 (0.126)	0.088 (0.106)	0.091 (0.138)	0.185 (0.122)	-0.113 (0.085)	0.056 (0.067)	-0.090 (0.097)	0.022 (0.064)	-0.008 (0.030)	0.003 (0.024)	-0.002 (0.019)	0.004 (0.014)
Water use management/infrastructure improvements	-0.006 (0.133)	0.048 (0.092)	0.076 (0.121)	-0.020 (0.082)	0.132* (0.070)	-0.005 (0.042)	0.042 (0.086)	-0.071 (0.051)	-0.009 (0.028)	-0.000 (0.023)	-0.004 (0.018)	-0.007 (0.012)
Income diversification	0.155 (0.141)	0.114 (0.093)	-0.045 (0.164)	0.008 (0.091)	0.070 (0.076)	0.134** (0.052)	0.125 (0.099)	0.084 (0.054)	-0.027 (0.032)	-0.008 (0.021)	0.034* (0.018)	0.010 (0.011)
Climate information utilization	0.107 (0.161)	-0.054 (0.114)	0.096 (0.168)	-0.097 (0.085)	-0.062 (0.072)	-0.026 (0.062)	0.050 (0.089)	0.065 (0.062)	-0.010 (0.036)	-0.014 (0.022)	-0.006 (0.017)	-0.020 (0.015)
Insurance purchase	-0.043 (0.148)	0.103 (0.094)	0.129 (0.168)	0.129 (0.091)	-0.038 (0.079)	-0.025 (0.077)	-0.118 (0.111)	-0.058 (0.071)	-0.024 (0.033)	-0.033 (0.029)	-0.064*** (0.022)	-0.036** (0.014)

Year and village fixed effects are included. Heteroscedasticity robust standard errors in parentheses. Control variables are included.

* p < 0.10, ** p < 0.05, *** p < 0.01

〈Table 4-1c〉 (Vietnam) Analysis of the Effects of Categorized Climate Change Adaptation Measures

Vietnam (Endogenous Switching Regression Analysis)	Income per Person (Log)		Agricultural Income per Individual (Log)		Consumption Expenditure per Head (Log)		Food Expenditure per Person (Log)		Satisfaction with Current Life		Optimism about Future Life	
	ATT	ATU	ATT	ATU	ATT	ATU	ATT	ATU	ATT	ATU	ATT	ATU
Variety/crop diversification	1.213*** (0.054)	-0.442*** (0.046)	1.504*** (0.060)	0.342*** (0.051)	0.470*** (0.030)	0.868*** (0.025)	0.187*** (0.023)	-0.377*** (0.024)	-0.099*** (0.008)	-0.233*** (0.006)	-0.002 (0.008)	0.049*** (0.006)
Adjusting farming practice	0.364*** (0.038)	-0.266*** (0.040)	0.576*** (0.044)	0.628*** (0.047)	0.124*** (0.021)	0.651*** (0.021)	-0.454*** (0.018)	-0.251*** (0.020)	-0.062*** (0.005)	-0.365*** (0.007)	0.087*** (0.005)	0.030*** (0.006)
Water use management/infrastru- cture improvements	0.300*** (0.047)	0.191*** (0.033)	0.372*** (0.057)	0.687*** (0.039)	0.175*** (0.021)	0.717*** (0.021)	-0.650*** (0.020)	-0.037* (0.020)	0.015*** (0.005)	-0.270*** (0.006)	0.073*** (0.006)	-0.184*** (0.005)
Income diversification	0.529*** (0.051)	-0.292*** (0.042)	1.656*** (0.069)	0.491*** (0.046)	0.242*** (0.025)	0.755*** (0.024)	0.043** (0.021)	-0.054** (0.024)	0.132*** (0.007)	-0.260*** (0.007)	0.015* (0.008)	0.020*** (0.006)
Climate information utilization	0.360*** (0.041)	0.139*** (0.038)	0.496*** (0.045)	0.718*** (0.045)	0.148*** (0.120)	0.423*** (0.025)	0.033** (0.017)	-0.306*** (0.022)	-0.089*** (0.005)	-0.265*** (0.006)	-0.007 (0.006)	0.013** (0.005)
Insurance purchase	-2.34*** (0.072)	0.903*** (0.046)	-1.619*** (0.074)	0.654*** (0.047)	0.304*** (0.058)	0.057** (0.025)	-1.455*** (0.031)	0.712*** (0.025)	0.122*** (0.009)	-0.216*** (0.007)	-0.056*** (0.009)	-0.211*** (0.006)

Heteroscedasticity robust standard errors in parentheses. Control variables are included.

* p < 0.10, ** p < 0.05, *** p < 0.01

The use of climate information can increase households' well-being and quality of life on its own, but in some cases it can also have synergistic effects when combined with other climate change adaptation measures. <Table 4-3> analyzes data from Laos to estimate the synergies between climate information use and different types of climate change adaptation measures, while <Table 4-4> estimates the synergies between climate information use and individual climate change adaptation measures. No synergies were found between climate information utilization and crop diversification, and no synergies were found between climate information utilization and varietal change measures for individual adaptation measures. This is to be expected given that crop or variety selection is determined by long-term and fundamental criteria rather than periodic climate information use, making it difficult to synergize the use of climate information in agricultural activities at the time of crop or variety selection and on an ongoing basis.

In the case of farming adjustments, the effectiveness is higher when accompanied by the use of climate information. This suggests that utilizing agricultural advice using weather and climate information for changes in farming methods, such as adjusting planting calendars or adjusting cultivation techniques, can lead to higher performance by enabling timely adjustments in farming methods considering weather conditions. Specifically, we found a limited but significant increase in household income when using climate information to adjust planting calendar, but no increase in agricultural income. This suggests that while it may be difficult to expect a significant increase in agricultural income through Adjusting Planting Calendar using climate information, it may contribute to an increase in non-farm income by enabling farmers to effectively carry out non-farm activities. Furthermore, when climate information is used to adjust cultivation techniques at a granular level, it tends to increase agricultural income significantly. This suggests that there may be significant synergies in agricultural production when climate information is combined with resumption technology adjustments.

However, climate information use does not appear to increase the effectiveness of climate change adaptation measures such as water management or income

diversification measures. This suggests that climate information use does not generally work in a way that increases the effectiveness of other climate change adaptation measures. For adaptation measures such as variety and crop diversification, water use management and facility improvements, and income diversification, where successful adoption depends on making decisions based on advance and generalized climate projections, this limited effect may be due to the different types of information needed rather than a lower need for climate information in adopting adaptation measures.²⁸⁾ Therefore, there is a need to closely examine the type and scope of climate information and agricultural advice provided to farmers to ensure that it is useful and relevant to farmers' various decision-making needs, so that climate information services can be designed to facilitate a range of climate change adaptation measures and work synergistically to contribute to actual improvements in agricultural productivity and livelihoods.

〈Table 4–2〉 (Laos) Analysis of the Effects of Individual Climate Change Adaptation Measures

Laos	(1) Income per Person (Log)	(2) Agricultural Income per Individual (Log)	(3) Consumption Expenditure per Head (Log)	(4) Food Expenditure per Person (Log)	(5) Satisfaction with Current Life	(6) Optimism about Future Life
Variety/crop diversification	0.082 (0.102)	0.140 (0.113)	0.117** (0.059)	0.022 (0.035)	0.015 (0.024)	-0.039* (0.020)
Adjusting farming practice	0.108 (0.115)	0.130 (0.124)	0.060 (0.057)	-0.002 (0.031)	-0.064*** (0.022)	0.045** (0.020)
Water use management/ infrastructure improvements	0.198* (0.111)	0.130 (0.114)	0.024 (0.049)	0.032 (0.031)	-0.028 (0.021)	-0.027 (0.021)
Income diversification	0.268** (0.104)	0.199* (0.113)	0.076 (0.056)	-0.010 (0.031)	0.017 (0.024)	0.030 (0.022)
Climate information utilization	0.216* (0.111)	0.264* (0.136)	-0.043 (0.049)	0.047 (0.034)	-0.076*** (0.027)	0.047* (0.024)
Gender (Female=1)	-0.058 (0.122)	-0.032 (0.154)	-0.051 (0.050)	0.020 (0.038)	0.012 (0.026)	0.004 (0.023)
Age (years)	0.092** (0.037)	0.048 (0.036)	0.034** (0.015)	0.021** (0.009)	0.016*** (0.006)	-0.002 (0.009)
Age Squared Term	-0.001** (0.000)	-0.000 (0.000)	-0.000** (0.000)	-0.000** (0.000)	-0.000** (0.000)	0.000 (0.000)

28) Through field research in Vientiane, Laos, it was confirmed that farmers' choice of rice varieties can vary significantly depending on expected climate conditions.

