A Study on Rice Production Efficiency and Sustainable Farming in the Vietnamese Mekong Delta

2022

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Abstract

In the restructuring policy of paddy sector to the year 2025 and 2030, Vietnam continues to move towards efficiency improvement and sustainable development targets. Since the year 2000, the orientation of intensive farming in the Mekong Delta, the “rice bowl” of Vietnam, has led to overuse of inputs such as fertilizers and pesticides. As a result, rice production in the region is now facing challenges including low efficiency, natural resource utilization and environmental pollution. For that reason, it is urgent and necessary to investigate about efficiency with regards to inputs management and the sustainable farming strategies of rice production in the Mekong Delta. This thesis comprises six chapters. In which, the introductory chapter presents the background of the study, followed by the discussion on research objectives and the significance of the study along with the organization of the thesis. Chapter 2 provides the present situation of the rice sector, environmental harms and some climate smart agriculture programs in Vietnam and the delta. The next chapters 3, 4 and 5 are carried out to: (i) measure the overall efficiency and calculate the excessive inputs usage – the input slacks – in special reference to farm size; (ii) assess the impacts of a climate smart agriculture practice on the economic performance of smallholders and (iii) evaluate efficiency and greenhouse gas emissions (GHG) mitigation capacity related to major rice variety groups in the Mekong Delta, especially aromatic and high-quality rice for export, respectively. Through the application of data envelopment analysis to the Vietnam Household Living Standard Survey 2016 dataset, the results of Chapter 3 indicate that small scale rice farms in the Mekong Delta obtain low overall efficiency at 59% due to overuse of inputs. Current excessive usage should be reduced with regards to seed cost by 28 USD/ha, pesticides by 61 USD/ha, and fertilizers by 155kg/ha. In addition, all types of efficiency could be improved and farmers could reach efficient production frontier if farm size is expanded overuse of inputs is minimized. The chapter 4 employs propensity score matching to estimate the impact of eco-friendly farming practice named “One Must Do, Five Reductions - 1M5R” on the economic performance of paddy households. It is concluded that this technical package helps farmers to reduce their production cost by 10%, increase a paddy’s selling price by 4.5% per kg, and obtain 10% more profit, compared to traditional farming households. The return on investment of 1M5R adopters increased by 22%. Chapter 5 uses slack-based super-efficiency measure data envelopment analysis with household survey data to analyze the overall efficiency and input slacks of rice production. Main findings are: aromatic and high quality rice groups achieve high efficiency and can contribute to GHG mitigation with small slacks of nitrogen and water use. Finally, the major findings of the study are discussed in Chapter 6. There is an advantage of encouraging farmers for expanding farm size and improving production efficiency and farm environment through reduction of chemical inputs. Particularly, the government should take more active and appropriate measures to monitor climate smart faming and design specific regional schemes for sustainable rice production in Mekong Delta and Vietnam.

Keywords: rice production, Mekong Delta, efficiency, small holders, sustainable farming, data envelopment analysis, propensity score matching, climate smart agriculture, aromatic rice, high quality rice.

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LIST OF ABBREVIATIONS

AWD	Alternative wetting and drying
BCC	Banker, Charnes, Cooper model
CCR	Charnes, Cooper, and Rhodes model
CSA	Climate smart agriculture
DEA	Data envelopment analysis
GHG	Greenhouse gas emissions
LFM	Large field model
MKD	Mekong Delta
N_2O	Nitrous oxide
PSM	Propensity score matching
SBM	Slack-based measure
SE	Scale efficiency
TE	Technical efficiency
1M5R	One must do, five reductions

Chapter 1 Introduction

1.1. Background

The rice industry plays an important role in the development of agriculture and rural areas, contributing to national food security, livelihoods of farmers, social security and stability. Rice production in Vietnam has many advantages in ecological conditions associated with the long-standing wet rice civilization. However, the development of rice sector is facing challenges due to low efficiency, natural resource over consumption, environmental pollution and the impact of climate change. Vietnam is one of the world's leading rice producers and exporters. Rice exports play an important role in the national socio-economic development. According to USDA[1] data, in 2020, Vietnam exported 6.17 million tons of rice with an export turnover of 3.07 million USD, accounting for 12.75% of the world rice export market share, ranked after India (35.61%) and Thailand (15.1%) (USDA). In terms of total rice production, Vietnam produced about 28.98 million tons in 2019, ranking fifth after China, India, Indonesia and Bangladesh with figures at 141, 118, 36.42 and 36.41 million tons, respectively. In particular, the Mekong Delta (MKD) plays an extremely important role in ensuring food security and rice exports of the country.

The MKD is a region with many potentials and advantages in agricultural production, especially the rice industry. In 2019, the MKD produced more than 24 million tons of paddy, which contributed to 56% of total national rice production quantity and 90% of the export volume (General Statistics Office – GSO, 2021). However, this region is also facing many difficulties and challenges including land fragmentation, environmental pollution, over consumed natural resources and severe impacts of climate change.

Firstly, small farm size and fragmented land are believed to be the disadvantages to agricultural development and input uses in Vietnam and the MKD. It is more difficult to improve productivity through mechanization, consistent investment in new technology and efficient water management (Smith, 2013). Based on agricultural census data in 2016 (GSO, 2018), the proportion of paddy households smaller than 2 hectares (ha) in the MKD is 83.4%. In which, 74,162 of households obtain smaller than 0.2 ha land size, equivalent to 6.51% of the total. This figure of households less than 2 ha of farmland is at 53.67% of the whole country. There have been studies indicated that small farms are highly productive (Bardhan, 1973; Sen,

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[1] Rice Yearbook, United States Department of Agriculture (2020)

1975; Heltberg, 1998; Lipton, 2009) and efficient (Carletto et al. 2013; Larson et al., 2014; World Bank, 2016). However, this statement seems to be not available anymore in the context of increasing labor wage and machinery use in large farms in Asian countries (Otsuka *et al.*, 2016). Although high proportion of very small and fragmented farms exists, there has to date not been studies that clarify the relationship between farm size with overall efficiency and input management in the MKD.

Secondly, the intensive rice farming practice has caused soil degradation and polluted natural environment through overuse of inputs in the MKD. Regarding the fertilizer nutrients use for agriculture, Vietnam consumed about 1.49 million tons of nitrogen (N), 731 thousand tons of phosphate (P_2O_5) and 511 thousand tons potash (K_2O) in 2019 (FAOSTAT, 2021). With every unit per crop land, Vietnam uses approximately 127 kg/ha of N, ranking the third after China at 198kg/ha and Bangladesh at 151kg/ha. This figure is much higher than other countries in Asia including India, Japan, Philippines, Thailand, Indonesia and Malaysia at 111, 84, 65, 59, 57 and 46kg/ha, respectively (FAOSTAT, 2021). It is estimated that about one-half to two-third of the fertilizer nutrients are not absorbed by plants, and those excessive fertilizers will drift into ground water or release as nitrous oxide (N_2O) (World Bank, 2016). Moreover, the use of pesticides in Vietnam has been increasing steadily since the year 2000. The import quantity of pesticides was 69,500 tons in 2010. Later, this figure climbed to 166,328 tons in 2014 and got a peak at 218,849 tons in 2018. In 2019, pesticides import volume declined to 198,892 tons (FAOSTAT, 2021). In the MKD, paddy farmers apply pesticides averagely 5.3 times per crop. There are several studies that reported about the pesticides residues in water, soil (Toan *et al.*, 2013) and the health risk of pesticides overuse to farmers' health (Chau *et al.*, 2015; Dasgupta, 2007). Coupling with the poor water management, it will be very harmful to the environment and natural resources of the country with the current improper use of inputs. Thus it is important to clarify the impact of climate smart farming practices, which aims to bring both economic and environmental benefits to participants.

Thirdly, the increasing greenhouse gas (GHG) emissions from paddy cultivation has also becoming a big concern in recent years. It is reported that, together with the intensive farming policy, the total GHG emissions from agriculture sector in Vietnam has been increasing significantly during the period from 1994 to 2013. Particularly, the emissions were at 52.4, 65.1, 88.3, 89.4 million tons of CO_2 equivalent in 1994, 2000, 2010 and 2013, respectively (MONRE, 2014). Through the data reported in the two national GHG emission inventory in 2010 and 2013, the amount of emitted CO_2 from irrigated rice cultivation has increased from 41.31 million tons to 42.51 million tons, respectively. Also, the direct N_2O emissions from agricultural soils also increased from 12.91 million tons in 2010 to 13.17 million tons in 2013 (MONRE, 2017). Thus, developing crops that, at the same time, ensure food production and reduce GHG emissions become the main targets and the most important criterion in the socioeconomic development progress of Vietnam and the MKD Decision No.1393/QDTTg. Although national policies for rice sector have been moving towards a cleaner production, the information on efficiency coupling with inputs overuse and mitigation capacity of major rice variety groups has not been well-understood in the MKD.

1.2. Thesis objectives

For all of the reasons listed above, the purpose of the thesis is to measure and identify the factors that affect the efficiency of rice production and its implication to sustainable farming in MKD. In addition, it investigates the impacts of a climate smart agriculture on the economic performances of rice smallholders and considers possibilities of low-emission rice farming in the MKD region. Some policy implications for the sustainable rice farming in the region will be given based on the empirical results of the objectives mentioned above.

The specific objectives and research questions regarding to the content of each chapter will be presented in Chapter 2, section 2.6.

1.3. Significance of the study

This study is expected to fulfill the gap of the previous studies about technical efficiency of rice production and the environment in Vietnam and the MKD. Every chapter of the thesis could be useful for readers and researchers to develop their research in developing countries which economy is based on paddy production. Firstly, it helps to identify directly the overuse of inputs through the slacks in production process and the disadvantages of small farms in the mechanization scheme of the country. At the same time, the overall efficiency of rice households are evaluated in a comprehensive method using slack-based measure in data envelopment analysis (DEA). In addition, the study also provides authorities a reference in program evaluation of an important climate smart agriculture technique. This could be a useful literature for future research to explore the impacts of agricultural policies in Vietnam to the beneficiaries in terms of economic outputs. Finally, the information on nitrogen fertilizer and irrigation slacks of rice variety groups could help to achieve sustainable and environmentally friendly agricultural production.

1.4. Organization of the thesis

The thesis is organized into 6 chapters as follows:

Chapter 1 introduces the current problems of paddy production in Vietnam and the MKD, the research objectives, the significance of the study and the structure of the thesis.

Chapter 2 describes the overview of rice production and the environment in MKD, the literature review and research framework.

Chapter 3 explores the sustainable farming techniques and farm size for rice smallholders in the Vietnamese Mekong Delta using a slack-based measure of data envelopment analysis (DEA) approach. In this chapter, the overall efficiency and input slacks of rice production will be assessed using a non-radial DEA technique of slack-based measure (SBM) in the first step. Next, the determinants of efficiency scores will be explored using a Tobit regression model. The role of paddy farm size to the efficiency and the excessive inputs usage has been emphasized in this chapter.

Chapter 4 measures the impact of a well-known climate smart agriculture (CSA) on the economic performance of smallholders in Vietnamese Mekong Delta: the “One Must Do, Five Reductions” (1M5R) technical practice introduced by the government. In the first stage, probit model was used to identify the determinants of farmers’ decision to participate in the 1M5R package. Then, propensity score matching method was employed to calculate the treatment effect of two groups of farmers: 1M5R adopters and non-adopters to reveal the effect of the program on paddy households.

Chapter 5 analyses the efficiency and the inputs slacks of major rice variety groups in the MKD using a slack-based super-efficiency measure in DEA. In addition, the potential reduction of GHG emissions by rice groups and CSA practices are also presented through the excessive usage of nitrogen and irrigation costs. Some further research topics about the cleaner production with aromatic and high quality rice are suggested.

Chapter 6 summarizes and discusses the results of chapters 3, 4, 5, presents some policy implication for the sustainable rice farming in the MKD, and identifies limitations of the study and suggests some future research topics.

Chapter 2 Rice production and the environment in the Vietnamese Mekong Delta: An Overview

This chapter will present the general background of rice production, the environment and some climate smart agriculture (CSA) policies towards sustainability in Vietnam and the Mekong Delta. First section describes the overview of rice production in Vietnam and the Mekong Delta. Next, some disadvantages and challenges of the rice sector will be presented, including: small scale paddy farms and land fragmentation, out-migration and reduced labor force in agriculture, the overuse of fertilizers and pesticides, the GHG emissions from paddy cultivation in Vietnam and the MKD. Thirdly, the context of agricultural restructuring policy towards future sustainable farming is introduced. The current status of some CSA programs including Large Field Model (LFM), “Three Reductions, Three Gains” (3R3G), “One Must Do, Five Reductions” (1M5R), Alternative Wetting and Drying (AWD) is explained in section 2.4. The next section 2.5 summarizes the literature review of the thesis. Finally, research purpose including research objectives, research questions and conceptual framework will be presented in details in section 2.6.

2.1. An overview of rice production of Vietnam and the Mekong Delta

2.1.1. Rice production of Vietnam

Vietnam is considered as one of the world's leading rice producers and exporters. During the period from 2016 to 2021, Vietnam’s total rice output, 27.4 mil tons, ranked fifth in global production, behind China, India, Indonesia, and Bangladesh (Figure 2.1). Export volume reached 6.17 mil tons in 2019, which ranked third after India and Thailand.

Data from the General Department of Vietnam Customs indicates that rice exports in 2020 reached 6.25 million tons with a value of US$3.12 billion, down 1.9% in volume but up 11.2% in value compared to 2019. In the context of the difficult market and affected by the Covid-19 epidemic, Vietnam's rice exports still achieved growth in value, with the annual average export price at about 499 USD/ton, increasing by 13.3% (59 USD/ton) compared to 2019 export price.

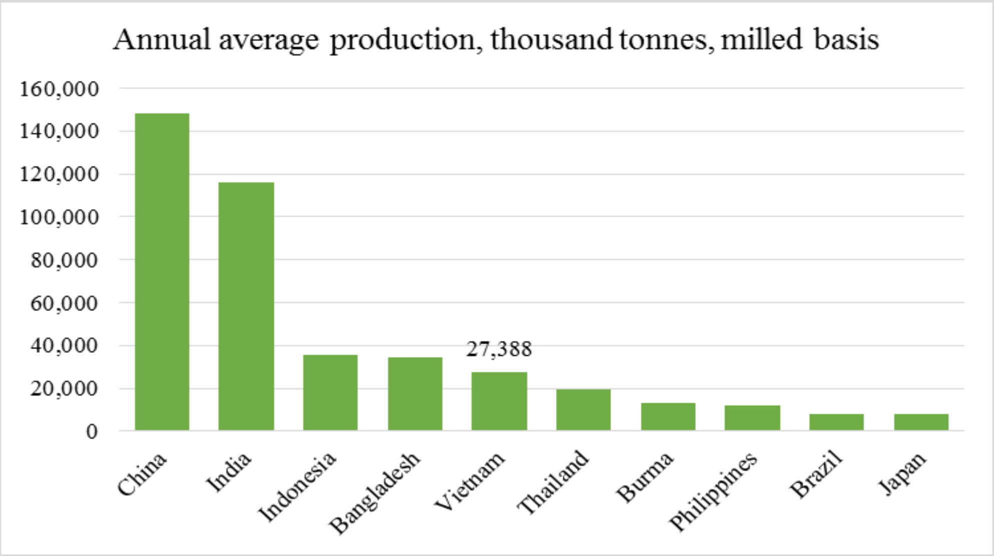


Figure 2.1. Top ten rice producing countries, 2016/2017 to 2020/2021

Source: USDA, Foreign Agricultural Service, Production, Supply and Distribution database.

As indicated in Figure 2.2, Asian countries are still the main regions that import the most rice from Vietnam, reaching about 3.68 million tons, accounting for 66.16% of the country's total rice exports. In which, some main export markets of Vietnamese rice are: (i) Philippines: 2.17 million tons, accounting for 35.54%; (ii) China: 810.1 thousand tons, accounting for 13.25%; (iii) Malaysia: 681.8 thousand tons, accounting for 11.15%; (iv) Indonesia: 92.5 thousand tons, accounting for 1.51%.