Laos	(1)	(2)	(3)	(4)	(5)	(6)
	Income per Person (Log)	Agricultural Income per Individual (Log)	Consumption Expenditure per Head (Log)	Food Expenditure per Person (Log)	Satisfaction with Current Life	Optimism about Future Life
Education Level (years)	0.016 (0.013)	-0.001 (0.015)	0.006 (0.006)	0.005 (0.004)	-0.002 (0.003)	0.002 (0.003)
Agricultural Engagement	-0.041 (0.204)	0.330 (0.205)	-0.237** (0.101)	-0.100* (0.051)	0.100*** (0.036)	-0.032 (0.039)
Farming Experience (years)	0.008* (0.005)	0.004 (0.005)	0.002 (0.002)	0.001 (0.001)	-0.002** (0.001)	0.001 (0.001)
Number of Household Members	-0.052 (0.033)	-0.042 (0.034)	-0.025* (0.014)	-0.010 (0.009)	-0.003 (0.006)	-0.017* (0.010)
Number of Adults in Household	-0.106** (0.054)	-0.104* (0.056)	-0.043* (0.023)	-0.049*** (0.013)	0.005 (0.010)	0.016 (0.011)
Asset Index	0.100** (0.043)	0.142*** (0.046)	0.050** (0.021)	0.020* (0.011)	0.035*** (0.009)	-0.010 (0.007)
Size of Agricultural Land (Ha)	0.007 (0.024)	0.013 (0.025)	0.000 (0.006)	-0.001 (0.002)	0.008*** (0.002)	-0.004 (0.003)
Access to Finance	0.105 (0.072)	0.158* (0.081)	0.049 (0.040)	0.005 (0.022)	-0.013 (0.016)	0.010 (0.013)
Number of Agricultural Extension Services	0.040** (0.016)	0.038*** (0.015)	0.008 (0.009)	0.002 (0.009)	0.002 (0.004)	-0.003 (0.003)
Access to Climate Information	-0.061 (0.118)	-0.023 (0.125)	-0.038 (0.054)	0.043 (0.030)	0.046* (0.024)	-0.064*** (0.021)
Awareness of Climate Change (Normalized to a 0-1 Index)	0.152 (0.220)	0.080 (0.248)	0.004 (0.122)	0.002 (0.066)	-0.079 (0.057)	0.108** (0.052)
Awareness of Drought Risk(Normalized to a 0-1 Index)	0.255 (0.213)	0.069 (0.246)	0.001 (0.102)	-0.023 (0.064)	0.013 (0.051)	-0.044 (0.043)
Awareness of Flood Risk(Normalized to a 0-1 Index)	-0.220 (0.188)	-0.116 (0.188)	0.078 (0.090)	0.018 (0.064)	0.036 (0.042)	-0.013 (0.039)
Experience with Drought (Normalized to a 0-1 Index)	-0.280* (0.155)	-0.164 (0.174)	-0.089 (0.070)	-0.039 (0.048)	-0.019 (0.034)	0.022 (0.027)
Experience with Flood (Normalized to a 0-1 Index)	-0.017 (0.158)	0.003 (0.170)	-0.087 (0.072)	-0.023 (0.042)	0.015 (0.037)	0.019 (0.032)
Social Network (Normalized to a 0-1 Index)	-0.339 (0.325)	-0.255 (0.334)	-0.247 (0.200)	-0.051 (0.092)	0.272*** (0.076)	-0.181*** (0.057)
Self-Efficacy (Normalized to a 0-1 Index)	-0.301 (0.296)	0.005 (0.314)	-0.159 (0.131)	-0.036 (0.090)	0.151** (0.067)	0.083 (0.054)
Constant	-0.032 (1.087)	0.519 (1.019)	0.475 (0.413)	0.101 (0.271)	-0.221 (0.166)	0.755*** (0.262)
Observations	273	273	273	273	273	273

Village fixed effects are included. Heteroscedasticity robust standard errors in parentheses.

* p < 0.10, ** p < 0.05, *** p < 0.01

〈Table 4-3〉 (Laos) Synergy Effect Analysis of Climate Information Utilization-1

Laos	(1)	(2)	(3)	(4)	(5)	(6)
	Income per Person (Log)	Agricultural Income per Individual (Log)	Consumption Expenditure per Head (Log)	Food Expenditure per Person (Log)	Satisfaction with Current Life	Optimism about Future Life
Adjusting Planting Calendar × Climate information utilization	0.457* (0.234)	0.166 (0.376)	0.034 (0.132)	0.091 (0.097)	-0.027 (0.063)	0.107* (0.057)
Crop Diversification × Climate information utilization	-0.152 (0.220)	0.090 (0.293)	-0.184 (0.127)	-0.054 (0.085)	0.006 (0.055)	-0.029 (0.048)
Changing Seed Variety × Climate information utilization	-0.249 (0.244)	-0.315 (0.266)	0.093 (0.104)	0.033 (0.080)	-0.001 (0.050)	0.040 (0.040)
Adjusting Planting Techniques × Climate information utilization	0.284 (0.220)	0.508** (0.233)	-0.004 (0.101)	0.076 (0.079)	0.031 (0.057)	-0.063 (0.047)
Adjusting Planting Calendar	-0.016 (0.119)	0.065 (0.131)	0.123* (0.067)	0.003 (0.036)	0.018 (0.028)	-0.053** (0.023)
Crop Diversification	0.114 (0.127)	0.098 (0.137)	0.092 (0.067)	0.002 (0.033)	-0.064*** (0.025)	0.046** (0.021)
Changing Seed Variety	0.254** (0.128)	0.171 (0.134)	0.004 (0.058)	0.020 (0.036)	-0.031 (0.025)	-0.029 (0.023)
Adjusting Planting Techniques	0.177 (0.130)	0.043 (0.137)	0.079 (0.073)	-0.037 (0.037)	0.008 (0.029)	0.045 (0.028)
Climate information utilization	0.130 (0.204)	0.131 (0.210)	-0.040 (0.079)	-0.001 (0.053)	-0.082** (0.039)	0.037 (0.033)
Control Variable	included	included	included	included	included	included
Observations	273	273	273	273	273	273

Village fixed effects are included. Heteroscedasticity robust standard errors in parentheses.

* p < 0.10, ** p < 0.05, *** p < 0.01

〈Table 4-4〉 (Laos) Synergy Effect Analysis of Climate Information Utilization-2

Laos	(1)	(2)	(3)	(4)	(5)	(6)
	Income per Person (Log)	Agricultural Income per Individual (Log)	Consumption Expenditure per Head (Log)	Food Expenditure per Person (Log)	Satisfaction with Current Life	Optimism about Future Life
Variety/crop diversification × Climate information utilization	-0.141 (0.230)	-0.205 (0.245)	-0.009 (0.100)	0.022 (0.068)	0.020 (0.052)	-0.007 (0.046)
Adjusting farming practice × Climate information utilization	0.499* (0.232)	0.618*** (0.258)	-0.078 (0.091)	0.013 (0.064)	-0.004 (0.051)	0.038 (0.043)
Water use management × Climate information utilization	0.162 (0.458)	0.337 (0.443)	0.285 (0.182)	0.200 (0.170)	0.020 (0.072)	0.099 (0.065)
Income diversification × Climate information utilization	-0.280 (0.318)	-0.209 (0.399)	-0.244 (0.208)	-0.024 (0.186)	0.070 (0.064)	0.006 (0.057)
Variety/crop diversification	0.158 (0.123)	0.166 (0.129)	0.044 (0.070)	0.005 (0.035)	-0.081*** (0.026)	0.014 (0.027)
Adjusting farming practice	0.027 (0.139)	-0.055 (0.148)	0.146** (0.061)	0.010 (0.039)	0.024 (0.029)	-0.032 (0.025)
Water use management/infrastructure improvements	-0.219 (0.280)	-0.220 (0.305)	-0.084 (0.076)	-0.042 (0.079)	0.002 (0.046)	0.016 (0.035)
Income diversification	0.364 (0.156)	-0.231 (0.161)	0.174** (0.088)	0.024 (0.055)	-0.092** (0.036)	0.067** (0.034)
Climate information utilization	0.046 (0.224)	-0.022 (0.233)	0.004 (0.088)	0.018 (0.058)	-0.093** (0.045)	0.022 (0.041)
Control Variable	included	included	included	included	included	included
Observations	273	273	273	273	273	273

Village fixed effects are included. Heteroscedasticity robust standard errors in parentheses.

* p < 0.10, ** p < 0.05, *** p < 0.01

4.5. Conclusions

This study analyzed the impact of climate change adaptation measures on farmers' livelihoods from various aspects, including farmers' income, consumption expenditure, and subjective quality of life, and found that the adoption of climate change adaptation measures can have different impacts on farmers' livelihoods and subjective quality of life. In particular, relatively low-cost and low-risk climate change adaptation measures, such as farming method adaptation, income diversification, and climate information utilization, had positive effects on increasing farmers' incomes and improving their livelihoods, while high-cost and high-risk adaptation measures, such as diversification of varieties and crops, water use management, and facility improvements, had limited effects.

In the Laos case, farming practices adjustments and climate information utilization had a positive impact on household income, while income diversification was also found to increase household income. In addition, climate information utilization had a limited but positive impact on increasing agricultural income. In the case of Vietnam, the average treatment effect (ATT) was estimated using an endogenous replacement regression analysis and found positive effects of climate change adaptation measures on household income, agricultural income, and household consumption expenditure. These results suggest that the adoption of climate change adaptation measures can have a positive impact on various aspects of household welfare, including farmers' economic performance and living standards, although the specific effects may depend on the characteristics and types of individual climate change adaptation measures.

In addition, the use of climate information, which is relatively low cost and difficult to implement, can have synergistic effects when used in combination with other climate change adaptation measures, and developing climate information services in a way that maximizes these synergies is expected to be a cost-effective policy and international development cooperation project that can improve the quality of life of farmers in LMICs while strengthening their capacity to cope with climate

change. We also found that farmers' access to agricultural extension services and finance has a positive effect on increasing their incomes. This suggests that policies that improve the transfer of agricultural technologies and information, and access to financial services, can help strengthen farmers' capacities and provide opportunities to generate stable incomes.

We find that the adoption of several climate change adaptation measures is negatively associated with farmers' satisfaction with their current life, suggesting that dissatisfaction with their current life due to climate change may be related to the adoption of climate change adaptation measures. On the other hand, climate change adaptation measures have different effects on farmers' optimism about their future life, so it is necessary to explore ways to increase the level of farmers' welfare and subjective life satisfaction together.

5. Proposal for a Sustainable Model of International Development Cooperation

5.1. Direction of Policy Implementation by Korean Government Policy

5.1.1. Analysis of Korean Government Policy Implementation and Future Directions

The Korean government has established the Comprehensive Basic Plan for International Development Cooperation (2021-2025), setting the medium- to long-term policy direction for its international development efforts. South Korea is a notable example of a country that transitioned successfully from a food aid recipient to a donor, attracting high interest from developing countries in its successful agricultural development experience. There is growing demand, particularly in the areas of climate-smart agriculture and digital agriculture ODA.

Relevant to this study, an important aspect of the government's plan is the goal to improve agricultural productivity by 2025 through the use of appropriate technologies that consider the agricultural capacities and regional climate and policy characteristics of recipient countries. According to the 2024 OECD DAC, Korea's green ODA—specifically climate-related ODA—increased by 35% compared to the previous year, a figure 29% higher than the DAC average. The outcomes of this study on climate information services for developing countries can thus provide valuable guidance for the Korean government's international development cooperation projects, aligning with both national priorities and global trends.

According to the 2023 Draft Strategy for Development Cooperation in Agriculture, the support for Southeast Asia focuses on developing high-quality agricultural value chains in line with local agricultural priorities. Examples include the Ministry of Agriculture's Capacity-Building Project for Sustainable Production and Distribution of High-Quality Rice Seeds in the Philippines and KOICA's Green

Circular Economy Support Program to Strengthen Agricultural Value Chains in Northern Vietnam. Vietnam and Laos have been designated as key cooperation partners; for Laos, the priority is strengthening agricultural productivity through improved crop marketability and enhancing post-harvest distribution capabilities. For Vietnam, climate change adaptation is a priority sector for aid, with plans to enhance the agricultural and fisheries value chain, covering processing, distribution, and sales, to support the modernization of Vietnam's agricultural and fisheries industries. The following is a list of KOICA's ongoing projects in the agriculture, forestry, and fisheries sectors in Laos and Vietnam for 2024.

〈Table 5-1〉 Ongoing Projects in the Agriculture, Forestry, and Fisheries Sectors in Laos and Vietnam

Country	Project Title
Laos	Digital Farmland Information Management Platform for Enhanced Food Security (2023-2026 / USD 8.8 million)
	Rural Development Project in Three Southern Provinces (2020-2024 / USD 9 million)
	Rural Development Implementation Strategy and Pilot Project for Farm Income Increase in Central and Northern Regions (2021-2025 / USD 12.5 million)
Vietnam	Green Circular Economy Support Project by Strengthening Agricultural Value Chain in Northern Region (2024-2029 / USD 20 million)
	Agricultural Productivity Enhancement Solution for Organic-Based Commodity Crops in the Mekong Delta Region (2024-2025 / USD 3 million)
	Educational and Research Capacity Enhancement Project for Hi-Tech Agricultural Development at Vietnam National University of Agriculture (2021-2030 / USD 9.09 million)
	Capacity-Building Project for Livestock High-Skilled Professionals at National Agricultural University (2021-2030 / USD 12.7 million)

Currently, there are three ongoing projects in Laos and four in Vietnam within the agriculture, forestry, and fisheries sectors. Most of these projects focus on strengthening agricultural value chains and enhancing the capabilities of agricultural workforce, which is somewhat distant from the climate-smart agriculture initiatives that are part of the Korean government's international development cooperation agenda. Therefore, the outcomes of this study are

expected to provide sustainable agricultural development experiences that can aid in the model development for future climate-smart, digital-based agricultural capacity-building projects.

Finally, KOICA's public-private partnership program, which is recognized for its flexibility in adapting to various business models, can be utilized (OECD DAC, 2024). In particular, one of KOICA's public-private partnership initiatives, the Creative Technology Solution (CTS) program, is noted for providing innovative technologies across a range of fields, including energy efficiency, smart agriculture, and education (OECD DAC, 2024). The demand for climate information services identified among farming households in Vietnam and Laos can be met through collaboration with private companies via KOICA's CTS and Inclusive Business Solution (IBS) programs. A list of potential domestic companies with climate-smart agricultural technologies that could collaborate in providing climate information services is as follows.

〈Table 5-2〉 Korean Climate-Smart Agriculture Companies

Company	Description
Farm○○	Farm Hannong uses smart farm solutions to monitor the growth status of crops, soil moisture, temperature, and other factors in real-time by utilizing IoT sensors and big data. They apply AI technology to crop protection research and provide pest prediction and control recommendation solutions to enhance agricultural productivity.
The KIB○○	The KIBAN develops various genetic resources through the combination of advanced biotechnology and breeding techniques, establishing an accurate breeding system and creating superior varieties through the re-establishment of breeding materials using multiple DNA molecular markers. This company has a branch in Thailand, allowing for rapid generation advancement and year-round research and development, enabling them to trial a variety of crops suitable for tropical, subtropical, and temperate regions, and propose suitable varieties for Southeast Asia.

Company	Description
Epi○○	Epinet develops agricultural bioclimatic application models by understanding the physiological and ecological responses of crops affected by weather and climate conditions, utilizing measurable data through empirical interpretation and statistical analysis. They produce digital precision maps with various spatial resolutions and data attributes, from small-scale to large-scale, integrating weather and climate data, including real-time and forecasted weather and future climate change predictions, effectively providing agricultural technology information to users.
Green○○	GreenLabs offers an integrated agricultural platform called "Farm Morning," providing solutions to optimize crop cultivation by combining data analysis, IoT, and AI technologies. This platform provides real-time information on soil conditions, weather forecasts, and crop health data, helping to improve resource management efficiency and increase crop yields. Such technologies are expected to significantly aid the modernization of agriculture in developing countries.
Tri○○	Tritidge is a startup that operates a unique trade platform for agricultural and fishery products globally, focusing on fulfillment services, intelligence services, and Exhibition 365. They process information acquired through direct trade transactions and market data to provide various data on transaction prices, export and import volumes, and quality of agricultural and fishery products. Exhibition 365 is an online trade fair concept that connects buyers and sellers from around the world, allowing diverse transactions beyond previous geographical and informational limitations. Through data analysis technology and the establishment of sustainable distribution channels, they expect to share strategies for enhancing economic effects with recipient countries.

5.2. Policy Implementation in Similar Programs by Major Donor Countries

5.2.1. The United States (United States Agency for International Development, USAID)

The United States establishes a Global Food Security Strategy every five years to systematically implement development cooperation and promotes the interagency 'Feed the Future' initiative based on this strategy. This program focuses on supporting smallholder farmers and communities in Asia, Central America, and Africa, pursuing a comprehensive approach that goes beyond simple food aid to enhance regional food security and improve nutrition.

In particular, it emphasizes long-term support for middle- and low-income countries to achieve food security and sustainable economic growth through climate change adaptation measures and climate-smart strategies. To this end, the program actively fosters collaboration with the private sector, with more than 60 U.S. companies currently participating in the program's network (LEE. H., & Yoon. J., 2021).

The private partnerships are based on mutually beneficial relationships. Participating companies support income generation for smallholder farmers while creating business opportunities for themselves, thereby jointly achieving public goals such as poverty reduction, improved nutrition, and enhanced food security in the region. This field-centered expertise and innovative approach serve as key drivers for the sustainable outcomes of USAID's international development cooperation programs.

5.2.2. France (French Agency for Development, AFD)

The French government has established and implemented a new comprehensive strategy in the agricultural and rural development sectors starting in 2022. This strategy focuses on two key tasks: sustainable agricultural development and strengthening food security. In particular, it sets major goals of enhancing the

economic power of smallholder farmers and systematically improving agricultural value chains.

A representative example of this strategy's implementation is the 'ASSET (Agroecology and Safe Food System Transitions in South-East Asia)' project. Running from 2020 to 2025, this project is being implemented in major Southeast Asian countries such as Laos, Myanmar, Cambodia, and Vietnam. It seeks to establish sustainable agricultural systems through agroecological approaches and transition to safe food production systems. This initiative is significant as it presents a model for agricultural development that is environmentally sustainable and socially responsible, going beyond mere productivity improvements.

5.2.3. United Kingdom (Department of International Development, DFID)

The United Kingdom invested a total of £2.6 billion in bilateral cooperation in the agricultural sector of middle- and low-income countries from 2016 to 2021, focusing on operating agricultural development programs and supporting research to improve agricultural productivity. A particularly notable example is the "CASA (Commercial Agriculture for Smallholders and Agribusiness)" program, which has been running in Indonesia, the Philippines, and Vietnam from 2017 to 2026. This program aims to build climate-resilient agri-food systems while simultaneously increasing smallholder farmers' income and strengthening food security.

An analysis of the international development cooperation strategies of major donor countries in the agricultural sector has revealed the following common features and implications:

(1) Climate Change Response-Centered Strategies

Many countries have set strengthening resilience through climate change adaptation as a key objective, actively introducing and disseminating climate-smart agricultural policies to emphasize the establishment of sustainable agricultural systems.

(2) Strengthened Strategic Partnerships with the Private Sector

By leveraging the technological expertise and capacity of private companies, countries are developing sustainable and innovative business models and seeking synergies between corporate expertise and the public interest goals of development cooperation.

These international trends can serve as an important reference for setting the direction of KOICA's future international development cooperation projects. Considering small-scale farmers, women farmers, and youth farmers who are vulnerable to climate change, and involving local communities and farmers' organizations, KOICA can achieve public objectives such as poverty, nutrition, and food security, while promoting self-reliance and sustainability through active participation of local communities. In addition, it is expected to build a more effective and sustainable business model for international development cooperation through strategic collaboration with domestic companies with expertise and capabilities in the field of climate-smart agriculture. This will enable an integrated approach to technological innovation and development cooperation, and contribute to increasing the effectiveness, efficiency, and sustainability of projects by leveraging the expertise of the private sector. In particular, collaboration with the private sector in partner countries can be utilized as an approach to economic and financial sustainability and win-win and shared growth through strengthening local business capacity and creating new markets.

5.3. Development Strategies of Partner Countries

Responding to climate change in agriculture is a complex task that requires close and coordinated cooperation between the international community, countries, and local communities. The countries in this study are establishing mid- to long-term development strategies in the field of agriculture and climate change as follows, and Korea is supporting them by establishing prioritized support strategies for the partner countries accordingly.

5.3.1. Vietnam Development Goals

Through the Socioeconomic Development Strategy (SEDS) 2021-2030, a long-term strategy for national development, Vietnam plans to become an emerging industrialized country and upper middle-income country by 2030, centered on science, technology, innovation, and digital transformation in the economic, social, environmental, and political and diplomatic fields. In the economic sector, the SEDS sets strategic goals related to agriculture, rural areas, and climate change, such as “developing regional and maritime economies and revitalizing rural development,” and in the environmental sector, “environmental protection and climate change response,” “natural disaster prevention and mitigation measures, and disaster management. In particular, Vietnam's Ministry of Agriculture and Rural Development has identified digitalization as a major challenge in the agricultural sector and has set specific targets through the Master Plan for Agricultural Production Development and the Agricultural Reconstruction Program, including achieving an agricultural output growth rate of 4-4.3% and an output value of VND100-120 million per hectare of farmland by 2030.

In 2022, Vietnam received about \$991 million in ODA, of which the country contributed about 6.6% (\$0.658 billion). The agriculture and fisheries sector received about \$40.8 million in ODA (222 projects), accounting for about 4% of total ODA, and the environment sector received about \$55.5 million (167 projects), accounting for about 5%.

Through the 3rd CPS (2021–25), Korea has identified transportation, health and sanitation, environment, education, and public administration as priority areas for its assistance to Vietnam. In particular, in the environment sector, the main strategies are to support the construction of eco-friendly infrastructure and capacity building to enhance climate change response capabilities, to support the expansion of eco-friendly energy and smart city infrastructure to transition to a carbon-neutral society, and to support forest cooperation and circular economy to mitigate climate change. Based on this, KOICA is strengthening its support to mitigate climate change damages such as drought, flooding, and sea level rise in vulnerable regions (e.g., Mekong Delta, Red River, etc.), including water resource management and irrigation projects, strengthening environmental management capacity, and developing smart agriculture and clean agriculture. KOICA's Country Program (CP) is also actively supporting agriculture, fisheries, and rural development by establishing 'Creating inclusive and sustainable rural peace villages' as a core CP program.