Africa is the second largest rice export market of Vietnam, reaching about 1.13 million tons, accounting for 18.54%. Followed up by the Americas: 392.7 thousand tons, accounting for 6.42%, Oceania: 260.8 thousand tons, accounting for 4.27%, the Middle East: 189.5 thousand tons, accounting for 3.1%, Europe: 87.2 thousand tons, accounting for 1.43%.

Regarding the type of rice for export, the export of white rice of all kinds accounted for 45.19% of the total rice export volume, reaching 2.76 million tons. Ranked second is fragrant rice, accounting for 26.84%, reaching 1.64 million tons. Followed by broken rice: 834.4 thousand tons, accounting for 13.65%, up 31.24%; sticky rice: 547.9 thousand tons, accounting for 8.96%.

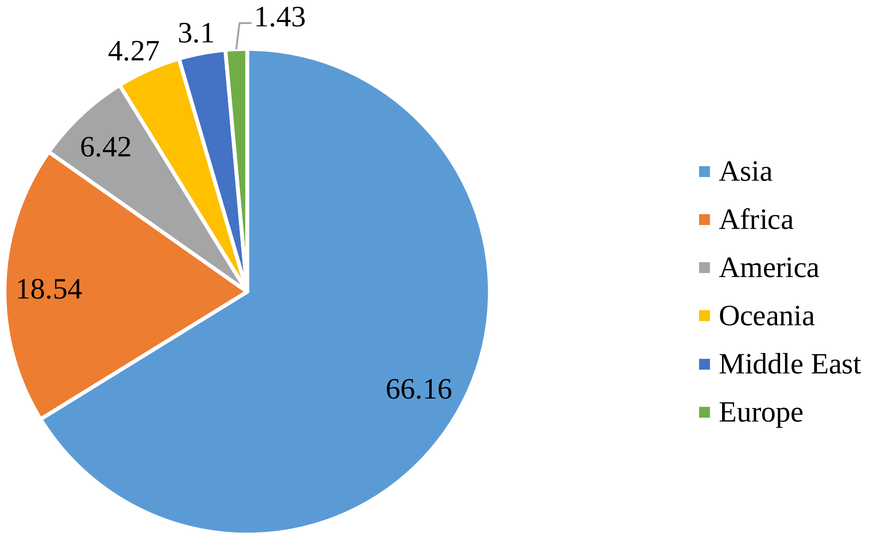


Figure 2.2. Vietnam’s rice exports share (%) in 2020

Source: Vietnam Chamber of Commerce and Industry – VCCI, 2020

To complete the legal corridor in meeting the requirements to enjoy preferential tariff quotas under European Union–Vietnam Free Trade Agreement (EVFTA), Vietnamese Government has issued Decree 103/2020/ND-CP dated September 4, 2020 regulating the certification of aromatic rice varieties on the list specified at point 8 subsection 1, section B, Annex 2-A of the Agreement. EVFTA enjoys import tax exemption within the quota when exporting to the European Union. The nine varieties of aromatic rice exported to the European Union are eligible for import tax exemption according to quotas, including: Jasmine 85; ST 5; ST 20; Miss Hoa 9; VD20; RVT; OM 4900; OM 5451; Tai Nguyen Cho Dao.

2.1.2. The geographic and climate conditions of the Mekong Delta

The Mekong Delta is an important economic and ecological region of Vietnam and is located in the lower part of the Mekong River and bordered by the East Sea (with a coastline of about 700 km) along the West, the Southwest, and the South. The MKD includes 1 city—Can Tho—and 12 provinces: Long An, Tien Giang, Ben Tre, Vinh Long, Tra Vinh, Hau Giang, Soc Trang, Dong Thap, An Giang, Kien Giang, Bac Lieu, and Ca Mau (Figure 2.1). According to the General Statistics Office (GSO) of Vietnam in 2018, the MKD had an area of 40,816.4 km^2 and a total population of 17,273,630 people (Figure 2.3). With the rich natural supply of freshwater and alluvial soils, it is an advantageous environment for a fruitful rice production in the MKD (GRiSP, 2013). The water resources management in this region is characterized by a complex rivers and canal systems that have been extensively developed during the past 20 years (MARD, 2016).

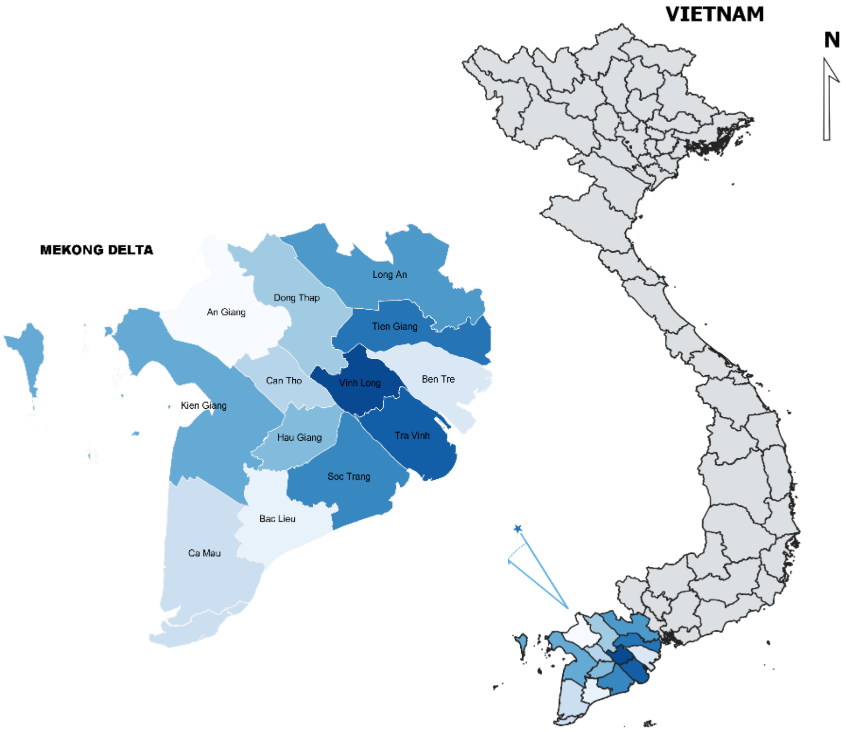


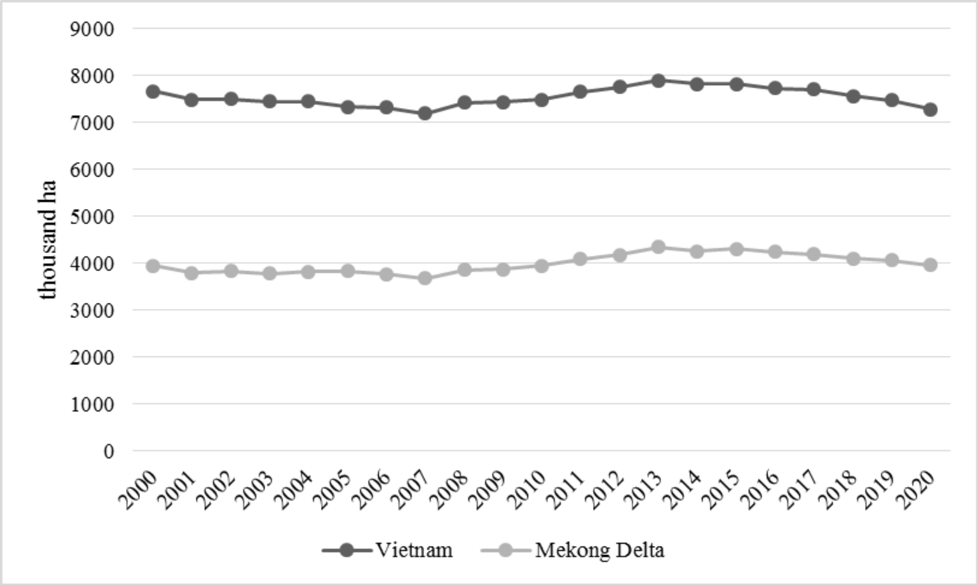
Figure 2.3. Map of Vietnam and the Mekong Delta

Source: Author's compilation, using GIS mapping

Traditional cultivation mainly based on available advantages and the targets to improve productivity through exploitation of natural resources are leading to ecological imbalance in the MKD. The fact is that the region's endowed advantages are gradually being eroded by external climate factors as well as internal agricultural and fishery production policies and habits. The three-season rice farming intensification has caused the declining quality of agricultural land. Also, farming areas inside the closed dike systems cannot receive alluvium becomes degraded, leading to chemical fertilizers and pesticides overuse.

2.1.3. The farming area and production volume of the MKD since 2000

The rice-growing area of the MKD region always ranks first in the country, accounting for 52% of the country's rice-growing area on average (Figure 2.4). In 2000, the rice-growing area of the whole MKD region reached 3,945.8 thousand hectares (ha), accounting for 51.5% of the country's rice-growing area. In 2015, it increased to 4,301.5 thousand hectares, accounting for 55% and in 2020 it became 3,963.7 thousand ha, accounting for 54.5% of the country total area. The decrease in farming area in recent years follows the targets of agricultural restructuring policy in Vietnam. This policy aims to increase the rice products quality and shift some ineffective paddy farming area to other crops or fruits cultivation.



Source: author's compilation from GSO data

Figure 2.4. Paddy farming area of Vietnam and Mekong Delta from the year 2000 – 2020

The rice industry of the Mekong Delta has been constantly changed from low-yielding rice varieties with 2-3 tons/ha to high-quality high-yielding varieties with 6-8 tons/ha. The rice yield of the region is higher than the national average in every year. Farmers also change from 1-2 rice crops/year to 3 rice crops/year towards intensive farming to increase productivity for export. As a result, the yield of each season and the whole year in the MKD increased gradually over years (Figure 2.5). Rice yield in 2015 reached 5.95 ton/ha and 0.19 ton/ha higher than the national yield. In 2020, MKD's average yield reached 6.01 ton/ha and higher than national average yield by 0.14 ton/ha. Especially in the winter-spring season in 2021, the MKD achieved 7.2 ton/ha, 0.37 ton/ha higher than the national winter-spring crop yield. Some provinces in the MKD that have highest yield of winter-spring season in 2021 as follows: Hau Giang reached 7.82 ton/ha; Bac Lieu reached 7.73 ton/ha; Kien Giang reached 7.62 ton/ha; An Giang reached 7.47 ton/ha; Dong Thap reached 7.32 ton/ha. In the 20 years from 2000-2020, the average rice yield of the whole region increased by 178 kg/ha, increasing by more than 7 million tons of rice, accounting for nearly 70% of the total increased rice production of the whole country. This improvement in yield thanks to the application of improved rice varieties, changing from low-yielding rice varieties at only 2-3 tons/ha to high-quality high-yielding varieties at 6-8 tons. /ha. In addition, the change of cropping seasons from 1-2 seasons/year to 3 main rice seasons/year coupling with renovation of rice variety structure and intensive farming process lead to increased rice yield of each season and the whole year in the MKD over the period.

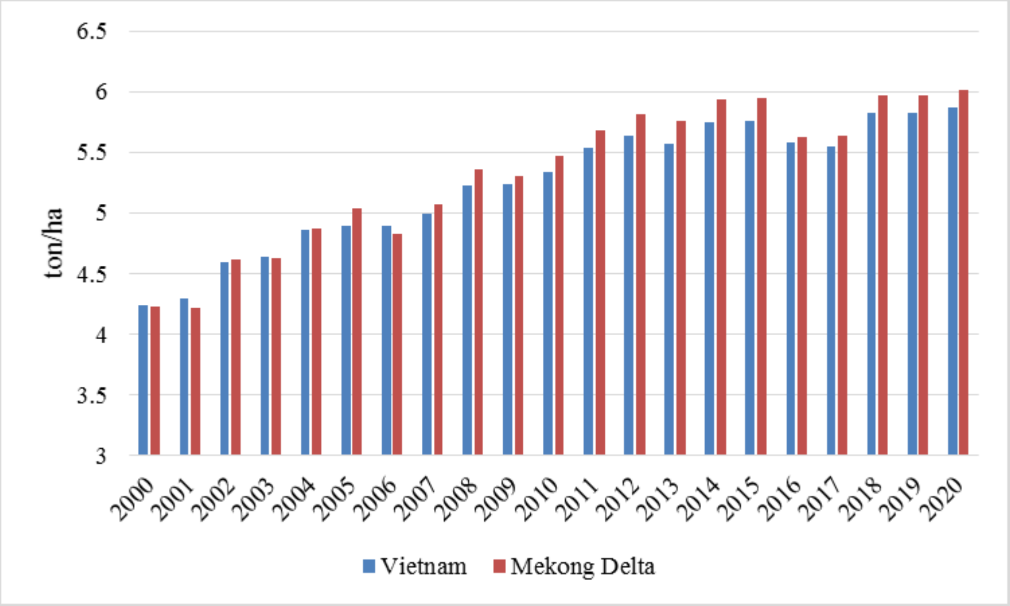


Figure 2.5. Paddy yield of Vietnam and Mekong Delta from the year 2000 – 2020

Source: author's compilation from GSO data

Promoting the intensive farming production has contributed to raising the region's rice production from 16.7 million tons in 2000 to 23.8 million tons in 2020 (Figure 2.6). Major contributors to the region's rice production are the three provinces Kien Giang, An Giang and Dong Thap. The rice production of these three localities accounts for nearly 50% of the whole region's production. In which, winter-spring season has the highest yield among the three main seasons, contributing about 44% of the whole year's rice production in MKD. The success of the winter-spring cropping season contributed greatly to the success of rice production in the region. Not only has the output increased rapidly, but the quality of rice is increasingly high, with specialty rice varieties such as IR64, OM1490, OM2031, VND95-20, MTC250, IR62032, Cho Dao, Jasmine, ST24 and ST25. Especially, ST varieties production for export are expanding in both farming area and output, increasing the competitiveness in the domestic and international market.

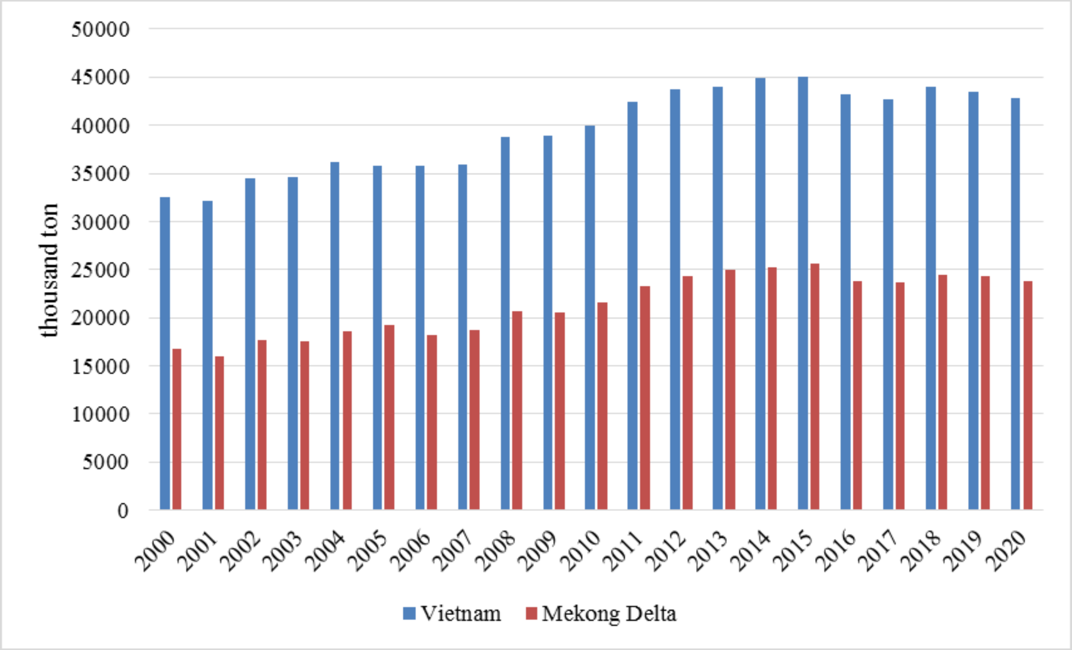


Figure 2.6. Paddy production of Vietnam and Mekong Delta from the year 2000 – 2020

Source: author's compilation from GSO data

2.2. Disadvantages and challenges to the rice sector of the Mekong Delta

2.2.1. Paddy sector made up by smallholders with land fragmentation

Agriculture in the Mekong Delta is made up of mainly small-scale businesses (Smith, 2013). This is also considered as one of the biggest obstacles for policymakers when proposing the mechanization application as well as advanced technical progress in rice production (Thang et al., 2017). There are recent studies which indicated about the disadvantage of small farms in the Asian countries when the labor wage increases and large farm tend to rent big machines for production and harvesting steps (Foster and Rosenzweig, 2010; Liu et al., 2013 and Otsuka et al., 2016). This statement is the motivation for me to develop the content of Chapter 3 about the farm size and environment.