5.3.2. Laos Development Strategy

Through its Vision 2030 (2016–2030) and National Implementation Strategy (2016–2025), Lao PDR aims to achieve innovative, environmentally friendly and sustainable economic growth, and to become an upper middle-income country. The 9th National Socio-Economic Development Plan 2021–2025 prioritizes improving living conditions to improve the quality of life of the people (well-being) and responding to climate change through environmentally friendly development and disaster risk reduction (environment) as policy priorities. In addition, through the National Agricultural Development Strategy, Lao PDR is pursuing sustainable food security, improving living conditions in rural areas, and building an environmentally friendly and sustainable agricultural system that takes into account local characteristics as core goals.

In 2022, Lao PDR received about \$466 million in ODA, of which the country's contribution was about 10.2% (\$0.476 billion). The agriculture and fisheries sector

received about \$40.7 million in ODA (150 projects), accounting for about 9% of total ODA, and the environment sector received about \$10 million (55 projects), accounting for about 2%.

In the 3rd CPS, Korea has selected water management, health and sanitation, energy, regional development, and education as the priority areas of support for Lao PDR. In particular, in the field of water management, policy capacity building to establish an integrated water management system and establishment of water resource management systems and infrastructure, and in the field of regional development, rural environment improvement to reduce the development gap between urban and rural areas, prevent disasters, and improve the quality of life of rural residents, and agricultural value chain enhancement to alleviate rural poverty and achieve food security were set as priority areas of support. KOICA's CP also has 'Inclusive and Sustainable Rural Development' as a key CP program, and is expanding its support for climate change response and agricultural and rural development with a focus on agriculture, fisheries, and rural development.

5.3.3. Development Needs in the Agricultural Sector of the Mekong River Basin

Climate information services, including Agro-Climate Information and climate-smart farming practices, are gaining traction in many low- and middle-income countries as an innovative way to address climate change in the agricultural sector. International cooperation programs such as DeRisk, SAMIS, and LaCSA in Vietnam and Laos have increased agricultural productivity through climate information services, while digital climate information systems have also been used to support farmers' adaptation to climate change in Ethiopia (AICCRA), Ghana (CSAIP), and the Mekong River Basin (ARCC, CSA). These examples demonstrate the growing demand in low- and middle-income countries for digital agriculture, climate-smart agriculture, and climate information services. Considering the development needs of these low- and middle-income countries, it is expected that Korea can play a leading role in this field of international development cooperation by developing customized digital climate-smart agriculture business models using

Korea's strengths in ICT and agricultural technology.

In this context, sub-study 3 of this study evaluated the effectiveness of climate change adaptation measures, focusing on the impact of climate information services on farmers' livelihoods, and found that climate information utilization can significantly contribute to increased household and agricultural incomes. In particular, it was found that climate information can have a synergistic effect when used in combination with other adaptation measures. In addition, low-cost, low-risk adaptation measures that can be utilized within the framework of current agricultural practices may be more effective than high-cost, high-risk adaptation measures in responding to climate change at the farm level, suggesting that approaches that utilize climate information services that can be applied at relatively low cost and risk may be effective.

These climate information services can help farmers make informed decisions by providing the basis for shifting to the items identified in Study 1 as effective farmer climate change adaptation measures, and can be a starting point for the transition to higher levels of digitally enabled climate-smart agriculture, such as mechanization. The results of sub-study 2, which analyzed the determinants of adoption of climate change adaptation measures, also found that in both Vietnam and Lao PDR, farmers with higher access to climate information and agricultural extension services tended to use more climate change adaptation measures. This confirms that access to climate information and agricultural extension services is an important factor influencing farmers' climate change adaptation decisions.

These findings are consistent with local demand research. In interviews conducted in Vietnam in collaboration with local research partners, local stakeholders identified scaling up ACB through collaboration with the Department of Crop Production of the Ministry of Agriculture and Rural Development as a priority. From 2020 to 2024, CIAT will provide ACB to more than 270,000 farmers in Vietnam, but a limited budget of about \$17,000 per year prevents nationwide expansion. Currently, farmers receive basic information through a mobile

application (Zalo), and there is a need to provide information through various channels. Therefore, international cooperation is needed to expand the provision of agrometeorological information beyond the Mekong Delta region to the entire country.

In order to secure the sustainability of international development cooperation projects, it is essential to plan and promote projects that utilize appropriate technologies in consideration of the infrastructure level and capacity of low- and middle-income countries. From this perspective, climate information services can be viewed as a digital climate-smart agriculture model of appropriate technology in that they can be utilized through basic mobile phones or the Internet without requiring high technical skills or infrastructure at the farm level. Of course, infrastructure, technology development, and human resource training are needed to build climate information service systems and platforms, such as establishing agro-meteorological information systems, early warning systems, and customized climate-smart agriculture suggestion systems, but these should be considered at the central level rather than at the level of individual farmers, and can be applied locally. Moreover, as shown in Chapter 1 (Table 1-1), Mekong Basin countries such as Vietnam and Lao PDR have relatively high levels of electricity access, internet access, and mobile phone subscriptions, indicating that they have at least the basic infrastructure to utilize climate information services at the farm level. Therefore, climate information services can be considered as an appropriate technology-based digital climate-smart agriculture model that can be practically applied and utilized in Mekong Basin countries.

On the other hand, given the low ND-GAIN indices of the Mekong Basin countries (100th in Vietnam, 121st in Lao PDR, 133rd in Cambodia, etc.), capacity building programs are needed for the operation and management of climate information services, as well as for their use at the farm level and application in practice. As shown in the results of sub-studies 2 and 3, agricultural extension services can be a good approach to strengthening farmers' capacity to respond to climate change. In addition, these capacity building programs should not only provide

information and technical training, but also work on non-cognitive skills such as self-efficacy and awareness. Such an integrated approach is expected to further enhance the efficiency, effectiveness, and sustainability of the business.

This study suggests that climate information services can be utilized as a practical and sustainable digital climate-smart agriculture model for climate change response in middle- and low-income countries. In particular, we would like to propose a new business model for international development cooperation in digital climate-smart agriculture that KOICA can design and explore in light of the results of this study and the local needs and capacities of partner countries.

5.4. Analysis of Similar Projects

This study aims to provide recommendations for future collaboration with international cooperative systems related to climate and agriculture through the analysis of similar projects. The goal is to contribute to the identification of international development cooperation policies and projects for addressing climate change in the future.

5.4.1. Accelerating Impacts of CGIAR Climate Research for Africa (AICCRA)

The Accelerating Impacts of CGIAR Climate Research for Africa (AICCRA) is a project implemented across Ethiopia in collaboration with CGIAR (Consultative Group on International Agricultural Research) and the World Bank, running until 2023. The main objective is to enhance the climate resilience of farmers and increase productivity by introducing climate information services and climate-smart agricultural technologies. The primary targets include smallholder farmers, livestock producers, and agricultural cooperatives, focusing on regions such as Amhara, Oromia, and SNNP throughout Ethiopia. A digital agricultural platform called Lersha was developed to provide farmers with climate information and agricultural recommendations. Additionally, a climate forecasting system utilizing satellite data and precision agriculture technologies was introduced to optimize crop management and water resource management. Furthermore, local training and workshops were conducted to strengthen the capacities of farmers and experts, assisting in climate data-based agricultural decision-making. As a result, over 450,000 farmers gained access to climate information services, improving agricultural productivity and climate resilience.

5.4.2. Ghana Climate-Smart Agriculture Investment Plan (CSAIP)

The primary goal of this project is to support the agricultural sector in Ghana in adapting to climate change, increasing productivity, and reducing greenhouse gas emissions. It also aims to promote sustainable agricultural development

through climate-smart agricultural technologies, making agricultural production systems more resilient to achieve both food security and economic growth. The project is implemented throughout Ghana, with a particular focus on climate-vulnerable areas such as the northern, central, and coastal regions, which are significantly impacted by climate change. The target participants primarily include smallholder farmers, agricultural cooperatives, women, and youth. This project is designed to help farmers effectively respond to climate change and ensure that all actors in the agricultural value chain can achieve better profits and stability. Additionally, it collaborates with various stakeholders, including agricultural institutions, NGOs, and government departments, to provide technical support and education.

The main activities include establishing a digital platform for providing climate forecasts and agricultural management information, enabling farmers to receive real-time information. Various workshops and training sessions were conducted to enhance the capacities of farmers and experts. Additionally, the introduction of water management and irrigation technologies for rice farming aimed to promote efficient water use and increase crop productivity. The key outcomes of this project are as follows: First, the introduction of various climate-smart technologies led to an increase in agricultural productivity of up to 44%, benefiting approximately 1.7 million farmers. Second, the project reduced agricultural risks associated with climate change, enhancing the economic stability of farmers and minimizing expected losses in key export crops. Third, it contributed to building a sustainable agricultural ecosystem in response to climate change while reducing greenhouse gas emissions.

5.4.3. Mekong ARCC Project – A Reference Case

The Mekong ARCC Project was implemented with support from USAID to strengthen climate change adaptation capacity in Mekong River Basin countries, including Laos, Thailand, Cambodia, and Vietnam. This project was carried out from 2011 to 2016, targeting local communities and farmers affected by climate

change in agriculture and livelihoods.

Through this project, various data were collected by monitoring climate variability in the Mekong River Basin in real-time using satellite data and remote sensing technologies. These data were utilized to provide guidelines that enabled local residents to receive real-time climate alerts through mobile messaging and warning systems and take appropriate actions.

Furthermore, community-led education programs were operated to train experts capable of utilizing climate data. Various participatory workshops were conducted to deliver knowledge related to climate change to local residents and enhance their ability to independently manage agricultural activities in response to climate change.

5.4.4. Climate-Smart Agriculture (CSA) Project – Best Practice Project

The CSA Project was initiated to enhance agricultural productivity while simultaneously addressing climate change. In Vietnam, the project was conducted from 2012 to 2015, while in countries such as Laos and Cambodia, it is still ongoing. The beneficiaries are smallholder farmers, and the key target areas include Dien Bien, Son La, and Yen Bai in Vietnam's northern mountainous region, as well as Luang Prabang and Houaphanh in Laos.