The proportions of rice fields in the MKD that smaller than 2 ha were 86.56% and 83.40% in 2011 and 2016, respectively (Figure 2.7). While the percentage of rice households smaller than 0.5 ha decreased through the period 2011-2016, the percentage of households with 0.5-2 ha and larger than 2 ha increased. A major structural change is happening in the rice industry in the MKD, proving by the significant decrease of rice farming households and the increase in the average farm sizes of rural households.

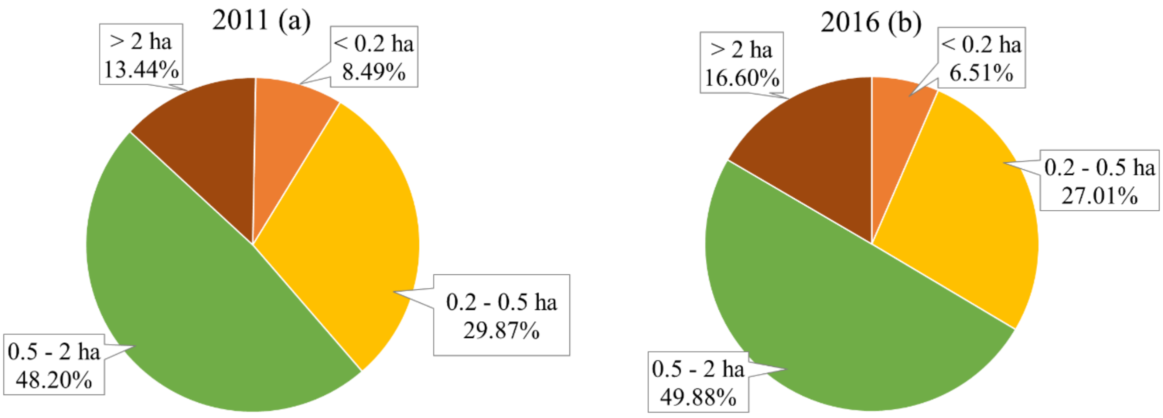


Figure 2.7. Rice farm size categories in the Mekong Delta in 2011 and 2016

Source: Rural, Agricultural and Fishery Census in Vietnam, 2016

Through the results of the two agro-censuses, the number of rice farming households in the MKD went down from 1.365 million in 2011 to 1.139 million in 2016 (GSO, 2018). This downward trend within five years indicates an average annual decrease at 3.3%. Particularly, smallholders who have sufficient other resources (labor, skills, financial means) have converted rice land to fruit crops, aquaculture, and other annual non-rice crops, or have sold the land to change to non-farm activities. From the year 2018 to the present, the most noticeable thing is that the agricultural sector in the MKD has been shifting from fragmented and small-scale production to concentrated, large-scale production. This trend follows the Resolution No. 120/NQ-CP of the Government on sustainable development of the MKD to adapt to climate change. The policy helps localities and people in the MKD actively adapt to climate change and improve their incomes.

2.2.2. Out-migration and the reduction in labor force for agriculture

Figure 2.8 presents the downward trend of labor in agricultural sector in Vietnam since the year 2000. In this year, there was more than 25 million people working in activities related to agriculture. This figure started to decline to 23.26 million in 2015 and strongly decreased to 14.86 million people in 2019.

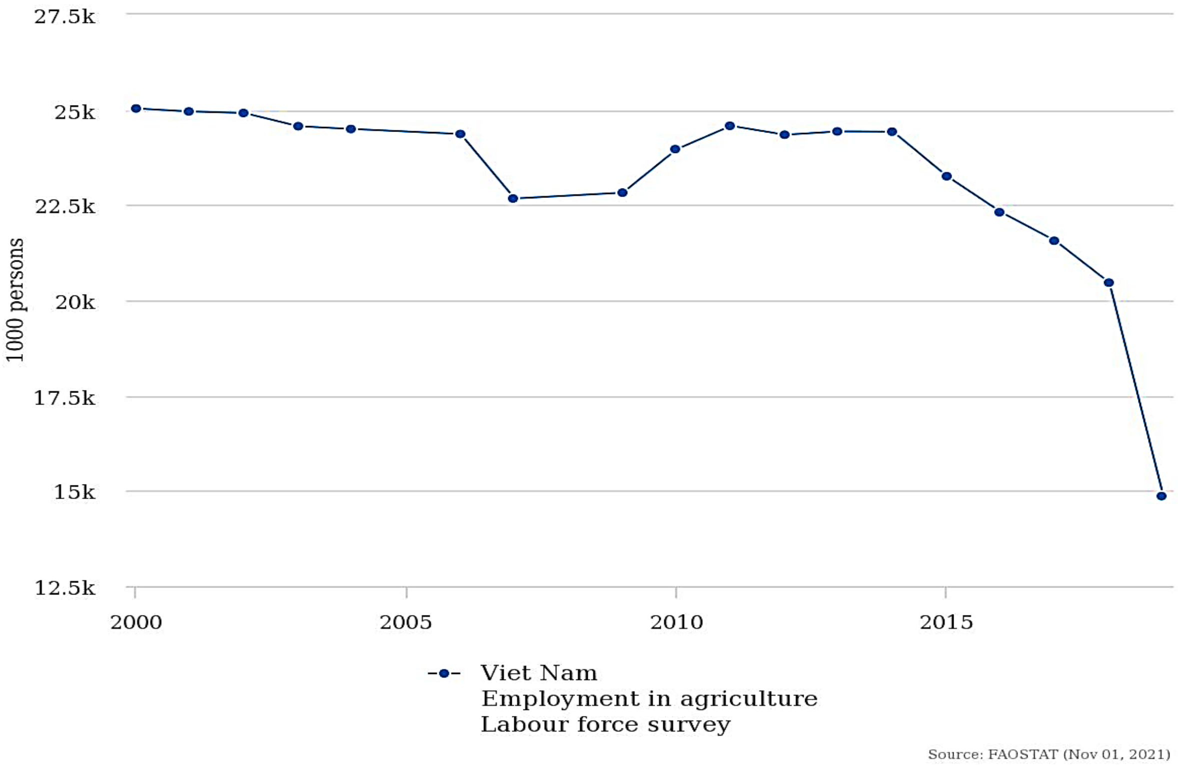


Figure 2.8. Vietnam employment in agriculture from 2000 to 2019

Source: FAOSTAT, 2021

The MKD is also experiencing important changes in demographics, quantity and quality of labor. First, during the period 2009 - 2019, the average population growth rate of the Mekong Delta is only 0.05%/year, much lower than the national average rate of 1.14%/year. The main reason for this situation is that the MKD has the highest net migration rate in the country, up to 39.9%, mainly due to the lack of employment opportunities and local economic opportunities. The fact is that since 2017, for the first time in its history of formation and development, the MKD has recorded an absolute decline in population (VCCI, 2020).

The quality of human resources of the MKD has been a problem but has not been solved for a long time. Regarding general education level, the literacy rate of the population aged 15 and over in the MKD is 94.2%, lower than the national average (95.8%) and only higher than the Central Highlands (91.3%). The proportion of population aged 15 years and over who have graduated from high school in the MKD is only 11.3%, the lowest and much lower than the national average rate of 17.3%. The rate of trained workers in the MKD is 13.6%, which ranks the lowest compared to other regions and the national average rate of 23.1%. In 2020, un-trained agricultural, forestry and fishery workers is 12.57 million people, accounting for 89.97% of the total number of workers in working age.

2.2.3. Excessive usage of seeds, fertilizers and pesticides

The orientations for agricultural intensification - especially three cropping seasons per year– have been becoming ineffective and unsustainable, especially causing a series of environmental harms. In terms of fertilizers, Vietnam's agriculture consumes about 10 million tons of synthesis fertilizer per annum, with about 80 % of this coming from domestic supply. About two-thirds of fertilizer are used for rice; other significant uses (between 5 and 10% of the national total) are for maize, coffee, and rubber. Fertilizer is also the largest cost-item in rice production.

As illustrated from Figure 2.9, the total use of fertilizers in nutrients of Vietnam has increased sharply after the year 2000 due to intensive farming strategy for export. In 2017, nitrogen (N) use reached a peak of 1.56 million tons. In terms of farming practices, surface water has become heavily polluted due to excessive use of fertilizers and pesticides to maintain intensive farming and increase agricultural output.

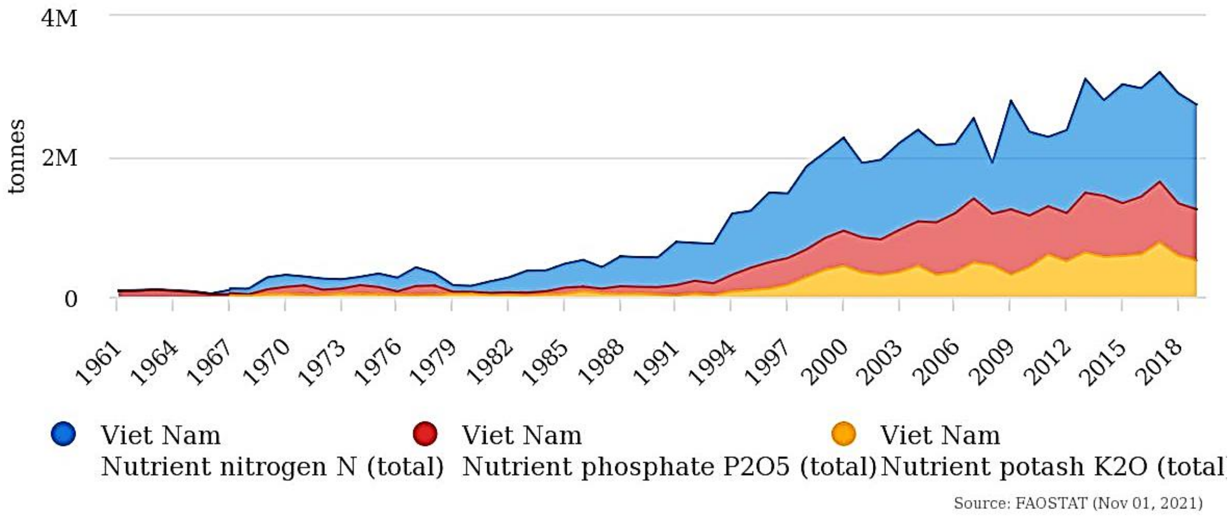


Figure 2.9. Fertilizers consumption in nutrients of Vietnam from 1961 to 2019

Source: FAOSTAT, 2021

As the main region of paddy production and export, farms in the MKD also consumes a lot of synthesis fertilizers. Most of farmers use much more fertilizers than the recommended rates, and N fertilizer is over-used compared to P_2O_5 and K_2O. Also, there is a rate of 54% of NPK fertilizer in the market that did not meet the required standards (Pham and Nguyen, 2013). The efficiency of fertilizer use is also low at only about 60% for N, 40% for P_2O_5, and 50% for

K_2O. The bad things come when the excessive fertilizers, especially N, are absorbed into the soil and water (percolation and runoff) and release the GHG emissions to the environment (Nguyen, 2013).

Regarding pesticides use, the imported volume is stable around 160 million tons/year, equivalent to 825-860 million USD. The data from Vietnam Pesticide Association show that rice is the crop that consumes the most pesticides, which accounts for 64.9% of the total quantity. Following up are industrial crops, vegetables and other plants. Among types of use, fungicide and pesticide are the two with largest proportion at 34% and 26%, respectively. The remaining are herbicide, fertilizer leaf, fumigation and other types.

There are several studies that report the improper use of pesticides in the MKD and its health's risks to the community. Berg and Tam's study (2012) reported that the application frequency of both herbicides and fungicides has more than halved since 1999 for all rice and rice-fish interviewed households in MKD, while insecticide applications has doubled for Integrated Pest Management (IPM) farmers (i.e., those who had already undergone IPM training) due to the insect outbreaks between 2005 and 2007 and major mass media campaigns by pesticide manufactures. The suboptimal pesticide management in MKD has led to a wide range of pesticide residues present in water, soil, and sediments over a long period (Toan et al., 2013). Health risks to farmers and communities using water sources with pesticide residues are becoming ever more evident. Clean water sources appear to be absent, and water-related health risk is becoming a serious issue in MKD due to pesticide pollution (Chau et al., 2015).

2.2.4. GHG emissions from paddy cultivation in Vietnam and the Mekong Delta

Paddy cultivation is considered as a large contribution of CH_4 emissions (Linquist et al., 2012), accounting for 10–14% of total global CH_4 emissions (Nazaries et al., 2013). Figure 2.10 presents the CH_4 emissions from rice cultivation of Vietnam in the period 2000 – 2019. In the year 2000, this activity emitted 1.35 Mt of CH_4, reduced to 1.27 Mt in 2007 and reached a peak at 1.39 Mt in 2013. This figure has been reducing since 2014 to the present at around 1.32 Mt. In the MKD, there is a recent study of Vo *et a*l. (2018) measured CH_4 emissions in different agro-ecological zones using a close chamber method. The results indicated that mean CH_4 emission rates varied significantly, ranging from 0.31 to 9.14 kg CH_4/ha/day.

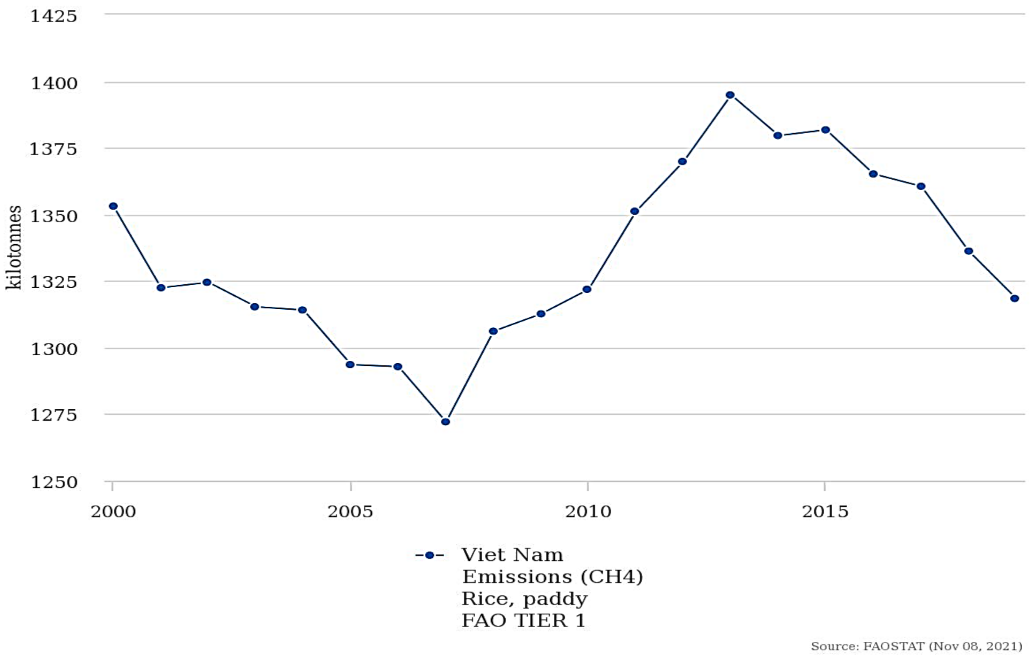


Figure 2.10. CH_4 emissions from rice cultivation of Vietnam from 2000 to 2020

Source: FAOSTAT, 2021

Regarding the nitrous oxide emissions (N_2O), Figure 2.11 displays the direct and indirect emission quantity from synthesis nitrogen fertilizers applied to agricultural soils of Vietnam from 2000 to 2019. The values ranges from 20.86 kt in 2000 to 24.54 kt in 2019 with direct N_2O. The total indirect N_2O from the volatilization and leaching of fertilizers differs from 6.78 to 7.97 kt during the period. There has been no study that mentioned or conducted on-field experiments about N_2O emissions through various N application rates on paddy fields in the MKD.

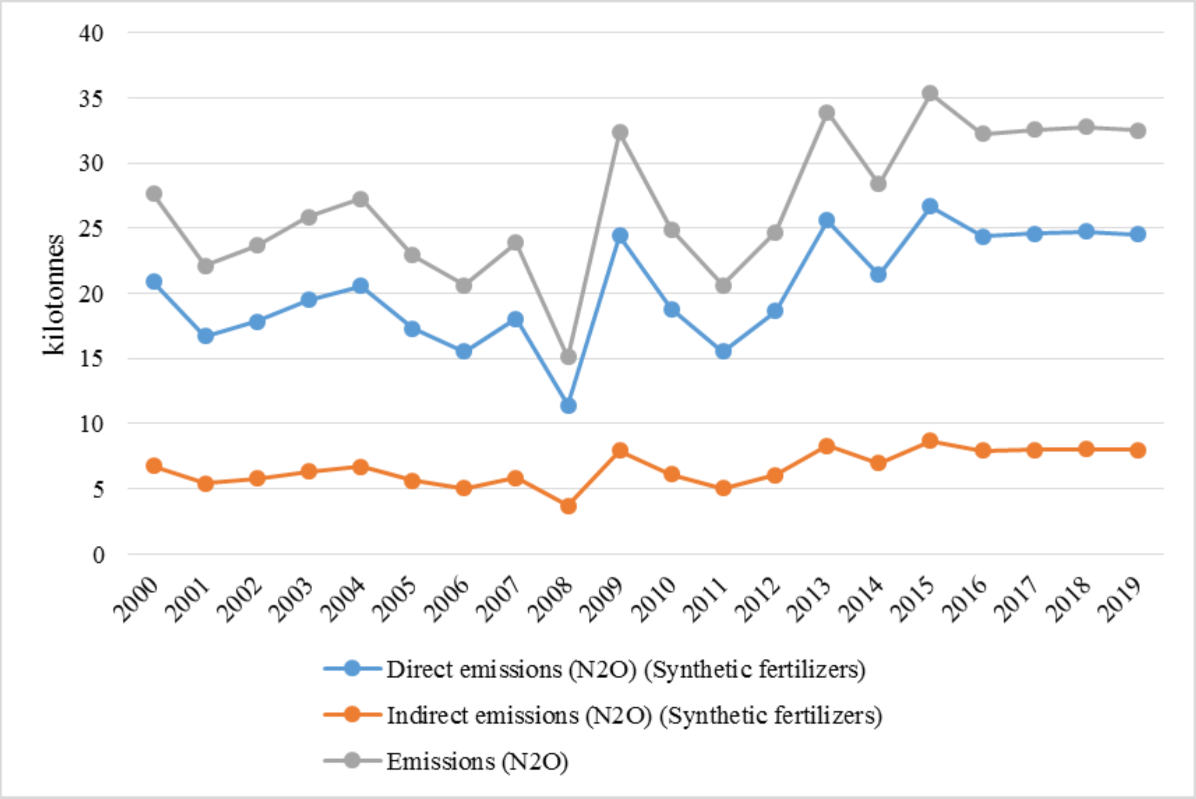


Figure 2.11. Direct and indirect N_2O emissions from synthesis fertilizer application of Vietnam from 2000 to 2020 (FAOSTAT, 2021)

Source: FAOSTAT, 2021

2.3. The agricultural restructuring policy

In 2013, Vietnamese Government has implemented the restructuring policy towards enhancing value and sustainable development for the agricultural sector by Decision 899/QD-Ttg. The policy has been updated for the period 2021 to 2025 with Decision 255/ QD-Ttg. The overall objectives of the policy are: improving quality, value and competitiveness in production; protecting the environment and ecology; increasing income for smallholders in rural areas; ensuring national food security. Importantly, it is necessary to promote the development of modern and clean agriculture, associating with climate change adaptation and connect with high-value agricultural products.

In special reference to paddy sector, the main target is to increase the proportion of high-quality rice cultivation areas in the total rice-growing area from 70 to 75% and the rate of using certified seeds is about 90%. Also, the development of organic rice production and diversify rice-based products should be promoted. Key rice production areas of the country are the Mekong River Delta and the Red River Delta.

2.4. Climate Smart Agriculture (CSA) programs for sustainable farming system

2.4.1. Climate smart agriculture definition

The most commonly-used definition of CSA is that provided by FAO (2010), which defines CSA as "a form of agriculture that contributes to the achievement of sustainable development goals. It integrates the three dimensions of sustainable development (economic, social and environmental) by jointly addressing food security and climate challenges. CSA is composed of three main pillars: i) sustainably increasing agricultural productivity and incomes; ii) adapting and building resilience to climate change; iii) reducing and/or removing greenhouse gases emissions, where possible" (FAO, 2013).

2.4.2. CSA programs and the implementation in Vietnam and the MKD

Large Field Model

To enhance the capacity of the small-scale rice sector, the Vietnamese government officially introduced the Large Field Model (LFM) in late 2011 through Resolution 21/2011/QH13. This model is embodied as a production organization that establishes a link between farmers and enterprises; it gathers small-scale farmers of the same agricultural products into larger groups, to create favorable conditions for the application of new technologies and for output price stability. In the LFMs, a reduction in rice production costs is achieved by taking advantage of economies of scale through application of modern agricultural machinery and thus reduced labor costs (Thang et al., 2017). The LFM is also the foundation for the application of advanced cultivation methods and the pursuit of CSA techniques. Paddy LFMs in the MKD occupied an area of 426,528 ha with the participation of 139,556 households, which accounted for only 10.05% of the total paddy area of the MKD (4.24 million ha) in 2016 (GSO, 2018).

The results of forming LFMs are also very limited. Most of the performance targets in the five years 2016-2020 have decreased. As of July 1, 2020, only 1,051 communes had large fields, accounting for 12.68% of the total number of communes in rural areas, decreases 31.51% points compared to 2016. The number of LFMs in Vietnam was 2,262 fields in 2016, in which 1,661 are paddy fields. However, LFMs in Vietnam decreased significantly to 1,657 fields in 2020 and the number of households participating in LFMs also decreased from 619,343 households in 2016 to 326,340 households in 2020. The total cultivated area of large fields decreased from 581,698 ha in 2016 to 271,000 ha in 2020. In 2020, on average, 1 large field had 197 households participating, equaling to 71.93% that in 2016. The average area of 1 large field is about 163.55 hectares, equaling to 63.86% of that in 2016. The main reason why the LFMs decline in number is the lack of resources of enterprises. At the harvest time, farmers usually sell fresh (wet) paddy and enterprises face many difficulties in preparing transportation, dryers and storage. Although farmers and enterprises have contracts, there are still cases where the enterprises cannot buy all products in time, then farmers will sell paddy to individual traders.

In the MKD, there was total 396 LFMs in agricultural sector with 77,885 participated households in 2020. The planted area of these 396 fields was 183,956 ha (before July 1st, 2020), of which only 50.6% of these having the farming contract beforehand (93,099 ha) (GSO, 2021). This figure is also much lower than the number of 580 LFMs in 2016 with 141,670 participated households and 428,847 ha (GSO, 2018). The specific downward trend of LFMs in paddy sector has not been updated yet in 2020.

Three Reduction, Three Gains (3R3G)

The "Three Reductions, Three Gains" (3R3G) campaign was developed as part of an international cooperation between the International Rice Research Institute (IRRI), Visayas State University (VSU) in the Philippines and Vietnam's Ministry of Agriculture and Rural Development (MARD). The three reductions reflects the reduction of seed rate, fertilizer use and insecticide spraying (Thang et al., 2017). It is expected that the three gains are the increase in net-farm profit, better health for farmers and an improved environment (Huan et al., 2005). The campaign was piloted in Can Tho, Tien Giang, and Vinh Long provinces in 2003.

A study of Huelgas *et a*l. (2008) reported the results of 3R3G campaign in provinces in the MKD. In An Giang province, there was an evidence of economic impact from 92USD/ha to 118USD/ha of increased net incomes per farm. This increase was equivalent to a reduction of 5 to 17USD/ton in the average cost of paddy production. However, the results for Can Tho were not similar to An Giang as non-adopters obtained better economic returns than adopters. Hence, successful results from An Giang farm-level data cannot be used as a proxy for the rest of the MKD since it could lead to an overestimation of the benefits.

One Must Do, Five Reductions (1M5R)

"One Must Do, Five Reductions" (1M5R) is a technological package that was developed during Phase IV of the IRRI's Consortium and promoted by the World Bank's Agricultural Competitiveness Project. More specifically, farmers who apply this technique are promoted to use certified seeds (One Must Do) and reduce the seed rate, use of fertilizers and pesticides, irrigation cost, and post-harvest losses (Five Reductions). In particular, this advanced technology is expected to be the best practice for intensive rice production in the MKD, and includes benefits, such as reducing production costs, increasing paddy yield, improving rice grain quality, enhancing farm profit, saving water and natural resources, reducing greenhouse gas emissions, and protecting the community's health (Phung et al., 2014). 1M5R has been recognized by the Department of Crop Production as technical progress, according to Decision No. 532/QD-TT-CLT, dated November 7, 2012. In 2013, data collected from just eight provinces in the MKD indicated that 34,500 farmers participated in training, and that about 240,000 farmers were implementing 1M5R over 300,000 ha (IRRI, 2012). This recognition caused the wide deployment of 1M5R rice production areas in the MKD. In addition, the Decision No. 555/QD-BNN-TT dated January 26, 2021 about the "Re-structuring rice industry in Vietnam to 2025 and 2030" project also indicates about the percentage of climate smart farming techniques applied area should be over 60% of the total paddy planted area, equivalent to 4.2 million ha.

It is indicated that the cropping pattern and the weather conditions still cause some difficulties for farmers to practice reducing fertilizer use, water use, and seed rate in 1M5R package (Connor et al., 2020). The main constraint to 1M5R application in Kien Giang and An Giang provinces were also the ineffective irrigation systems and the fear of farmers that if the amount of fertilizer is reduced, the rice yield may decrease. Hence, some households in the MKD still keep the high rate of fertilizer use (Son et al., 2013).

Alternative Wet Drying (AWD)

AWD has mainly been promoted in Asia with a widespread adoption in Bangladesh, Philippines, and Vietnam (Lampayan et al., 2015) in An Giang Province (a study from 2009 to 2011) (Tivet and Bolakia, 2017). AWD is a water-saving technology developed by International Rice Research Institute (IRRI). Particularly, lowland (paddy) rice farmers can apply to reduce their water use in irrigated fields while traditional irrigation technique – continuous flooding (CF) – keep a thin layer of water continuously on the field surface 70- 80% of the life cycle of rice plants. In AWD technique, the field surface is only flooded for 15-25% of the total life cycle time of rice plants (Yamaguchi et al., 2016) (Figure 2.12). There is evidence that AWD help reducing total water usage by 15%-40% compared with CF, with no major negative impact on paddy yield (Humphreys et al., 2010). In the MKD, farmers in An Giang Province who adopted AWD reported lower labor cost and irrigation frequency than non-adopters. Net income of adopters was also higher by 26% thanks to the increased rice yield by reduced lodging.

There have been various studies that assess the GHG emissions mitigation under AWD and other water-saving strategies. Firstly, AWD was mentioned to possibly reduce CH_4 emissions in the IPCC methodology (IPCC, 2006) and it is estimated that CH_4 emissions reduced by 48% in AWD fields compared to CF rice fields. In addition, studies of Pandey et al. (2014) and Xu et al. (2015) also reported a CH_4 mitigation potential of AWD that ranges from 48 to 93%.

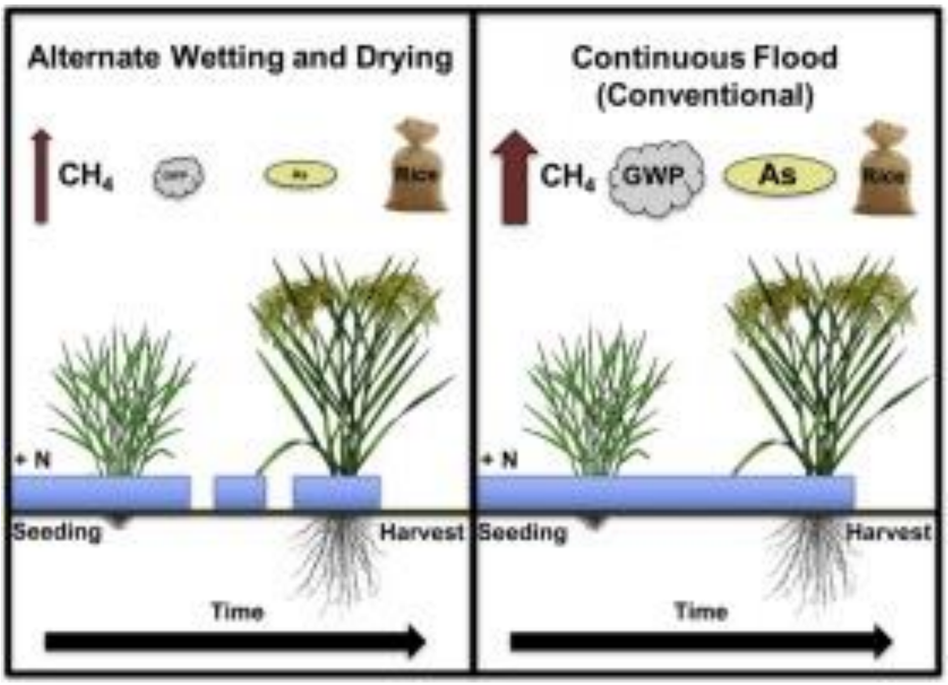


Figure 2.12. Graphical illustration of AWD and CF paddy fields (LaHue et al., 2016)

However, applying AWD may face the tradeoffs (Ahn et al., 2014; Wang et al., 2012) in terms of higher emitted nitrous oxide (N_2O), a GHG even more potent than CH_4 with a GWP of 298 times (IPCC, 2006). Linquist et al. (2015) claimed that there is no overall reduction in GWP associated with AWD concerning to the above mentioned trade-offs. Interestingly, study of LaHue et al. (2016) experienced a reduced seasonal CH_4 emissions by 60–87% while maintaining low annual N_2O emissions. In the MKD, study of Son et al. (2013) indicated that AWD is a new technique in the 1M5R technical program. However, the proportion of farmers who do not know and do not apply this technique is quite high at 67% and 43% in Kien Giang and An Giang provinces, respectively. Only 15% and 25% of farmers in these two locations know and apply this technique, respectively. Main constraints to water management are: high pumping cost of individual and small groups of households, incomplete sub-region dike systems and far distance from canals.

2.5. Literature review

2.5.1. Definitions of production efficiency and program impact evaluation

Production frontier and technical efficiency

Firstly, the productivity of a decision making unit (DMU) is introduced as the ratio of the output(s) to the input(s) that being used to produce that output(s). Also, we need to discriminate the terms "productivity" and "efficiency" although they have been used interchangeably by scientists over the years. The production frontier illustrated in Fig. 2.13 represents the maximum output that being produced by each input level. From the production frontier *OF'*, we can see that *B* and *C* are efficient DMUs while *A* is inefficient. Technically, DMU *A* could reduce the input to the level associated to *C* when producing the same level of output (or increase output to the level similar with B when not requiring more input).

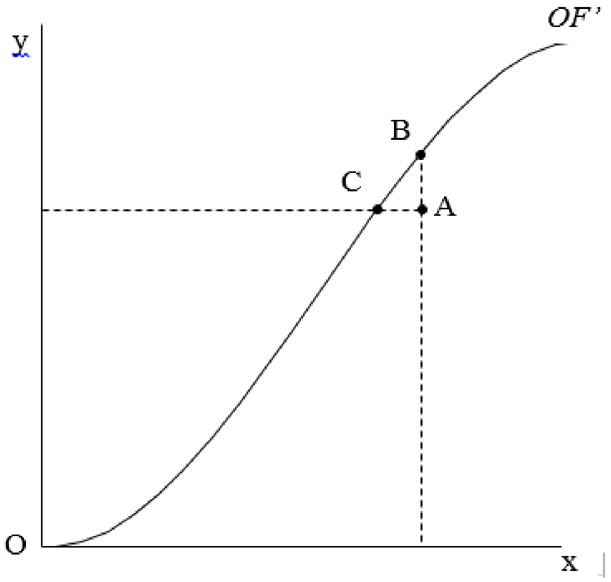


Figure 2.13. Production frontiers and technical efficiency (cited from Coelli et al., 2005)

Hence, DMUs operate either on the frontier if they are technically efficient, or beneath the frontier if they are not technically efficient.