This project supports farmers by establishing a digital climate information system that allows them to make crop management decisions based on real-time weather information (monitoring climate risks using satellite data and remote sensing technologies and providing early warning systems based on this data). Additionally, it promotes the efficient use of agricultural resources through water and soil management technologies, enabling better responses to climate challenges such as droughts and floods.

Moreover, programs were conducted to educate local farmers on climate adaptation technologies. In Vietnam, workshops and training sessions were held

to help agricultural workers acquire new farming techniques and learn climate risk management strategies. In Laos, collaboration with local communities facilitated easier access to climate information for farmers and supported the adoption of various agricultural practices to address climate change.

5.5. Proposal for International Development Cooperation Models for Climate Change Adaptation in Sustainable Agriculture

Based on the findings of this study, we propose to identify and establish effective pilot ODA project models for climate change adaptation, aiming to inspire interest in follow-up research. By collaborating or linking with international networks, we intend to suggest project components that can practically contribute to addressing multidimensional development challenges. This initiative seeks to strengthen international cooperation on the transnational challenge of climate change and ultimately enhance global capacity to respond to it. Potential projects for participation or development include the following:

Firstly, Vietnam's Mekong DPO Project: The Vietnamese government announced the "Master Plan for Mekong Delta Development" in 2022, emphasizing the need for climate change adaptation strategies. Accordingly, the Mekong Delta Region Development Policy Operation (Mekong DPO) is being implemented for 2025–2030 (KOTRA, 2023). Participation in this project could be considered. Some institutions involved in this project, such as the Asian Development Bank (ADB) and Korea Eximbank, are leading coastal road construction projects in the Tien Giang region, a primary area of study in this research. This can be linked to the development of an international cooperation project, such as the "Increase Income through Improvement of Agricultural Product Distribution Systems."

Secondly, by connecting with the Asian Mega-Deltas (AMD) Initiative led by the Consultative Group on International Agricultural Research (CGIAR), new project models such as the "Automation of Integrated Climate Change Information Systems to Enhance Climate Resilience" can be proposed. The findings of this study can also serve as a foundational resource for establishing climate change adaptation strategies at the national level. Currently, CGIAR has transitioned to the "One CGIAR" system, adopting an integrated approach to global issues. By dynamically restructuring partnerships, knowledge, assets, and global networks, CGIAR is working to address and resolve interdependent challenges facing today's

world. In Asia, the AMD initiative addresses climate change and socio-ecological issues in major delta regions (e.g., Vietnam, Cambodia, Myanmar, Bangladesh, India), aiming to improve the resilience, inclusivity, and sustainability of these areas to support human prosperity and welfare. Additionally, Professor Kwang-Hyung Kim from our research team is involved in the DeRISK and AMD projects, enabling the identification of impactful follow-up projects linked to these initiatives. This effort could contribute to discovering international development cooperation policies and projects with institutions like CGIAR—where Korea's participation and contributions have been relatively limited—focusing on climate and agriculture. For instance, an international development cooperation project in the field of climate change adaptation could include the "Development of Climate Information Service Content and the Establishment of Automated Climate Information Service Systems."

5.5.1. Proposal for International Development Cooperation Models in Laos

Laos has achieved meaningful outcomes through agricultural meteorological services such as SAMIS and LaCSA. However, these projects have shown limitations, necessitating new approaches to effectively address the ongoing climate threats facing Laos' agricultural sector.

First, repairing and upgrading outdated meteorological stations is urgently required to secure high-quality weather data. Additionally, machine learning technologies should be utilized to enhance satellite map-based annual crop production monitoring systems, and IT systems for predicting climate disasters such as floods and droughts must be advanced. Furthermore, it is essential to expand the user base of climate services. Beyond the farmers (contractors, farmer groups, etc.) in the four provinces currently receiving pilot services, the agricultural products and services offered by LaCSA should be distributed nationwide. Institutional capacity must also be strengthened, and related systems improved to enable the effective use of agricultural climate information and services in agricultural planning and other relevant sectors.

The first proposal of this study is to expand LaCSA, whose effectiveness has already been demonstrated, into a national-level project. This expansion is expected to impact approximately 2.33 million agricultural workers, equivalent to 32% of Laos' total population. Through this initiative, farming households could benefit from enhanced climate resilience, improved agricultural productivity, increased income, and greater capacity to respond to extreme weather events.

The second proposal involves implementing targeted project activities in specific regions. This would include LaCSA content distribution training, advisory training for agricultural workers outside farms, and LaCSA advisory farmer group training. This region-specific approach would address individual farming households' concrete issues and could strategically leverage external resources, such as those provided by KOICA, to maximize project effectiveness.

The logframe and expected outcomes of the proposed project are as follows:

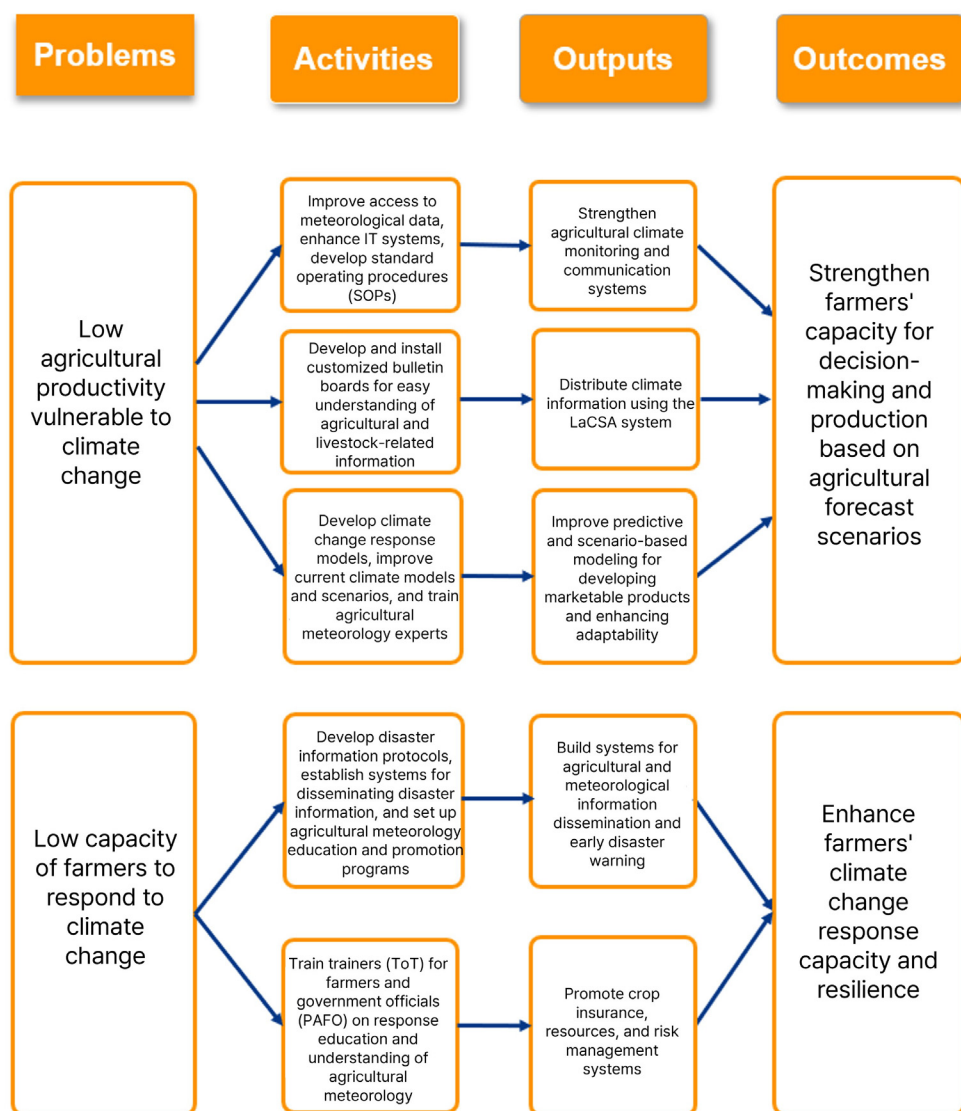
〈Table 5–3〉 Laos ODA Model Proposal: Project Logic Model (Logframe) and Expected Outcomes

Description	Indicators	Verification Method	Assumptions
Outcome 1: Capacity building for generating diverse agricultural decision-making and forecasting scenarios			• No changes in government agricultural policy • Active participation from beneficiaries • Establishment of electrical infrastructure • No withdrawal of partner organizations
Output 1.1: Strengthening agricultural climate monitoring and integrated information systems • Repair and additional installation of weather stations • Improvement of IT systems and development of Standard Operating Procedures (SOP) for operation and maintenance	• Installation and improvement of weather stations • Development of SOP	• Installation reports for weather stations • Availability of weather observation data • Installation quotations • Field verification reports • IT system improvement reports • SOP documentation	
Output 1.2: Expansion of the LaCSA System's Scope • Integrate agricultural and livestock recommendations into weekly and monthly LaCSA posts, including the addition of new crops • Develop a bulletin board for farmers, suppliers, traders, etc.	• Number of integrated posts on vegetables, tea, legumes, bamboo, livestock, etc. • Existence of a bulletin board with content not only for farmers but also for suppliers, traders, and other stakeholders	• Posts covering new crops • Posts including livestock information • Bulletin board development report	
Output 1.3: Capacity building for developing adaptation options for key agri-food value chains based on forecasting and scenario modeling • Develop products that respond to climate variability by applying the latest technologies and methods • Improve future scenarios using the latest climate models from CMIP6 and additional crops and agricultural systems, including livestock • Train students (future government officials and experts) to become agricultural meteorology specialists	• Number of products that respond to climate variability • Improved future climate scenarios • Number of newly trained graduates in agricultural meteorology	• Product patents • Report documenting the process of improving future climate scenarios • Graduation certificates of students	

Description	Indicators	Verification Method	Assumptions
Outcome 2: Strengthened distribution system for posts and other materials for various agricultural stakeholders			
Output 2.1: Establish nationwide distribution of agricultural meteorological advisories and early warnings for various agricultural stakeholders • Develop protocols and guidelines to integrate district-level disaster information into LaCSA • Distribute loudspeakers (1,000 units) and posters (8,500 for 1,500 schools) to communities, and deliver LaCSA information to farmers and agricultural extension agents on a large scale through farmer group coaching • Develop a dissemination mechanism to distribute agricultural meteorological advisories produced in Output 1.2 to external agricultural stakeholders (district-level pilot project)	• Existence of protocols and guidelines for integrating district-level disaster information into LaCSA • Number of LaCSA posts per region • Number of farmers and agricultural personnel who attended LaCSA group coaching sessions by region	• Guideline report • Photos of posted materials • Attendance lists for training sessions	
Output 2.2: Promotion of the application of agricultural meteorological advisories and risk management measures across the agri-food value chain • Provide a "Training of Trainers (ToT)" program to PAFO and DAFO in selected regions for applying LaCSA recommendations • Ensure that trained PAFO and DAFO personnel adopt LaCSA recommendations to facilitate farmer education for at least two seasons • Support education for off-farm stakeholders on methods to apply LaCSA advisories	• Number of "Training of Trainers (ToT)" programs provided to PAFO and DAFO • Number of educational sessions supported for off-farm stakeholders on applying LaCSA advisories	• Program announcement notices • List of trained participants	

〈Table 5-4〉 Proposal for Laos ODA Model: Theory of Change (Example)

Project to Establish a Climate Information Platform for the Agricultural Sector in Laos



5.5.2. Proposal for International Development Cooperation Models in Vietnam

The DeRISK project in Vietnam has made meaningful contributions to the agricultural sector and received positive evaluations from the Vietnamese government. However, the stable provision of agrometeorological services in Vietnam remains challenging without continued funding support from external donors. These challenges arise due to several limitations:

First, there is a lack of sufficient human resources for producing and distributing agrometeorological bulletins. Second, weather and climate information must be purchased from regional hydrometeorological agencies and is transmitted manually, which is inefficient. Third, a data-sharing system among government agencies (agriculture, hydrology, meteorology) has not yet been established. Addressing these issues is critical to improving the time and cost efficiency of developing agrometeorological bulletins in the long term.

To tackle these challenges, a national-level Agro-Climatic Digital Platform (ACDP) should be developed to integrate data and information from various sources and provide large-scale services. Priority application areas for the platform could include Vietnam's key vulnerable agricultural regions, such as the Mekong Delta, Central Highlands, South Central Coast, and Red River Delta.

To successfully establish and operate the Vietnam ACDP, preparations in three key areas are necessary. First, a technical foundation for the development and maintenance of the ACDP must be established. Second, an effective delivery system for agricultural climate information through the ACDP must be built. Third, systematic training programs for the operation and utilization of the system must be developed. Specific implementation measures include conducting a comprehensive investigation of climate risks and pest outbreaks for key target crops and building a crisis management system using machine learning technology. Additionally, training on climate disaster and agricultural disaster modeling and their applications, as well as system operation and maintenance, should be provided to enhance the

capacity of ACDP operators. Furthermore, education on interpreting and utilizing information should be conducted to enable farmers to effectively use the ACDP.

This initiative is part of an expansion project for the Mekong Delta ACB, aiming to evolve into a national-level digital platform capable of integrating data from various sources to provide tailored agrometeorological alerts and recommendations to diverse user groups on a large scale. The project is expected to span four years, with the first year dedicated to platform design and scope definition, followed by three years of system development, pilot operations, and ACDP deployment.

The target areas of this project are the four major vulnerable agricultural regions in Vietnam: the Mekong Delta, Central Highlands, South Central Coast, and Red River Delta. The beneficiaries of the project are farmers and agricultural workers in these four regions, and the specific project implementation structure is as follows:

Key Implementing Agencies

- Department of Crop Production (DCP)
- Bioversity International
- International Center for Tropical Agriculture, Hanoi branch (CIAT Hanoi)

Key Partner Institutions

- National Hydro-Meteorological Forecasting Center (NHCMF)
- Institute of Meteorology, Hydrology and Climate Change (IMHEN)
- Vietnam Academy of Agricultural Sciences (VAAS)
- National Research Institutes (CLRRI, FCRI, FAVIRI, WASI)
- Provincial Departments of Agriculture and Rural Development (DARDs)
- Local Agriculture and Rural Development Offices
- Local and Regional Hydro-Meteorological Observation Centers

The specific outcomes expected from the collaboration with these relevant institutions are outlined in the following logical framework.

〈Table 5–5〉 Vietnam ODA Model Proposal: Project Logic Model (Logframe) and Expected Outcomes

Description	Indicators	Verification Method	Assumptions
Outcome 1: Coordination for the Development and Operation of Vietnam ACDP (Agricultural Climate Decision-making Platform)			• No changes in government agricultural policy • Active participation from beneficiaries • Establishment of electrical infrastructure • No withdrawal of partner organizations
Output 1.1: Establishment of a National Steering Committee • Establish a Technical Working Group (TWG) with clear Terms of Reference (ToR) alongside key stakeholders • Hold regular operational meetings throughout the ACDP development process, providing consultation and serving as a key body for the entire process (The Steering Committee currently leads efforts to analyze the scope and status of the ACB approach, identify needs and gaps, assess institutional requirements, create a detailed work plan and schedule, and develop a monitoring and evaluation plan.)	• Establishment of a National Steering Committee with clear Terms of Reference (ToR) • Number of meetings held	• TWG reports • Meeting minutes • List of meeting participants	
Output 1.2: Data Collection and Intellectual Property Development • Assign and oversee data collection and intellectual property development tasks to relevant agencies and national/regional experts, with clear deadlines • Coordinate necessary training for data collection and intellectual property development with relevant government agencies • Review the quality and format of collected data and intellectual property before linking to the ACDP system	• Number of national/regional experts responsible for data collection and intellectual property development • Availability of training required for intellectual property development	• List of experts • Attendance list for training sessions • Data quality report	
Output 1.3: Development of the ACDP System • Support contracting for ACDP system development • Coordinate data collection and intellectual property development alongside ACDP development • Provide training on the modeling components of ACDP	• Status of support for the system development contract • Availability of training on modeling components	• Contract document • Training attendance list	

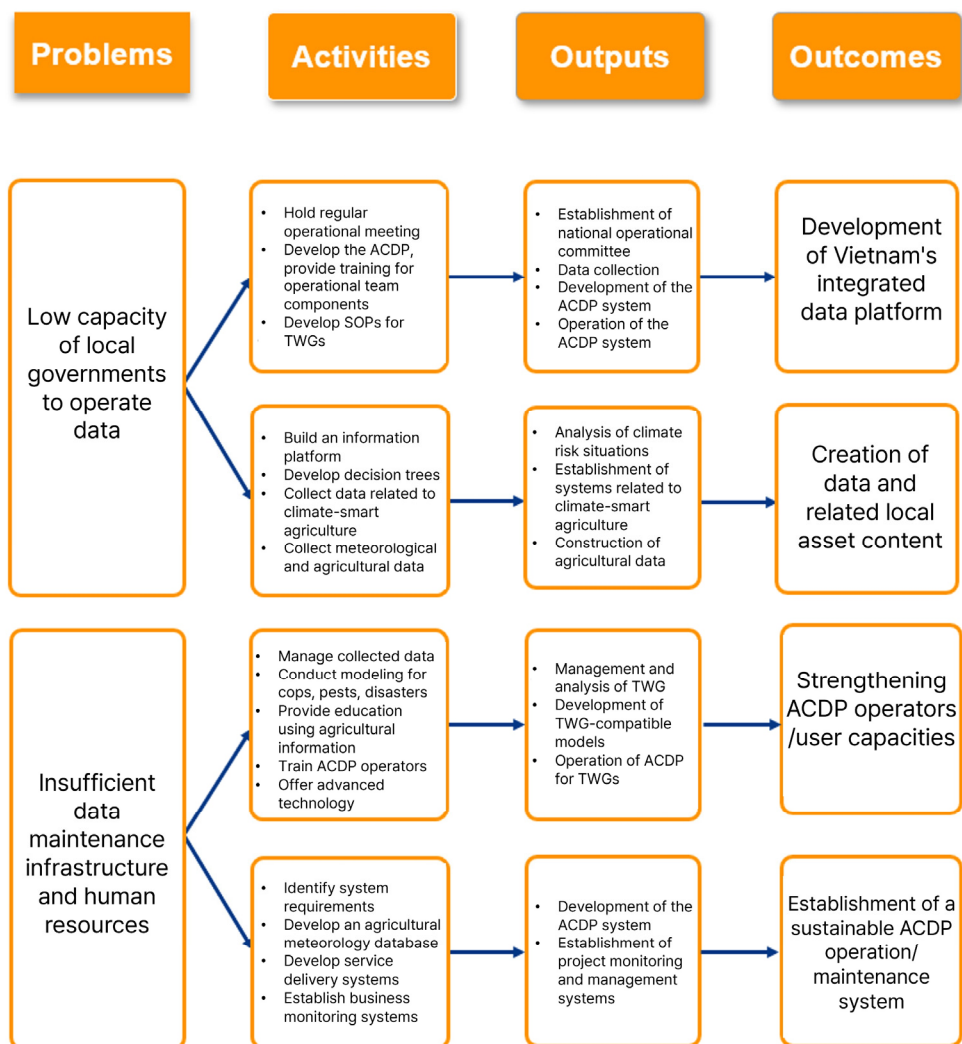
Description	Indicators	Verification Method	Assumptions
Output 1.4: Operation of the ACDP System • Develop Standard Operating Procedures (SOP) defining the roles and responsibilities of provincial/district-level TWGs for ACDP operation • Coordinate training on the operation and maintenance of the ACDP, as well as the dissemination and use of ACDP agricultural meteorology posts suitable for local contexts	• Development of SOP for operation • Number of training sessions on the dissemination and use of ACDP agricultural meteorology posts	• SOP development report • Training attendance list	
Outcome 2. Development of Intellectual Property (Contracts with Government Agencies)			
Output 2.1. Assessment of Climate Risks and User Needs • Identify key target crops, climate, and pest/disease risks, along with major user decision-making needs to be supported in each region; review existing climate information platforms and networks • Verification of assessment results by TWG and regional stakeholders at national and regional levels (validated through emails and phone calls with DCP and supporting agencies)	• Number of target crops and identified pests/diseases • Number of selected regions • Number of personnel involved in this part	• Risk identification report • Verification results report	
Output 2.2. Crop Decision Trees (CDT), Pest and Disease Management Options, Climate-Smart Agricultural Practices • Develop CDTs by crop experts; finalize CDTs for selected crops at the regional level; verify CDTs on a regional scale • Develop pest and disease management options for selected pests and diseases; verify management options, first by national agencies and second by regional stakeholders (validation via email and phone communication) • Collect climate-smart agricultural practices documented in literature through surveys and expert consultation (develop a database of climate-smart agricultural practices across various spatial scales)	• Number of contacts made for option verification in pest and disease management (e.g., number of experts contacted) • Volume of information on climate-smart agricultural practices (in GB)	• CDT performance evaluation report • Documentation for option verification	