Particular methods of frontier analysis are Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA), which have been developing rapidly in theory as well as in practice. The parametric SFA is characterized by being defined a priori except for a finite set of unknown parameters that are estimated from data. Meanwhile, non-parametric DEA model is characterized by being much less restricted a priori. In stochastic models, one make a priori allowance for the fact that the individual observations may be somewhat affected by random noise, and tries to identify the underlying mean structure stripped from the impact of the random elements. In deterministic DEA models, the possible noise is suppressed and any variation in data is considered to contain significant information about the efficiency of the DMUs and the shape of the technology (Bogetoft and Otto, 2011).

Traditional DEA, including Charnes, Cooper, and Rhodes (CCR) and the Banker, Charnes, Cooper (BCC) models focus on proportional (radial) changes—the same percentage reducing in all inputs or the same percentage increase in all outputs. To deal with the problems of input overuse in the MKD, slack-based measure (SBM) which is a non-radial DEA will be used. SBM can at the same time calculate overall efficiency and the input slacks (excessive usage) of paddy farms. Details on CCR, BCC and SBM models are given in Chapter 3, section 3.1 and 3.3.

Impact evaluation

Public programs in developing countries are designed to reach certain goals and beneficiaries. Programs impact evaluation comprises qualitative and quantitative methods, as well as ex ante and ex post methods. Qualitative analysis, using in-depth and group-based interviews, seeks to measure potential impacts that the program may generate and the extent of benefits to recipients. Meanwhile, quantitative methods assesses precisely the mechanisms by which beneficiaries are responding to the intervention and its results can be generalizable. It is quite important to understand whether such programs actually work, as well as the level and nature of impacts on intended beneficiaries. The obvious need for impact evaluation is to help policy makers decide whether programs are generating intended effects; to promote accountability in the allocation of resources across public programs; and to fill gaps in understanding what works, what does not, and how measured changes in well-being are attributable to a particular project or policy intervention.

Variants of impact evaluation include randomized evaluations, propensity score matching, double-difference methods, use of instrumental variables, and regression discontinuity and pipeline approaches. Each of these methods involves a different set of assumptions in accounting for potential selection bias in participation that might affect construction of program treatment effects (Khandker et el., 2010).

2.5.2. Previous studies on efficiency and climate smart agriculture in the MKD

Efficiency of rice production

The most recent study on efficiency of Ho and Shimada (2019) uses data of 352 rice farm households in Long An, Ben Tre, and Tra Vinh provinces in MKD to apply the SFA. The results indicate that the overall mean technical efficiency of rice farming is at 77% and most of rice farms in the MKD are operating at decreasing returns to scale. In addition, adaptation response, agricultural extension services, the area of farm, and geographical location are key influencing factors of rice farms' inefficiency. Le et al (2017) employ the two-stage DEA to discover efficiency of 200 rice farmers in Dong Thap province. Farmers in this study achieve relatively high overall technical efficiency and scale efficiency at 80.1% and 96.6%, respectively. Education has positive impact while credit access, training and rice cultivated area showed negative influences on technical efficiency. Earlier in 2011, Khai and Yabe also use SFA to explore the technical efficiency using Vietnam Household Living Standard Survey and efficiency score is high at 81.6%. Determinants of efficiency in this study include intensive labor, irrigation and education. With a hybrid methods that combine SFA and DEA into efficiency measurement, the results are shown that technical efficiency is at 76% and the average scale efficiency score was nearly 1. Farmers' experience and adoption of advanced farming practices are believed to have positive impact on efficiency scores. In general, studies about efficiency of rice production in the MKD are limited and there has been no study that integrates efficiency estimation and the overuse of inputs' calculation. Also, there is no connection between the biggest constraint "small farm size" and efficiency of households in those previous studies.

Climate smart agriculture and impact evaluation studies

The most recent studies about CSA in the MKD are studies of Connor et al. (2020) and Tran et al. (2020). Connor et al. (2020) identify the factors that influence the decision to adopt the 1M5R package. The authors also indicate that farmers had difficulties reducing fertilizer, water use, and seed rate. The decision to join in 1M5R package are the ease of implementation, education, satisfaction, and non-rice income. Meanwhile, Tran et al. (2020) conclude that the decision to join in CSA techniques is positively affected by gender, age, memberships in agricultural organization. There are also some local studies on difference between 1M5R adopters and non-adopters in the MKD (Chi et al., 2013; Son et al., 2013; Tin et al., 2015). These studies mainly imply that households participate in 1M5R obtain higher profit than conventional households. The main constraints of 1M5R application are listed as the surface of rice field was not leveling and ineffective operation of irrigation systems. Difficulties of seed reduction are the golden apple snail management and the fear of lower rice yield.

Regarding impact evaluation studies in Vietnam and the MKD, Duong and Thanh (2020) employs propensity score matching combined with the difference-in-difference (PSM–DID) method to measure the effects of modern rice varieties in Vietnam. Empirical findings indicate that only large landholders significantly improve their productivity by adopting modern varieties, while the effect of adoption on value-added is negligible regarding farm size. Tran (2020) uses endogenous switching regression model to estimate the effects of adoption of CSA technologies including water-saving techniques and improved stress tolerant varieties on net rice income. Specifically, net rice income is more likely to increase with the adoption of these two CSA techniques whether adopted singly or in combination with other technologies. However, the largest increase in income at 36.75 million dong/ha/year is obtained from applying improved stress tolerant varieties joint with water-saving technique in all provinces. Ho and Shimada (2019) measured the effects of climate smart agriculture and climate change adaptation on the technical efficiency of rice farming in the MKD. In this study, the decision to join in CSA is affected by cultivated area, agricultural extension services, belief in climate change as well as geographical locations. Importantly, participants in CSA could achieve higher technical efficiency by 5%–8% compared to non-participants.

In general, studies about CSA and impact evaluation in rice production in the MKD are limited. Also, comparing the effect of a CSA by descriptive statistics when not considering other socio-economic factors may lead to bias. Until the present, there has been no study that explores the impact of “One Must Do, Five Reductions” (1M5R) technique on its adopters. Among the CSA programs, 1M5R deals directly with inputs reduction strategies in the MKD since it comprises six components: Must use certified seeds; Reduce seeds, fertilizers, pesticides, irrigation and post-harvest loss. Reducing N fertilizer and water use is also very important actions in the context of sustainable farming by mitigating with GHG emissions.

2.6. Purpose of the research

2.6.1. Thesis objectives

In order to fulfill the research gaps of production efficiency and impact of CSA on paddy households in the MKD, this thesis is purposed:

(i) To measure efficiency and identify the determinants of the efficiency of rice production in the Vietnamese MKD, including: pure technical efficiency, global technical efficiency, scale efficiency, mix efficiency and overall efficiency in special reference to farm size.

(ii) To access the impacts of a climate smart agriculture – "One Must Do, Five Reductions" on the economic performances of rice smallholders in the MKD.

(iii) To calculate the overall efficiency and input slacks, especially N fertilizer and irrigation slacks, of major rice variety groups and to consider low-emission rice farming in the MKD region.

(iv) To suggest policy implications for the sustainable rice farming in the region based on the empirical results of the objectives mentioned above.

2.6.2. Research questions

Based on research objectives, following specific research questions should be answered correspondingly to chapters 3, 4 and 5.

In chapter 3, the answers for these questions should be given:

(i) What are the production efficiencies of rice farms in the MKD?

(ii) Do small farms in the MKD perform efficiently and use inputs effectively?

(iii) What are the key determinants of efficiency scores of rice farms?

(iv) Does farm size have a positive effect on farms' efficiency?

In chapter 4, the answers for these questions should be given:

(i) What are the factors that determine the decision to adopt "One Must Do, Five Reductions" technical package of rice households?

(ii) How does the 1M5R technical package helps rice households to improve their economic performance?

In chapter 5, the answers for these questions should be given:

(i) What are the overall efficiency of major rice groups in the MKD?

(ii) Do aromatic and high quality rice groups appear efficiently and contribute to low-emission farming?

(iii) Which are best ranking paddy farms in terms of efficiency and efficient input management?

2.6.3. Research framework

The conceptual framework of the whole thesis is illustrated in Figure 2.14. In the context of CSA promotion and the agricultural restructuring policy in Vietnam which focuses on sustainable production, this study will be expected to achieve the three main targets including: (i) improving efficiency and reducing chemicals use to protect the environment; (ii) reducing production cost and increasing output and farm-gate price to increase smallholders' income; (iii) promoting rice production that associated with climate change mitigation by reducing N use and irrigation cost. Empirical data obtained from different sources will be analyzed using DEA and PSM methods in order to point out practical references and evidence-based policy making. First, chapter 3 will employ slack-based measure (SBM) of DEA to engage the production efficiencies estimation and the input slacks calculation. Second, chapter 4 will assess the impact of well-known "One Must Do, Five Reduction" technical package on the economic performance of households using the propensity score matching (PSM). Finally, chapter 5 will present the potential of GHG mitigation in special reference to major rice groups in the MKD through the N and water overuse measurement, coupling with overall efficiency calculation. Those empirical findings will shape a picture of sustainable rice farming and expect to change the traditional behavior of farmers in the MKD region.

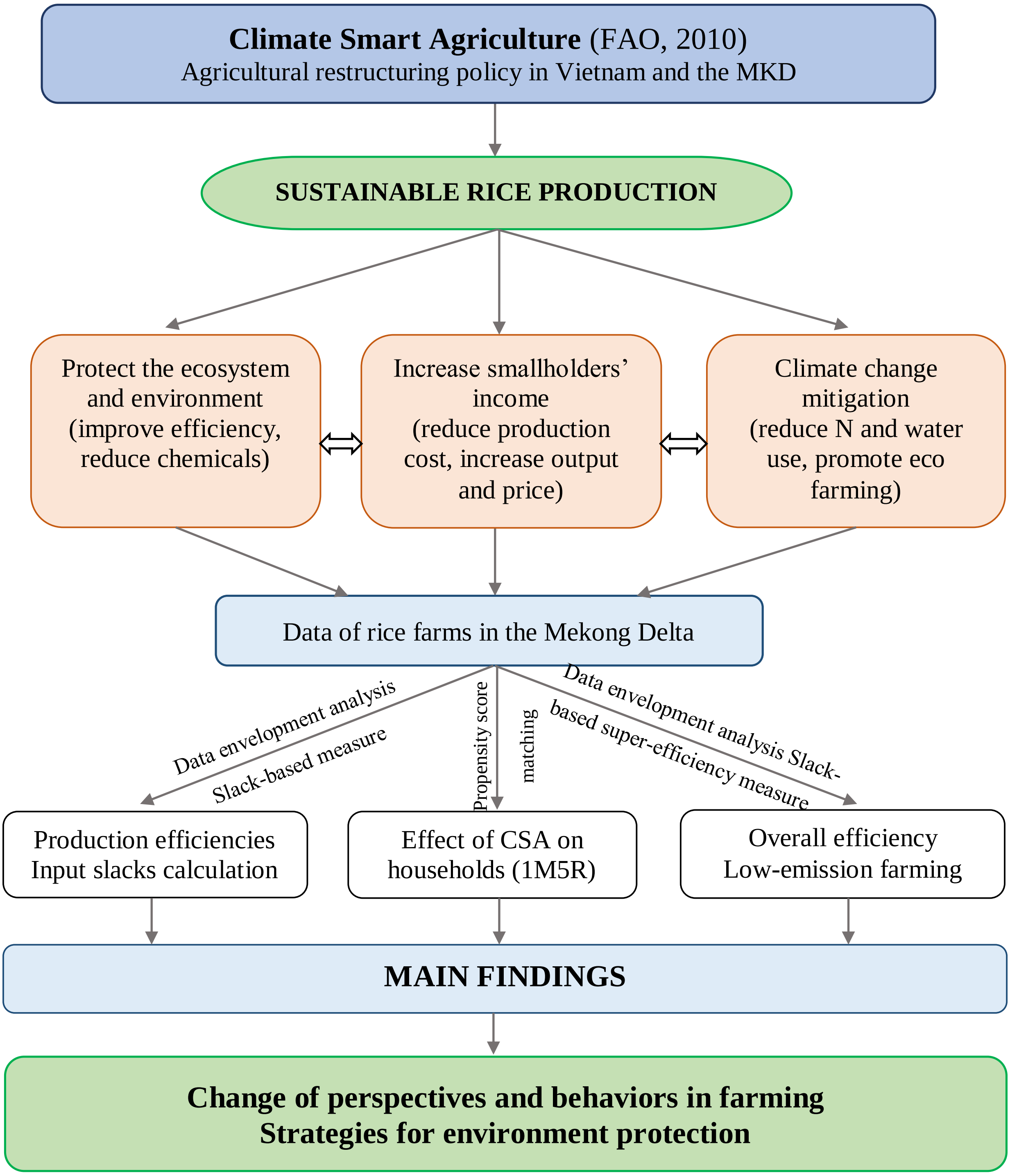


Figure 2.14. Conceptual framework of the thesis

Chapter 3 Farm size and the overall efficiency of rice production in the Vietnamese Mekong Delta

Abstract

Small farm size and fragmented land are considered constraining agricultural development. This chapter uses the Vietnam Household Living Standard Survey 2016 (VHLSS 2016) dataset to measure the technical efficiency of rice smallholders and its determinants, including farm size, in the Mekong Delta. Data envelopment analysis was employed to examine efficiency scores in the first stage based on data of 506 paddy farms. The overall efficiency calculated through slack-based measure was low at 0.59 and the input slacks are quite large. This indicated that local farmers have not been using their resources efficiently in producing paddy. Further, farms smaller than 2 hectares in transition faced low overall efficiency at 54% and higher slacks in terms of all input types. The second-stage Tobit result showed that all types of efficiency could be improved if farmers expanded their farm size and reduced the over-use of inputs. Thus, enabling small farms to achieve economies of scale through collective farming in the Large Field Model will be critical for upgrading production efficiency and reducing slacks as labor costs rise and natural resources are constrained. It is recommended that farmers should follow strictly to eco-friendly farming packages in order to reduce their current excessive usage of seed cost by 28 USD/ha, pesticides by 61 USD/ha, and fertilizers by 155 kg/ha to reach efficient production frontier. The government needs to take measures to replicate and closely monitor climate smart agriculture programs in large-scale production to improve the overall efficiency of paddy sector, in addition to the important goal of protecting the environment and natural resources of the region.

3.1. Introduction

Asian countries, including Vietnam, remain characterized by the duality of modern and traditional systems because of the sustained dominance of a large number of smallholders who may not meet the conditions required to enter the modern value chains (Yamauchi et al., 2021, Otsuka 2013). Several existing literature has provided some evidence about the relationship of paddy farm size and the efficiency. By increasing the operation scales of paddy farms, it is possible to increase the allocative and scale efficiencies (Watkins et al., 2014). In the context of Chinese agriculture, the consolidation of fragmented lands could improve production efficiency by lowering transaction costs in mechanization (Wang et al., 2020). In Japan, it is suggested that increasing the scale of farming is an effective way to improve technical efficiency (Li et al., 2018) and enhance the energy efficiency of highly mechanized rice production (Masuda, 2018). Similarity, Tu et al. (2021) drawn a conclusion that land accumulation from tiny plots is positively associated with both technical and environmental efficiencies of rice production in the Vietnamese Mekong region.

The Mekong Delta (MKD) is well known as a key rice producing area that plays a particularly important role in ensuring Vietnam’s national food security and exports. Every year, the Mekong region contributes to more than 50% of the rice production and 90% of the total national rice exports. By the end of 2018, the paddy cultivated area of the MKD reached 4.11 million hectares (ha), representing a proportion of 58% over the total figure of the country. Productivity was estimated at 5.97 tons/ha which is higher than national average yield at 5.82 tons/ha; total output reached 24.5 million tons and accounted for 55.8% of the paddy volume of whole country (GSO, 2020). However, rice production in Vietnam appears to be highly fragmented and small farms are often rendered less efficient by consisting of tiny plots. In the Red River Delta, 97% of holdings in 2011 were under 0.5 ha. In MKD region, about 83% of farmers’ land size is less than 2 ha. Nationally, the average size of a paddy holding is only 0.44 ha, meanwhile this figure is 1.2 ha in the MKD (World Bank, 2016). Certainly, the rapid increase in tractor use in Vietnam would be associated with an increase in the relative advantage of large farms (Liu et al., 2020). Also, tractors or combine harvesters are mostly concentrated in the large landholding groups, especially those exceeding 3 ha. Moreover, larger-scale farmers in the MKD had more opportunities to access formal credit access for their production investment purpose from agricultural or commercial banks, whereas smaller-scale farmers had to rely more on informal credit sources in their local areas (Quang, 2017).

Understanding production efficiency and farm size in developing countries has become a major interest of many scientists. Some previous studies have analyzed the technical efficiency (TE) of paddy smallholders, using the parametric stochastic frontier approach (SFA) (Ho, 2019; Khai and Yabe, 2011; Ebers et al., 2017; Nguyen et al., 2003), non-parametric data envelopment analysis (DEA) (Watkins, 2014; Linh, 2015; Le, 2017; Krasachat, 2004; Khosroo, 2013; Islam, 2011; Dhungana, 2004; Li et al., 2018; Brázdik, 2006), or a hybrid (Huy, 2009). Overall, studies on production efficiency in the MKD are limited in number, and most of them draw out conclusions about efficiency scores without the connection with farm size and sustainable agricultural programs in local areas.

Regarding radial DEA approach, Charnes, Cooper, and Rhodes (CCR) and the Banker, Charnes, and Cooper (BCC) models reflect the common proportional maximum reduction of all types of input. However, in the reality, especially in the rice sector, not all of the inputs will be reduced in the proportional way (like labor, material, capital, etc.). If we want to consider the efficiency scores as the only indexes to evaluate the performance of households as decision making units, the radial approaches may mislead the decision since they neglect these important slacks in reporting the efficiency scores. A slack-based measure (SBM) (Tone, 2001)—which is a non-radial DEA approach—is first introduced in our study to calculate the overall and mix efficiencies of rice smallholders in the MKD. This scalar measure deals directly with input excesses or output shortfalls in production steps and only be determined by consulting the reference set of decision making unit (DMU) which is not affected by statistics of the whole dataset. Overall efficiency calculated through SBM is considered to be an important indicator for regional agricultural development since it is the product of the three efficiencies, i.e., global technical, scale and mix efficiencies. Furthermore, based on the slack analysis from SBM, some recommendations will be presented to bridge efficiency improvement strategies including farm size and natural environment protection by reducing chemical inputs in the delta.

Therefore, this chapter will: i) estimate the production efficiencies of paddy households with respect to technical, scale, mix and overall efficiencies and input slacks, ii) examine how farms' socio-economic indicators, including farm size, are influencing production efficiency, and iii) provide the implication to sustainable rice farming in MKD. Because of the high usage of agrochemicals (Berg and Tam, 2012; Huan et al., 2008) and the characteristically small scale of rice farms, our research will apply input-oriented DEA to estimate the technical efficiency of rice production.

The structure of this chapter is as follows. Section 2 presents an overview of the rice production in the Vietnamese MKD. Section 3 explains the methodology and data used here. Section 4 presents results and discussions. The last section concludes, with policy recommendations for sustainable rice farming in MKD.

3.2. Overview of rice production in the Vietnamese Mekong Delta

The MKD has always played a very important role in the paddy industry as well as in national food security. It accounted for more than 50% of the total Vietnamese rice farming area and rice production during the 20-year period from 1996 to 2016. During this period, Vietnam's rice production was driven by a focus on meeting production targets with high yielding varieties for export rather than raising rice quality. Agriculture in the MKD is still largely based on small scale production by a large number of smallholders. According to the World Bank Rural Development Strategy (World Bank, 2003), smallholders are those farmers "with a low asset base and operating in less than 2 ha of cropland". In Asia, examples of the average sizes of smallholder farms are 0.24 and 0.32 ha in Bangladesh and Vietnam, respectively (FAO, 2015). The total number of smallholder households involved in the MKD's rice industry in 2016 was 1,138,995, most of whom owned small and fragmented land holdings. Figure 3.1, based on agricultural census data, shows the average farm size and share of rice households in Vietnam and Mekong Delta in 2016. There, about 53.7% of Vietnamese farm households have less than 0.2 ha, 35% have between 0.2 and 0.5 ha, 12.3% between 0.5 and 2 ha, and 2.6% more than 2 ha. The proportions of farms smaller and larger than 2 ha in the MKD were 83.4% and 16.6%, respectively[2] (GSO, 2018). This figure of smallholders represents the main barrier to the development of sustainable farming systems and advanced technology application for intensive rice production.

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[2] Descriptive data from Rural, Agricultural and Fishery Census in Vietnam, 2016.

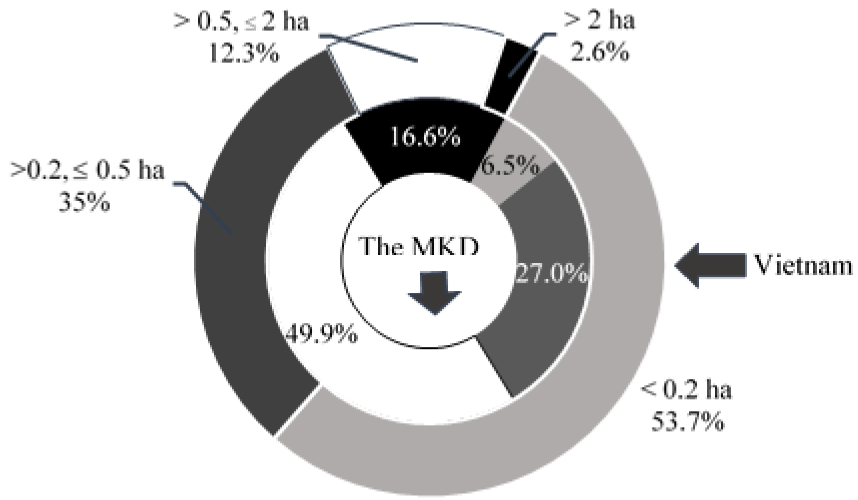

Figure 3.1. Average farm size and share of rice households in Vietnam and the MKD

Source: Rural, Agricultural and Fishery Census in Vietnam, 2016

Paddy sector required approximately 65% of the country's total fertilizer demand (GSO, 2014). In the MKD, the closed dyke system that allows for intensive rice cultivation has caused soil degradation, especially a lack of alluvium; this has been aggravated by the excessive use of chemical fertilizers by farmers in this region. It was reported that seed density and the use of nitrogenous fertilizer doubled over the period 1990–2004 from 95 to 144 kg/ha and 70 to 140 kg/ha, respectively; these amounts of input use far exceeded the quantity recommended by the government (Huan et al., 2008). The agricultural sector in the MKD has been facing a big concern in the form of pesticide pollution of the environment and of drinking water resources.

Fertilizer and pesticide expenses are also the primary reason for the extremely high cost of rice production. In the 2014 crop year, farmers in the MKD spent about 255 USD on fertilizers and 245 USD on pesticides per hectare, accounting for approximately 50% of the total rice production costs (1,097 USD/ha). These figures are much higher than those of Thailand, with 243 USD/ha for fertilizers and 102 USD/ha for pesticides of a total production cost of 1,366 USD/ha (MOST, 2016). To address the concern about an unsustainable rice sector, some climate smart agriculture (CSA)[3] techniques have been implemented in Vietnam and the

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[3] Climate smart agriculture (CSA) is defined by the FAO (2010) as a form of agriculture that sustainably helps farmers to increase productivity, enhance resilience, reduce greenhouse gas emissions, and achieve national food security.

MKD to improve the quality of rice products and protect the environment. One of the best-known CSA techniques in Vietnam, One Must Do Five Reductions is a technology package that was developed during Phase IV of the Irrigated Rice Research Consortium of International Rice Research Institute (IRRI) and promoted by the Agricultural Competitiveness Project of the World Bank. In 2013, data collected from just eight provinces in the MKD indicated that 34,500 farmers participated in training, and that about 240,000 farmers were implementing "One Must Do, Five Reductions" over 300,000 ha. Farmers are urged to use certified seeds—the "One Must," or the one thing they must do—while the "Five Reductions" refer to reductions in sown seed density, nitrogen application, pesticide use, water use, and post-harvest losses (IRRI, 2012).

3.3. Methodology and data

3.3.1. Measuring efficiency of rice production using data envelopment analysis (DEA)

DEA is a nonparametric linear programming (LP) approach for measuring the relative efficiency among a set of decision making units (DMUs), which represent rice households in this study. This tool originated from Farrell (1957), but the term "data envelopment analysis" became more popular following the works of Charnes et al (1978) and Banker et al. (1984). A DEA model can be input-oriented (minimizing inputs while maintaining the same level of outputs) or output-oriented (increasing outputs with the same level of inputs). Due to the specificity of the Vietnamese rice sector, which mainly relies on limited resources, an input-oriented DEA model is more appropriate to measure efficiency scores than an output-oriented model. There are two types of DEA approaches, namely, radial and non-radial. For radial DEA, CCR and BCC models are very well known in DEA literature, while an SBM (Tone, 2001) is a non-radial method that deals directly with input slacks in each rice field. The details of each model are described briefly as follows:

The Charnes, Cooper, and Rhodes (CCR) model

The CCR model (Figure 4) is built on the assumption of CRS (constant returns to scale) of the DMU's activities. The input-oriented CCR model evaluates the efficiency θ^* of a DMU by solving the following LP:

$$\text{[CCR-I]} \quad \theta^*_{CCR} = \min_{\theta,\lambda} \theta \qquad \text{subject to} \quad \begin{aligned} -y_i + Y\lambda &\geq 0, \\ \theta x_i - X\lambda &\geq 0 \\ \lambda &\geq 0 \end{aligned} \;, \qquad (3.1)$$

where θ is the scalar, λ is a *Nx1* vector of constants (assumes that there are data on *N* farms). The value of θ^*_{CCR} obtained is the efficiency of the i^{th} rice farm and it ranges from 0 to 1. If the θ^*_{CCR} of a farm is equal to 1, that household is fully technically efficient; otherwise, it is not efficient (Coelli et al., 2005).

The Banker, Charnes, Cooper (BCC) model

The CRS assumption is appropriate when all DMUs are operating at an optimal scale. However, in reality, imperfect conditions in production may cause a farm not to be operating at optimal scale. Banker, Charnes, and Cooper (1984) proposed the BCC model under VRS situations by adding the convexity constraint *N*1'λ = 1 to equation (1) to provide:

$$\text{[BCC-I]} \quad \theta^*_{BCC} = \min_{\theta,\lambda} \theta \qquad \text{subject to} \quad \begin{array}{l} -y_i + Y\lambda \geq 0, \\ \theta x_i - X\lambda \geq 0 \\ N1'\lambda = 1 \\ \lambda \geq 0 \end{array}, \qquad (3.2)$$

where θ is the scalar, *N1* is an *Nx1* vector of 1, and λ is an *Nx1* vector of constants (Coelli, 2005). The BCC score ranges from 0 to 1. The production frontier of the BCC model will contain more efficient DMUs than the CCR frontier (as shown in Figure 4). A DMU is called efficient when θ^* = 1; otherwise, it is inefficient.

Scale efficiency

If a DMU is fully efficient in both the CCR and BCC scores, it is operating at the most productive scale (Cooper et al., 2007). If a DMU has the full BCC efficiency but a low CCR score, then it is operating locally efficiently but not globally efficiently, due to the scale of the DMU. Therefore, the scale efficiency (SE) of a DMU is defined by the ratio of the two CCR and BCC scores. The TE that is calculated by the CCR model can be decomposed into pure technical efficiency (PTE), by using the BCC model under VRS assumption, and SE. This is to define whether the inefficiency of DMUs results from inherent causes or from disadvantages in the conditions under which the DMUs are operating (Cooper et al., 2007).

SE is defined as follows:

$$\text{SE} = \frac{\theta^*_{CCR}}{\theta^*_{BCC}}, \qquad (3.3)$$

where θ^*_{CCR} and θ^*_{BCC} are the CCR and BCC scores of a DMU, respectively. The SE of a DMU will be not greater than 1. With SE = 1, rice fields achieve SE or constant return to scale, while

SE < 1 indicates scale inefficiency of that field. As seen in Figure 3.2, rice fields between B and C are fully efficient (100%) in both the CCR and BCC scores, and are hence operating at the most productive scale (SE = 1). The BCC-efficient but CCR-inefficient rice field A is operating locally efficiently $\left(\frac{LA}{LA}=1\right)$ but not globally efficiently $\left(\frac{LM}{LA}<1\right)$ due to the inefficient scale $\left[\left(\frac{LM/LA}{LA/LA}\right)<1\right]$.

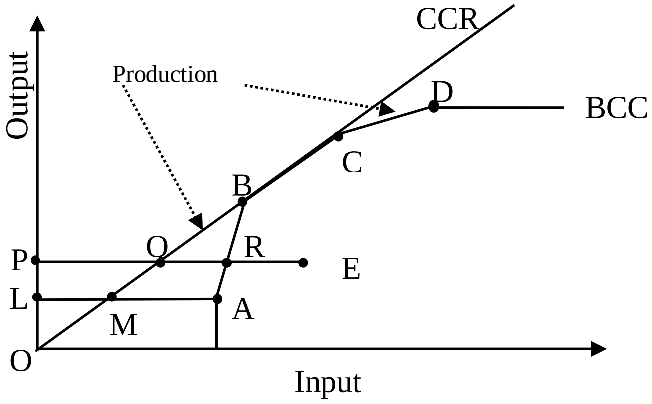

Figure 3.2. Production frontier of the CCR, BCC models and scale efficiency (Cooper et al., 2007)

The SBM model

CCR-type models evaluate radial (proportional) efficiency, but do not take into account the input slacks. Therefore, an SBM overall efficiency was introduced to reflect the nonzero slack in inputs of DMUs. The input-oriented SBM model under the constant returns-to-scale assumption (Tone, 2001) evaluates the efficiency ρ^* of a DMU (x_o, y_o) by solving the following linear program:

$$\text{SBM-I} \quad \rho^* = \min_{z^-,\lambda} 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{z_i^-}{x_{io}} \qquad \text{subject to} \quad \begin{aligned} & x_0 = X\lambda + z^-, \\ & y_0 \le Y\lambda, \\ & \lambda \ge 0, z^- \ge 0 \end{aligned} \qquad (3.4)$$

where λ is the intensity vector, and z^- represents non-radial input slacks vector. The SBM ρ^* was strongly related to the CCR θ^* model, and a particular DMU is SBM-I efficient if and only if it is CCR-I efficient.