Description	Indicators	Verification Method	Assumptions
Output 2.3. Data Collection • Collect or connect meteorological and climate data needed for the ACDP agricultural database • AGather agricultural data required for the ACDP database, including soil, land use, administrative shape files, crop statistics, historical data on pests/diseases, agricultural disaster occurrences, crop statistics, and near real-time agricultural data	• Volume of meteorological and climate data (in GB) • Volume of agricultural data (in GB)	• Data analysis report	
Outcome 3. Capacity Building for ACDP Operators and Users			
Output 3.1. Appropriate Data Management and Analysis for TWG and Data Providers • Analyze and apply meteorological/climate data using specific data analysis and software tools • Utilize specific data analysis tools to integrate meteorological/ climate data in the analysis of agricultural data	• Number of analysis outputs produced • Number of experts involved	• Data analysis results report	
Output 3.2. Appropriate Modeling Training for TWG • Provide training on modeling and application for crops, pests and diseases, and climate disasters • Train on methods to transform meteorological information into agriculture-related data and apply it to farm management • Conduct statistical modeling using historical climate and agricultural data	• Number of training participants • Number of training sessions	• Training attendance list • Modeling results report	
Output 3.3. Operation and Use of ACDP by TWG • Provide training on ACDP operation, including system configuration, data collection, and ACB production • Conduct technical training for sustainable maintenance of ACDP • Offer general agrometeorology training as well as advanced agricultural meteorology services training for key stakeholders • Train extension agencies and farmers on the interpretation and use of ACB	• Number of training participants • Number of training sessions	• Training attendance list	

Description	Indicators	Verification Method	Assumptions
Outcome 4. Development of the ACDP System (Contracts with Service Providers)			
Output 4.1. Development of the ACDP System • Review existing or new databases and products from relevant national agencies (both climate and agriculture) • Identify system requirements through consultations with key stakeholders • Provide functional and technical specifications for the ACDP system • Develop the ACDP agricultural meteorology database: quality control (QC) for climate and agricultural data, database development, and a system for real-time data access and/or upload • Develop the ACDP information production system: downscaling seasonal forecasts, statistical outputs for models, pest and disease modeling and management system (covering 12 major pests and diseases for 4 crops), irrigation (ET) support tools, and crop decision tree operations • Develop the ACDP service delivery system: deliver monthly and weekly ACB using a semi-automated hybrid approach at city, provincial, and national levels • Develop ACDP web and app platforms	• Number of personnel involved in system development • Number of ACBs provided • Web access records • Number of app downloads	• System development report • ACB outputs • Existence of web and app platforms	
Output 4.2. Support for Testing and Deployment for Project Management and System Owners • Provide comprehensive project management services to ensure timely completion and delivery • Offer full support to system owners for testing and deployment	• Number of personnel involved in service management	• Survey Results from Service Recipients	

〈Table 5-6〉 Proposal for Vietnam ODA Model: Theory of Change (Example)

Vietnam Agricultural Climate Digital Platform Development Project



It is worth noting that all of the business models presented above include elements of ICT projects to improve data accessibility. As discussed above, in order to ensure the effectiveness and sustainability of international development cooperation projects, it is essential to plan and implement projects utilizing appropriate technologies in consideration of the infrastructure level and capacity of low- and middle-income countries.

The reality is that many low- and middle-income countries lack the relevant infrastructure (such as power and telecommunications networks) and specialized human resources, which must be carefully considered in project planning to ensure the effectiveness and sustainability of the program. Given that most ICT projects are being implemented in capital and large cities, where infrastructure and human resources are concentrated, and there are few success stories, analog methods should also be considered to implement ICT projects in rural areas where infrastructure and training expertise are relatively scarce.

Mekong River Basin countries such as Vietnam and Laos have relatively high levels of electricity access, internet access, and mobile phone subscriptions, so the basic infrastructure for utilizing climate information services at the farm level is considered to be in place. Therefore, climate information services can be considered as an appropriate technology-based digital climate-smart agriculture model that can be practically applied and utilized at the farm level in Mekong Basin countries. However, to enhance the effectiveness and sustainability of the project in rural areas, a hybrid approach can be applied to the project that combines digital-based climate information services with analog methods. Programs such as DeRISK, SAMIS, and LaCSA, which have been implemented for farmers in Vietnam and Laos, have experience in using analog methods such as village bulletin boards and loudspeakers, and expanding the use of local mobile messenger applications (such as Zalo). Similar programs in neighboring countries (such as AICCRA in Ethiopia, CSAIP in Ghana, and ARCC and CSA in the Mekong Basin) have also included activities that combine digital climate information systems with analog methods to support farmers' adaptation to climate change.

In addition, given the low ND-GAIN index of Mekong Basin countries, capacity building programs are needed for the operation and management of climate information services, as well as for their use at the farm level and application in practice. Agricultural extension service can be a good approach to strengthen farmers' capacity to cope with climate change, and capacity building programs should not only provide information or technical training, but also strengthen non-cognitive skills such as self-efficacy and awareness. Such an integrated approach is expected to make the program more efficient, effective, and sustainable.

Therefore, this study proposes a business model focusing on the use of climate information services, which is the most realistic way of climate-smart agriculture using digital technology, considering the human, physical, and institutional capacities, including infrastructure, of low- and middle-income countries. In addition, the proposed business model includes the use of analog village bulletin boards and loudspeakers as well as digital platforms to distribute climate information, and the use of agricultural extension service and farmer organizations to strengthen human, physical, and institutional capacities to compensate for the limitations of existing projects using ICT technology. It is expected that digital-based climate-smart agriculture, which applies low-level appropriate technologies such as climate information services, can serve as an important foundation for middle- and low-income countries to transition to high-level climate-smart agriculture in the medium to long term.

The demand for climate information services is expected to grow along with the ever-increasing demand for digitally-based climate-smart agriculture in middle- and low-income countries. Therefore, based on Korea's advanced ICT and agricultural technology and economic development experience, it is expected that Korea can play a leading role in international development cooperation in the field of digital climate-smart agriculture using climate information services by identifying international development cooperation projects.

6. Conclusion

6.1. Summary

This study analyzed the current status of climate change adaptation in the Mekong River basin countries vulnerable to climate change, and empirically analyzed the determinants of the adoption of climate change adaptation measures at the farm level and the multidimensional effects of adaptation measures. Through this, we have presented policy implications that can provide practical help to farmers and policy decision-makers in LMICs vulnerable to climate change. In addition, the study presented a way to discover and link effective international development cooperation project models for responding to climate change by establishing scientific grounds for responding to climate change through convergence empirical research.

In detail, Study 1 found that agricultural productivity in the Mekong River basin countries is significantly declining due to abnormal weather conditions such as rising temperatures and increased precipitation variability, and that farmers' incomes and food security are being seriously threatened by an increase in extreme weather events such as droughts, floods, and salt intrusion. In particular, it was found that the Mekong River delta has greater variability in rice productivity than other regions. In response, Vietnamese farmers are increasing the proportion of rice cultivation area, and we also found a steady increase in the expenditure on agricultural machinery per unit area. However, future climate simulations showed that the negative impact of climate change on farmers' income can be adjusted through the proportion of crop groups. In particular, in the Mekong Delta region, these adaptation measures can increase farmers' profitability by up to 50%, so crop proportion adjustment can play an important role in responding to climate change in the region.

Therefore, we found that in order to respond to the effects of climate change experienced by farmers in the Mekong River Basin, first, climate change adaptation measures such as changing the crop composition and promoting mechanization at the farm level are necessary; second, education and financial support for farmers to switch crops and infrastructure investment support at the government level are important; and third, a program plan organized at the regional level is necessary to create a positive ripple effect of neighbor effects, which is the interaction between neighboring farmers.

In Study 2, we analyzed various factors that affect the decision to introduce major climate change adaptation measures in the agricultural sector ((1) Adjusting planting calendar, (2) Crop diversification, (3) Changing seed variety, (4) Field preparation, (5) Adjusting planting techniques, (6) Water use management, (7) Improve water facilities, (8) Income diversification, (9) Using Agro-climate information, etc.) by focusing on the fact that LMICs with insufficient capacity to respond to climate change are responding to climate change mainly through adaptation rather than mitigation.

The results of the household survey conducted for the analysis showed that the majority of farmers in Vietnam and Laos perceived that climate change was actually occurring and had experienced damage from floods and droughts. In addition, many farmers expected that climate shocks such as droughts and floods would occur in the future due to climate change, and although the majority of households had a positive perception of climate change adaptation measures, relatively few farmers used climate information to introduce actual adaptation measures.

In addition, the analysis of the factors influencing decision-making showed that no factor was common to all decisions to introduce adaptation measures, but that (1) agricultural extension services, (2) access to agro-climate information, and (3) self-efficacy had a positive impact on the introduction of adaptation measures. In particular, it was found that agricultural extension services promote the introduction of adaptation measures, and financial access contributes to

strengthening the capacity to introduce adaptation measures.

Based on these research findings, the following policy implications were drawn. First, in order to promote the adoption of climate change adaptation measures by farmers, policy support is needed to improve farmers' awareness of climate change and to provide them with access to practical climate information. Second, the capacity of farmers to respond to climate change and implement adaptation measures should be strengthened through educational programs on climate-smart agricultural technologies in conjunction with agricultural extension services. Third, it is necessary to design support measures that are tailored to the characteristics of farmers, including non-cognitive skills such as self-efficacy, to induce effective changes in behavior to respond to climate change. Fourth, efforts are needed to enhance the capacity of LMICs to respond to climate change through cooperation with international cooperation systems or international development cooperation programs that utilize climate information such as agricultural and forestry meteorological services.

In detail, Study 3 aimed to comprehensively analyze the various impacts of climate change adaptation measures on the quality of life of farmers, analyzing the impacts on quality of life in various aspects such as income, consumption, and health, as well as agricultural productivity. The effects of climate change adaptation measures were analyzed in terms of (1) household income, (2) agricultural income, (3) household consumption expenditure, (4) food consumption expenditure, and (5) subjective quality of life for farmers in the Mekong River basin. This allowed us to assess the differences in quality of life outcomes between farmers who have adopted adaptation measures and those who have not, and shed light on the effects of climate change adaptation measures from multiple perspectives.