Mix efficiency

Mix efficiency was first introduced by Tone (2001), and later explained by Cooper et al. (2007). The mix efficiency is also based on orientation, which is the input and output mix of efficiency. For the purpose of this paper, we continue with the input orientation of mix efficiency, consistent with both the CCR-I and the SBM-I model in the paragraphs above. Cooper et al. (2007) defined input mix efficiency as follows:

$$\text{MIX-I} = \frac{\rho^*}{\theta^*_{CCR}}, \tag{3.5}$$

where ρ^* and θ^*_{CCR} are the SBM and CCR score of a DMU. Mix efficiency score is not greater than 1, when ρ^* is equal to θ^*, mix efficiency is 1. From Equation (3.3) and (3.5) above, the non-radial efficiency SBM score can be decomposed into radial and mix efficiency measures, as follows:

$$\text{SBM-I [non-radial efficiency]} = \text{TE}_{\text{CRS}} \text{ [radial efficiency] x ME [mix efficiency]}$$

$$\text{or SBM} = \text{CCR x ME} = \text{BCC x SE x ME.} \tag{3.6}$$

3.3.2. Determinants of efficiency of rice production in MKD

The Tobit regression model (Tobin, 1958) is applied in the second stage to estimate the association of production efficiency and household characteristics. Since all the efficiency scores of rice households range from 0 to 1, the Tobit model is more appropriate than OLS regression. Some previous studies also employed the Tobit model as a second-stage regression technique in efficiency studies (Watkins et al., 2014; Li et al., 2018; Khosroo et al., 2013; Linh et al., 2015).

$$y_i^* = \beta_0 + \sum_{m=1}^{M} \beta_m x_{im} + \varepsilon_i, \varepsilon_i \sim \; IN(0, \sigma^2), \tag{3.7}$$

where β_m are unknown parameters, y^*_i is a latent variable representing the efficiency score for field i, x_{im} represents explanatory field characteristic variables associated with field i, and ε_i is an error term that is independently and normally distributed with a mean of zero and constant variance σ^2. The latent variable y_i^* is expressed in terms of the observed variable y_i (the efficiency scores calculated using DEA analysis in the first stage), as follows:

$$y_i = \begin{cases} y_i^* & \text{if} \quad 0 < y_i^* < 1 \\ 0 & \text{if} \quad y_i^* \leq 0 \end{cases}$$

3.3.3. Data

The study uses the Vietnam Households Living Standard Survey (VHLSS) dataset of 2016. Since the year 2002, the VHLSS has been conducted every 2 years by the GSO to monitor the living standards of the Vietnamese population. The VHLSS includes content that reflects the living standards of residents in the 63 Vietnamese provinces and cities, such as: demographic characteristics of household members, farm size, household incomes and expenditures, education and working status, housing assets and facilities, participation in credit and poverty reduction programs, and some other information. The 2016 VHLSS was conducted nationwide with a sample size of 46,995 households in 3,133 communes/wards, which were representative at the national, regional, urban, rural, and provincial levels. Among the 46,995 households surveyed in 2016, 37,596 households were interviewed about income and other topics, 9,399 households were investigated about income, expenditure, and topics such as education, health care, housing, electricity, water, sanitation facilities, and participation in poverty reduction programs. First, 1,905 observations from the MKD were extracted based on their codes by province, district, commune, locality, and household levels. In the next step, households that had produced plain rice utilizing either family or hired labor in the last 12 months were identified, to analyze production efficiency using data from sheet 4B11 of Section 4 – Income.[4] The final sample consisted of 506 observations of rice farms from the MKD.

A DEA model with one output and six inputs was used to calculate the efficiency scores among rice smallholders. The output is defined by the total plain rice yield (tons/ha) for a crop year. The six inputs comprises four inputs with monetary units. They are the total seed, pesticides, hired labor and machinery expenditures per hectare for a crop year. The remaining inputs are the total quantity of chemical fertilizers used (including N, P_2O_5 and K_2O in kilograms per ha) and the working hours of family members for rice farming activities in one crop year. In this study, per ha data is used for the direct calculation of slack/ha since it is clearer for policy recommendation on clean farming and inputs reduction strategies based on data per

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[4] The other sections in VHLSS 2016 are: 1 – Household information; 2 – Education; 3 – Health; 5 – Expenditures; 6 – Assets and durable goods; 7 – Housing; and 8 – Participation in supported programs. Section 4 consists of 30 pages; other pages present information about rice production costs and costs of other households whose focus is crop and fruit production, livestock, fishery, or forestry.

land unit. Some previous studies that also employed DEA to analyze the efficiencies of agricultural farms with data per land unit (Nandy and Singh, 2020; Ullah et al., 2019; Masuada, 2016. Bolandnazar et al., 2014).

Table 3.1 shows the descriptive statistics of one output and six inputs that were included in the efficiency estimation for the year 2016. It can be seen that, to produce the average rice yield of 5.78 tons/ha/year, households have to pay 73.64 USD for rice seeds, 115 USD for pesticides, 54 USD for hired labor, and 152.66 USD for renting the machines. Households use more than 460 kg of total synthesis fertilizers on their farms. Family members contribute to the production with 187 working hours on average.

Table 3.1. Information on output and inputs of rice farms used in DEA

Variables	Unit	Mean	Std. Dev.	Min	Max
Output – Rice production	tons/ha	5.78	1.35	0.85	10.17
Inputs					
Seed cost	USD/ha	73.64	48.43	10.15	879.31
Pesticide cost	USD/ha	115.95	85.08	0	937.94
Hired labor cost	USD/ha	53.77	64.59	0	612.80
Machinery cost	USD/ha	152.66	61.67	0.00	485.19
Fertilizer quantity	kg/ha	460.67	173.89	0	1763.8
Family labor	hour/ha	187.41	287.81	0	2110

Source: Author's calculation from VHLSS 2016 survey data (N = 506)

The explanatory variables used in the Tobit regression analysis are listed in Table 3.2, including gender, age and education level of household heads, family members, formal credit status of households, the farmer's association membership, rice farm size and the quadratic of farm size. In all, 83% of household heads are male, and the average age of household heads is 51.4 years old. The education level of household heads is quite low, with the mean at nearly 6 years. There is also big variability of farm size among rice farms in the MKD with the size ranging from 0.1 ha to 31.88 ha with an average of 3.05 ha per household.

Table 3.2. Summary statistics of variables used in Tobit regression analysis

Variables	Unit	Mean	Std. Dev.	Min	Max
Age	years	51.42	12.55	26	89
Education	years of schooling	5.87	3.45	0	12
Family members	persons	4.09	1.43	1	9
Farm size	hectare	3.05	3.61	0.10	31.88
Gender (dummy)	% male	0.83	0.37	0	1
Credit status (dummy)	% yes	0.46	0.49	0	1
Farmer Association (dummy)	% yes	0.15	0.36	0	1

Source: Author's calculation from VHLSS 2016 survey data (N = 506)

3.4. Results and discussion

3.4.1. Technical efficiency of rice production in Vietnamese Mekong Delta

The input-oriented efficiency scores including BCC, CCR, SE, SBM, and ME are indicated in Table 3.3. The summary statistics for TE are presented under both CRS and VRS. The mean CCR, TE score under CRS, is 0.71 and ranges from 0.15 to 1, whereas the mean BCC, TE score under VRS, is 0.81 and ranges from 0.20 to 1. The mean BCC score indicated that 195 households were fully efficient with a score of 1, and the remaining 311 households were inefficient, with TE scores less than 0.81. The results of the CCR model show that only 62 households have a global TE of 1, while the remaining 444 households are considered technically inefficient. Compared to some recent studies using DEA to estimate the rice production efficiency of MKD, including Huy (2009) and Le et al. (2017), the mean CCR and BCC calculated in this study were lower.

The mean SE score among paddy farms was 0.88, which implies that most households operate at near the optimal farm size. This result is lower compared to an SE score of 0.96 of MKD rice farms from the study of Huy (2009), Indonesian farms at 0.90 (Brázdik, 2006), and Nepalese farms at 0.93 (Dhungana et al., 2004) and equal to Bangladesh farms (Islam et al., 2011). Farmers in the MKD could improve their rice yield by about 12% if they could reach an optimal scale of operation. The overall efficiency SBM-I score is 0.59, which is the lowest figure among all types of efficiency, as is expected due to input slacks. Further, the non-radial efficiency by SBM score can be decomposed into radial efficiency CCR and ME scores. The average ME score that reflects the balance of inputs used by rice households in MKD is about 83%. The decomposition of overall efficiency (SBM) into BCC, SE and ME will help identify the causes to overall inefficiency. Although small farm size and overuse of inputs are different problems, they all contributed to the overall inefficiency by scale inefficiency and input slacks, which is SBM = BCC x SE x ME.

Table 3.3. Input-oriented efficiency scores of rice households in MKD

	N = 506	BCC_I	CCR_I	SE_I	SBM_I	ME_I
Summary efficiency						
Mean		0.81	0.71	0.88	0.59	0.83
Std. Dev.		0.20	0.20	0.13	0.22	0.11
Min		0.21	0.15	0.36	0.11	0.51
Max		1	1	1	1	1
Farm size						
<= 2ha	261	0.79	0.66	0.84 (0.15)	0.54	0.80
		(0.21)	(0.20)		(0.22)	(0.12)
> 2ha	245	0.82	0.75	0.91 (0.09)	0.65	0.85
		(0.17)	(0.18)		(0.19)	(0.08)
t-stat		– 1.84*	– 5.09***	– 5.78***	– 5.59***	– 5.16***
Gender						
Male	424	0.81	0.72	0.89 (0.13)	0.60	0.83
		(0.19)	(0.19)		(0.21)	(0.11)
Female	82	0.78	0.65	0.84 (0.16)	0.55	0.83
		(0.20)	(0.20)		(0.22)	(0.12)
t-stat		– 1.19	– 2.86***	– 3.05***	– 2.17**	– 0.02
Credit status						
Yes	235	0.80	0.69	0.86 (0.14)	0.57	0.82
		(0.20)	(0.19)		(0.20)	(0.10)
No	271	0.81	0.72	0.89 (0.12)	0.61	0.83
		(0.19)	(0.20)		(0.23)	(0.11)
t-stat		0.57	2.11**	2.70***	2.36**	1.29
Frequency distribution (%)						
≤50%		7.71	17.00	1.58	37.35	0
> 50% ≤ 60%		11.86	15.42	3.56	18.58	2.17
> 60% ≤ 70%		13.04	14.43	6.72	15.22	11.07
> 70% ≤ 80%		14.03	18.77	11.26	10.67	23.91
> 80% ≤ 90%		9.29	13.44	16.01	5.53	35.97
> 90% ≤ 100%		44.07	20.95	60.87	12.65	26.88
Number of efficient DMUs		195	62			
Number of inefficient DMUs		311	444			
Total		506	506			

Notes: Standard deviation in parentheses; *, ** *and* *** *indicate 10%, 5% and 1% significance levels, respectively.*

Source: author's calculation

Regarding the cultivated farming area classification, paddy fields with farm size greater than 2 ha achieve significantly higher efficiency for all score types. Particularly, larger farms obtain pure TE (BCC), global TE (CCR), SE, SBM and ME at 82%, 75%, 91%, 65% and 85%, respectively. Those figures of small farms are listed sequentially at 79%, 66%, 84%, 54%, and

80%. Due to better SE and mixture of inputs, larger farms have a significantly higher overall efficiency (SBM) compared to smaller farms. This result is consistent to recent literature of Foster and Rosenzweig (2010), Liu et al. (2013) and Otsuka et al. (2016), which implies that the advantage of small farms relying on family labor is declining and large farms' advantages are enhanced by the use of farm machinery as the general wage rate increases in Asian countries. Household heads in the MKD are mainly male; paddy fields managed by male household heads have a significantly higher production efficiency in terms of technical, farmland scale, and overall efficiency, although the difference in pure TE (BCC) was marginal. It is also indicated that the participation in credit program do not positively contribute to efficiency improvement of paddy fields in MKD.

Among 506 rice-farming households observed in SBM analysis, only 22% operated at CRS, wherein their output increased proportionately with the increase in inputs. From the results of previous studies about the returns to scale characteristics in developing countries, rice farms in MKD have a larger proportion of units that achieved CRS than farms in Bangladesh, with 8% (Coelli et al., 2002); Indonesia, with 5% (Brázdik, 2006); and Nepal, with 11% (Dhungana et al., 2004), but less than that in Thailand, with 32% (Krasachat, 2004). From the estimation, about 65% of households operate at increasing returns to scale (IRS), reflecting the need to expand the production operation scale in coming years to achieve an ideal TE, while 13% of the farms are exhibiting DRS and operating at a larger scale than the optimal size.

Concerning to the strategy to minimize input cost, the result of the SBM model in Table 3.4 presents the slacks, the level and the proportion of inputs that needs to be reduced on average and by farm size. The presence of these slacks points to suggestions for inefficient households to achieve the efficiency frontier, and especially the inputs cost reduction. Specifically, farmers in the MKD can possibly cut down approximately 27.81 USD/ha of seeds cost, 60.80 USD/ha of pesticides cost, 77.88 USD/ha of machinery cost and 155.61 kg/ha of the amount of fertilizers that they are using to reach the efficiency frontier. Similarly, the expenses of hired labor and the working hours of family labor, and machinery should also be reduced by more than 36USD/ha, 119 hour/ha, and 77.88 USD/ha respectively. The heterogeneity of input slacks and percentage of reduction based on farmland area is also described in this table. Paddy fields greater than 2 ha reflect not only higher efficiency scores but also lower slack of inputs, in which statistical significance of seeds cost, machinery cost, fertilizer quantity and family labor working hour per ha. Moreover, the required reduced percentage figures of land plots smaller than 2 ha are also significant at the level of 1% with pesticides cost and the four input items mentioned above. The Anh et al. (2020) implied that household size and the number of family labor decreased when farm size increases. This perhaps reflects the trend of out-migration from the larger, more prosperous farm-households. Those large farms are also more mechanized and employed hired labor. Meanwhile, smaller farms often rely on family labor to generate profits and make better use of available resources when opportunities for agricultural jobs in rural areas are declining. Another difficulty related to machinery service is that there are too few tractors and harvesters to service the 1.5 million ha of rice land at the time of harvest. Averagely, there are only three two-wheel tractors per 100 ha and two harvester per 100 ha, respectively. Therefore, the cost of machinery service is quite high and small farms that want to save their production cost by not using hired labor are obviously not affordable for big machines renting. It can be concluded that small farms relying on family labor in our study lose their advantage, while large farms' advantages and efficiency are enhanced by the use of farm machinery. This statement was also pointed out in previous studies of Foster and Rosenzweig (2010), Liu et al. (2013) and Otsuka et al. (2016). Transplanters machine are also not using in the MKD although transplanting seedlings is a critical, labor-intensive activity. If there could be perfect machinery services like tractors for land leveling or transplanters instead of broadcasting seeds, farmers could save much inputs including seeds and irrigation. The graphical presentation of slacks based on land size is also illustrated in Figure 3.3.