In the analysis of the effects of climate change adaptation measures, low-cost and low-risk adaptation measures such as adjusting farming methods, diversifying income, and using climate information had a positive effect on improving farmers' income and welfare, while high-cost and high-risk adaptation measures such as

diversifying varieties and crops and managing water use had a limited effect. It was also found that using climate information in combination with adjusting farming methods had a synergistic effect.

Based on the research results, the following policy implications were drawn. First, in order to gradually strengthen the climate change adaptation capacity of farmers in LMICs with weak climate change response capabilities, support is needed to encourage farmers to actively use low-cost and low-risk adaptation measures. In addition, high-cost and high-risk adaptation measures require a policy approach at the government and community level rather than at the level of individual farms. Second, considering that agricultural extension services and financial accessibility have a positive impact on increasing farm income, it is necessary to support the strengthening of farmers' capabilities and the improvement of financial accessibility using agricultural extension services at the community level. Third, considering that the use of climate information can enhance the capacity of farmers to respond to climate change and produce synergistic effects when combined with other adaptation measures, efforts should be made to improve access to climate information services so that farmers can actively use agricultural extension services linked to agro-meteorological information. In addition to simply acquiring information, policies that support the strengthening of skills and capabilities so that this information can be used in actual agriculture should also be accompanied.

6.2. Dissemination

The results of this study have been shared with domestic and foreign researchers and stakeholders through various channels, and will be shared further in the future. First, the results of Sub-study 1 were presented to the academic community at the Asian Association for Environmental and Resource Economics (AAERE 2024) held in Taiwan on August 26-27, 2024 under the theme of “The Impact of Climate Change on Agricultural Yields in Vietnam and the Effectiveness of Adaptation Strategies.” In addition, the results of Sub-study 1 and Sub-study 2 were presented at the 11th International Symposium on East-Asian Agricultural Economics 2024, held in Japan on October 27-28, 2024, under the titles “The Impact of Climate Change on Vietnam's Rice Yield and the Effectiveness of Producer-side Adaptation Strategies (Sub-study 1)” and “Factors Influencing Climate Change Adaptation among Farmers in the Mekong Delta (Sub-study 2).” In addition, the results of Sub-study 2 and Sub-study 3 will be presented at the Winter Economics Joint Conference to be held in Seoul in January 2025, and will be fed back to various researchers and stakeholders.

By presenting the research results at various academic conferences, we will collect feedback from various experts to reflect more practical academic and policy implications and revise and develop them into academic papers, and in the future, we will submit the results of this study to excellent domestic and international journals. We expect that this research outcome feedback will contribute to the expansion of the international community's climate change research and knowledge ecosystem. In addition, feedback on the research results will be provided internally at KOICA through the Development Cooperation Issue Seminar (DISKO).

The results of this study can be used as basic data for the establishment of development plans not only in Korea but also in the Mekong Delta countries, which are the target regions of the research. It can also be used as a resource for establishing action plans across multiple fields, including improving distribution infrastructure through improved market access, increasing agricultural productivity by identifying

crop losses, and developing a capacity-building curriculum for public officials using a digital climate information system.

To increase the local utilization of the research results, the main contents of the research will be translated into local languages and returned to the academic and stakeholder communities in Vietnam and Laos. To this end, the research results will be shared through feedback workshops, seminars, and data sharing, centering on local research partnerships. Through this, we will contribute to academia and policy by providing research results to stakeholders such as researchers and government officials in the Mekong River basin and providing policy recommendations tailored to local conditions.

6.3. Limitations and Suggestions

This study is significant in that it empirically analyzed the multidimensional effects of climate change and the effectiveness of adaptation measures for farmers in the Mekong River basin using econometric methods to derive policy implications and present an international development cooperation model for responding to climate change in the agricultural sector, but it has the following limitations.

First, due to limited time and resources, this study focused on adaptation measures, which are the two important pillars for responding to climate change in the agricultural sector, rather than mitigation measures. In particular, it is not easy for farmers in LMICs with insufficient capacity to respond to climate change to individually introduce mitigation measures. Therefore, this study focused on the practical adaptation measures that can be taken by farmers in the Mekong River Basin to respond to climate change. Therefore, the analysis of the decision-making factors for the introduction of mitigation measures, the effectiveness of mitigation measures, the integrated approach of adaptation and mitigation measures, and the resource (water, energy, etc.)–climate change NEXUS approach were excluded from the scope of the study. However, considering the importance of agriculture in LMICs, this is also an important topic to be addressed in the formulation of agricultural and climate change policies, and further research on this topic is expected to provide more comprehensive and effective climate change response measures.

Second, this study was conducted on farms in some countries in the Mekong River basin, which may limit the external validity of the research results. However, it may provide policy implications for other regions or countries with similar geographical, political, economic, and social contexts to the Mekong River Basin. For example, the Nile River basin in Egypt, the Ganges-Brahmaputra-Meghna (GBM) delta in Bangladesh, and the Irrawaddy delta in Myanmar are all important agricultural production areas like the Mekong River basin, but they are also vulnerable to climate change. Even among developed countries, the Mississippi

River basin that runs through the central part of the United States is so large in terms of agriculture that it produces 92% of the country's agricultural exports and 78% of the world's feed grains, but it is suffering from a decrease in farmland due to floods and dam construction, and is actively exchanging information with the Mekong River Commission for sustainable development. As such, we expect that the results of this study will contribute to solving the global challenge of climate change through academic and policy implications using the results of this study in regions that are experiencing similar problems in similar situations and environments to the Mekong River Basin. In addition, as shown in the results of Detailed Study 1, the results of the Mekong Delta region are similar to those of Vietnam as a whole, but are more vulnerable to climate change, and are expected to provide standards that can be used in research and policy formulation, especially in regions vulnerable to climate change. In this context, the results of this study are likely to be used internationally to help research and policy-making on climate change responses in the agricultural sector in various regions.

To address these limitations, the following research tasks are proposed.

(1) Empirical research on integrated climate change response combining adaptation and mitigation

An empirical analysis of the interaction between adaptation and mitigation measures and their synergistic effects and potential conflicts is needed to develop policies for an integrated approach to climate change response in high-income countries as well as in LMICs. In the future, demand for international development cooperation projects in the agricultural sector for integrated adaptation-mitigation approaches to climate change is expected to increase, so research is also proposed to develop relevant business models and guidelines.

(2) Research on the NEXUS between resources, food, and climate change

Climate change is not a problem limited to one field, but a problem in which various aspects such as water, energy, and food security are linked as a system. Therefore,

research is required to respond to climate change in an integrated manner from the perspective of the NEXUS between water, energy, and food security. This is essential to understand the complexity of responding to climate change by considering the interconnected aspects and to come up with multidimensional sustainable solutions. To this end, we propose research on climate change that integrates water, energy, and food security through the introduction of climate-smart agricultural technologies tailored to local conditions.

(3) Research on climate change in regions with diverse environments and situations

By expanding the scope of research beyond the Mekong River basin to include several LMICs with diverse environmental, economic, and social characteristics, we can identify the universal effects and regional particularities of climate change adaptation measures. This will expand our understanding of climate change responses and policy-making in the agricultural sector, and we expect that it will contribute to solving the global challenge of climate change.

(4) Longitudinal study of the medium- and long-term effects of climate change adaptation measures in the agricultural sector

There is a need to conduct a longitudinal study to assess the sustainability and medium- and long-term effects of climate change adaptation measures. Such studies can provide important information for policy design and implementation by providing a deeper understanding of the effects of climate change adaptation measures in the agricultural sector. It also provides the basis for setting the mid- to long-term policy direction by analyzing the long-term feasibility of adaptation measures. For example, this study only analyzed the short-term effects of insurance, but longitudinal studies can analyze the medium- and long-term effects of insurance on farmers' ability to manage various climate risks, practice sustainable agriculture, and maintain a stable quality of life. This is expected to contribute to the establishment of more comprehensive and long-term policies to address climate change. In addition, by analyzing the long-term feasibility of

adaptation measures, we provide essential evidence for setting mid- to long-term policy directions. For example, this study only analyzed the short-term effects of insurance, but longitudinal studies can be used to analyze the mid- to long-term effects of insurance on farmers' ability to manage various climate risks, practice sustainable agriculture, and maintain a stable quality of life. This is expected to contribute to the establishment of more comprehensive and long-term policies to address climate change.

Climate information services using agro-climate information are attracting attention in many LMICs as an innovative alternative to address climate change. For example, international cooperation programs such as DeRisk, SAMIS, and LaCSA, which have been implemented in Vietnam and Laos, have increased agricultural productivity using climate information services, and Ethiopia's AICCRA, Ghana's CSAIP, and the Mekong River Basin's ARCC and CSA have also supported farmers' response to climate change through digital climate information systems. These cases show that the demand for digital agriculture, climate-smart agriculture, and climate information services is continuously increasing in LMICs. Accordingly, it is expected that Korea will be able to play a leading role in this field of international development cooperation based on its ICT technology by discovering and evaluating the effects of customized international development cooperation business models in the fields of agriculture and climate change. However, in order to ensure sustainability, it is essential to plan and implement projects using appropriate technologies in consideration of the infrastructure level and capabilities of LMICs.

Therefore, in this study's Detailed Study 3, the effects of climate information services on farmers were evaluated, focusing on the effects of climate change adaptation measures, and based on this, a new international development cooperation project model was proposed in Chapter 5. In particular, from the perspective of appropriateness and sustainability, considering the high percentage of the population with access to electricity, internet, and mobile phone subscriptions in countries along the Mekong River, such as Vietnam and Laos, the use of climate

information services for climate change adaptation in the agricultural sector can be said to be a digital climate-smart agricultural model based on appropriate technology that can be practically applied and utilized locally. In addition, considering the low National Adaptation Capacity (ND-GAIN) index of the countries in the Mekong River Basin, the project will be able to further increase its efficiency, effectiveness, and sustainability by providing an educational program to strengthen the capacity to operate, manage, and use climate information services.

If similar international development cooperation projects are discovered and formed in the future, it is necessary to conduct a comprehensive impact evaluation study that covers all stages of the project from the planning stage to systematically evaluate the effectiveness of the project. Through this, we expect to discover best practices for effective and sustainable international development cooperation projects for digital climate-smart agriculture and develop them into signature projects in the field in Korea.

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