Table 3.4. Input slacks and required percentage decrease of each input on average and farm size

	N = 506	Seeds (USD/ha)	Pesticides (USD/ha)	Fertilizers (kg/ha)	Hired labor (USD/ha)	Family labor (hour/ha)	Machinery (USD/ha)
Input slacks		27.81	60.80	155.61	36.32	119.61	77.88
<= 2ha	245	31.24	62.08	176.48	37.16	212.95	84.47
> 2ha	261	24.15	59.43	133.37	35.41	23.91	70.85
t-stat		1.70*	0.40	2.94***	0.36	9.29***	2.45**
Required % decrease		(– 30.32)	(– 46.75)	(– 30.33)	(– 45.74)	(– 42.02)	(– 47.90)
<= 2ha	245	(– 33.72)	(– 54.20)	(– 33.85)	(– 44.00)	(– 53.41)	(– 53.13)
> 2ha	261	(– 26.69)	(– 38.80)	(– 16.25)	(– 47.54)	(– 29.89)	(– 42.32)
t-stat		– 3.12***	– 5.38***	– 4.63***	1.06	– 9.02***	– 3.96***
Projection		46.16	55.50	304.89	18.69	67.81	74.78

*, ** *and* *** *indicate 10%, 5% and 1% significance levels, respectively.*

Source: author's calculation

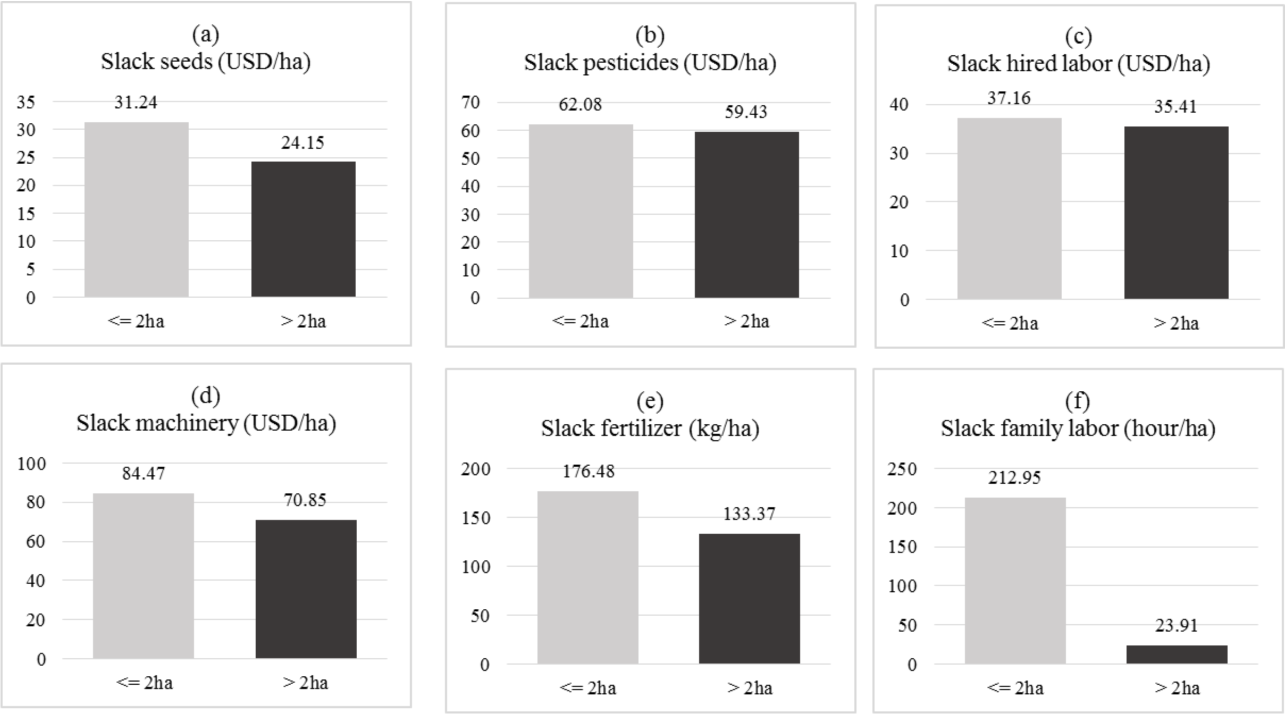

Figure 3.3. Input slacks by land size category of households in MKD

Source: authors' compilation

Based on the SBM results, if one rice household could possibly reduce 50% of slacks for fertilizer—about 78 kg/ha—there would be a reduction of more than 333 million kg of fertilizer for the entire MKD region in a crop year.[5] This eradication of excessive input usage could only be potentially implemented when more households in the MKD participate in the smart agriculture farming systems recommended by the Vietnamese government like "One Must Do, Five Reductions" (Tho et al., 2021). Specific technical indicators in the eco-friendly farming package are: seed sowing density should be from 80 to 100 kg/ha, nitrogen fertilizer should not exceed 130 kg/ha, spraying pesticides frequency should be not more than 4 times. When seed quantity is reduced to the amount of 80–100 kg/ha, pests and diseases will decrease compared to a thick seeding situation. Therefore, farmers can reduce the amount of pesticide and nitrogenous fertilizer use and save much water for irrigation. In addition, applying the Alternative Wetting and Drying could solve the problem of high irrigation cost. This is a water-saving technology developed by IRRI that lowland rice farmers should apply to reduce their water use in irrigated fields. Traditional irrigation technique usually keeps a layer of water continuously on the field surface in 70%–80% of the life cycle of rice plants. In contrast, in the

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[5] The planted area of paddy land in the MKD in 2016 was 4,241.1 thousand ha (GSO, 2017)

Alternative Wetting and Drying technique, the field surface is only flooded for about 5 cm of the total life cycle time of rice plants. Adopters of this water-saving practice can reduce the total water usage for rice production by 15%–40% and does not require N-fertilizer management differently compared to the traditional continuous flooding procedure, with no major negative impact on rice yield (Yamaguchi et al., 2016; Humphreys et al., 2010; Cabangon et al., 2004). The results for SBM score and input slacks are also in line with indicators of the LFM (Thang et al., 2017) and CSA programs launched by Vietnamese government in recent years.

3.4.2. Factors influencing the efficiency of rice production in the Vietnamese Mekong Delta

The result of Tobit regression of farm characteristics and production efficiency is displayed in Table 3.5. Three variables are found to impact the efficiency of rice farms in the MKD, including educational level of household heads, family members, farm size, farm size squared, credit status and gender of household head. First, the education of the household head is believed to have a positive impact on the SE of rice farms. This means that farmers who are well educated are expected to have better skills and knowledge to manage larger-scale farms. In previous studies, it was also implied that the more educated farmers are more energy efficient (Khosroo et al., 2013) and technical efficient ((Khai and Yabe, 2011; Le et al., 2017) in comparison with their less educated counterparts. However, household heads in this study have very low education level and old age (see Table 2). Those households which prefer traditional cultivation could find it difficult for practicing CSA models and follow up contract farming with enterprises in the MKD. For that reason, financial support from enterprises for innovations and young start-ups in agriculture could help to develop the rice sector in the near future.

The variable family members, or household size has a significantly negative impact on the overall and mix efficiencies of paddy farms at the significance level of 5%. This indicates the ineffective use of family labor in small rice farms in the MKD, as referred to the very high slack of home labor working hour in Table 4. Indeed, there is a rapidly growing machine rental market in Vietnam in recent decades (Liu et al. 2020; and Zhang et al. 2011) which represent a change from labor-intensive to capital-intensive systems. Hence, the advantage of small farms relying on family labor is declining, while large farms' advantages are enhanced by farm machinery (Otsuka et al., 2016).

The cultivated land size has an important role in determining rice production efficiency, with significantly positive impacts on SE, SBM and ME scores. Smaller farms could be less efficient due to difficulties in water pumping, transportation, and on-time inputs contribution from local suppliers. It is also harder for farmers who own small and fragmented land to apply mechanization and technical advances in production steps. This result is also consistent with the above statistic that most rice farms in the MKD are operating at IRS as mentioned in section 4.1. Therefore, an increase in farm size or land accumulation into larger farms could enable households in the MKD to achieve higher technical (Ho and Shimada, 2019; Nguyen et al., 2003) and environmental efficiencies (Tu et al., 2021). In Japan, this statement was also analyzed and concluded in the study by Li et al. (2018) and Otsuka (2013), when the real wage rate continues to increase in high-performing countries in Asia. Moreover, we have found a negative effect of farm size squared on scale efficiency, i.e., inverted-U relationship. From this regression result, taking the first order partial derivative of scale efficiency with respect to farm size, it is possible to find the threshold optimal scale for rice production in the MKD. This means that when paddy farms increase larger in size, the effect on scale efficiency scores is increased. However, if the field size exceeds the threshold optimal scale, which is around 21.81 ha, the scale efficiency could decrease due to i) farmers have to hire more workers and it is difficult to control their working attitudes, ii) limited capital coupling with underdeveloped input market made it difficult to ensure the quality of input suppliers, and iii) the low management capacity of farmers due to low educational level (Duyen and Khiem, 2018). There were some local studies that mentioned about the maximum scale threshold corresponding to paddy production, which is about 5.2 ha (Dung and Ninh, 2015) and ranging from 6.94 ha to 7.18 ha (Duyen and Khiem, 2018), depending on cropping season. We have not found this statistically significant inverted U-shaped nonlinear relationship between farm size and overall efficiency or mix efficiency. In order to deal with the deficiency of fragmented rice land, the Vietnamese government implemented the LFM in 2013 (Decision 62/2013/QD-TTg, MARD). The LFMs also provide farmers with advantages for the application of advanced cultivation methods and to follow strictly modern techniques. Also, the LFMs must be within the agricultural development plan of the region and have the production scale of about 300 - 500 ha (Thang et al., 2017). However, the application rate of the LFM and CSA is still very low (about 10%) due to poor condition of infrastructure and irrigation systems. Thus, promoting the participation of rice companies into the LFM is important since those corporations can rent land from farmers to form their raw material areas, provide inputs and implement farming contracts with every household in the model.

The next variable, credit status, has negative and significant coefficients, implying that obtaining a loan could result in scale and overall inefficiencies of rice farms. This can be explained by the granting of agricultural loans for unsuitable purposes to borrowers, or by the stress of interest payment that could lead to the inefficient management of inputs. Especially, paddy smallholders in the MKD usually buy inputs from closely local suppliers and highly rely on the short-term store credit in the beginning of each season and mainly live off the quantity of rice at harvest time (The Anh et al., 2020). This result indicates that the credit program was not effective for improving the TE of small-scale farms in the MKD, as similarly concluded by Le et al. (2017) and Nguyen et al. (2003). There were arguments of Binam et al. (2004); Bozoḡlu and Ceyhan (2007) that credit program helped farmers improve their technical efficiency. Therefore, special credit programs from banks granting to groups of household/cooperatives that engage in CSA models should be promoted extensively. With the strict standards on the level of chemicals use in rice products providing to both domestic and international markets, those households that produce rice in CSA models would be very important factors in the sustainable farming theme in the region.

The last dummy variable that has a positive effect on scale efficiency is gender. In this case, man household heads appear to be more efficient in managing large farms than their female counterparts. In Vietnam, male-headed households have obtained a larger share of cropland versus female-headed households. Also, Vietnamese culture considers male receive family property inheritance, male possibly get larger landholdings (Thang et al., 2016). Thus, the argument that women farmers are less efficient than male farmers (FAO 1985) is acceptable in our study.

Table 3.5. Tobit regression analysis of factors affecting efficiency of rice households in MKD

	SE		SBM		ME	
Variables	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
age	–0.00003	0.00055	–0.00090	0.00092	–0.00029	0.00047
education	0.00341	0.00204 *	–0.00211	0.00337	–0.00131	0.00171
family members	0.00090	0.00457	–0.01387	0.00758 **	–0.00925	0.00384 **
farm size	0.01658	0.00402 ***	0.02038	0.00675 ***	0.01113	0.00342 ***
(farm size)^2	–0.00038	0.00021 *	–0.00009	0.00036	–0.00010	0.00018
credit status (dummy)	–0.03980	0.01277 ***	–0.05469	0.02111 ***	–0.01715	0.01071
gender (dummy)	0.03207	0.01799 *	0.04233	0.02978	–0.00540	0.01512
farmer assoc. (dummy)	–0.00010	0.01783	0.00390	0.02951	–0.00204	0.01497
Constant	0.81670	0.04132	0.65310	0.06846	0.87716	0.03474
Observations	506		506		506	
Log likelihood	185.23786		– 59.53239		244.24168	

SE: scale efficiency; SBM: slack-based technical efficiency (overall efficiency); ME: mix efficiency.

Note: *, ** *and* *** *indicate 10%, 5% and 1% significance levels, respectively.*

3.5. Conclusion

This study is the first to evaluate rice production efficiency in the Vietnamese MKD using both radial and non-radial DEA approaches. Non-radial DEA, including SBM and ME scores, helps eliminate restrictive and problematic radial DEA when quantifying overuse of inputs such as seeds, fertilizer, or pesticides. Almost 65% of households in the MKD exhibited IRS, while only 22% showed CRS. Rice farms in the main region of national production and export scored 0.71, 0.81, and 0.88 for global TE, PTE, and SE, respectively. The SBM overall efficiency and mix efficiency scores, applied to rice production data in Vietnam, resulted in 0.59 and 0.83 respectively, which are quite low due to the presence of input slacks revealed in the SBM analysis. The slack-based SBM reveals that when inefficient farms could improve not only the production efficiency but also the quality of the surrounding soil and water sources for the subsequent seasons by reducing fertilizer and pesticides.

Paddy farms with greater farm size obtain higher efficiency, since they obviously have greater advantages in water pumping, transportation, and mechanization. Land accumulation from small holders into larger fields/paddy cooperatives, officially called the LFM, should be encouraged and monitored more actively in every province of the MKD. Farmers who engage in the LFMs could take advantage of economy of scale to apply modern agricultural machinery (such as tractors) and thus reduce the labor costs. Also, the LFMs created a basis to apply advanced cultivation methods and to follow strictly CSA techniques such as: One Must Do, Five Reductions, Alternate Wetting and Drying and System of Rice Intensification. More specifically, rice farms in the MKD should prioritize participating in CSA farming models to enhance the quality of products and protect the natural resource environment. Promoting the participation of rice enterprises into the LFM and CSA programs could be such an urgent action of the government.

Chapter 4 The impact of a climate smart agriculture on the economic performance of rice smallholders in the Vietnamese Mekong Delta

Abstract

The “One Must Do, Five Reductions” (1M5R) program was certified in 2013, by Vietnam Ministry of Agriculture and Rural Development, as a national approach to promoting the best management practices in lowland rice cultivation. The main idea behind 1M5R is the use of good-quality/certified seeds (the One Must Do) as well as the reduction of seed rates, pesticide use, fertilizer inputs, water use, and postharvest losses (Five Reductions). However, the impact of these farming practices is not well understood. This study employs the propensity score matching (PSM) approach to investigate the factors that affect the adoption of the 1M5R practice and to estimate this technique’s impact on the economic performance of rice cultivation. Primary data were collected through a household survey of 380 rice farms in four provinces in the Mekong Delta (MKD), Vietnam. The results indicate that adopting the 1M5R technique is significantly correlated with the educational level of household heads, their memberships in paddy cooperatives, and their attendance to previous training classes. Additionally, the 1M5R technical package helps farmers to reduce their production cost by 10%, increase a paddy’s selling price by 4.5% per kg, and obtain 10% more profit, compared to traditional farming households. The return on investment for adopters increased by 22%. While the findings show that a sustainable farming technique is advantageous to local farmers, they fail to present any paddy yield increase in treatment fields. To scale up this program to other areas in the MKD, well-educated farmers who are still traditional producers/non-adopters should be positively invited for training classes of the program.

4.1. Introduction

The Mekong Delta (MKD), the world's third largest delta, comprises 54% of Vietnam's rice production areas and produces 55% of Vietnam's total rice output (GSO, 2018). Since the late 1990s, rice production in MKD has intensified rapidly, resulting in an overreliance on agrochemicals to achieve higher yields as well as rising production costs and environmental unsustainability (Tu, 2015; Tong, 2017). Compared to other agricultural countries in the region, Vietnam ranked second (430 kg/ha) after China (503 kg/ha), in terms of fertilizer consumption, while other countries, such as India (166 kg/ha), Thailand (162 kg/ha), and the Philippines (157 kg/ha), consume relatively low amounts of fertilizers per hectare of arable land (FAO, 2016). Each year, over 10 million tons of fertilizers are consumed in Vietnam, of which 80% are supplied by domestic factories. Approximately 60.6% of this amount is used to cultivate rice, and the rest is used to cultivate maize, coffee, sugarcane, fruits, and vegetables (IFA, 2017). Fertilizer is also the costliest item, compared to other crop production costs. In the period 2014–2015, Vietnam consumed 2.6 million tons of nitrogen (N), phosphorus (P_2O_5), and potassium (K_2O), of which, 60% (1.6 million tons) was N fertilizer used for rice production. According to the Soil and Fertilizers Research Institute, the N use efficiency for rice plants in Vietnam is still low, at only 35–40%, and fertilization is imbalanced. Specifically, too much N is used, compared to P_2O_5 and K_2O. The calculated data across 5 years (2008–2012) indicate that the ratio of applied nutrients N: P_2O_5: K_2O is 3.3:1.5:1.[6] Thus, the excessive use of N not only generates waste and pollutes the environment, but it also creates a suitable environment for pests and diseases to develop (SFRI, 2016). This poses both economic and environmental risks and challenges in achieving sustainable agricultural development in the nation.

The Vietnamese agricultural sector also uses large amounts of pesticides, despite many integrated pest management programs having been implemented for many years. A recent report by the Vietnam Environment Administration (Ministry of Natural Resources and Environment) states that, on average, Vietnam uses 15,000–25,000 tons of pesticides each year. There is also proof that farmers and communities that use water sources with pesticide residues, in Vietnam and along the MKD, face serious health risks. The study by Dasgupta (2007) showed that 35% of the MKD farmers who were medically tested showed signs of contamination by the

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[6] Recommended fertilizer amounts, each season, for rice varieties with growth time between 85 and 100 days (kg/ha) are (i) Alluvial soil: winter–spring season (90–100 kg N; 30–40 kg P_2O_5; 30–40 kg K_2O); summer–autumn season (75–90 kg N; 30–40 kg P_2O_5; 30–40 kg K_2O). (ii) Light acid sulfate soil: winter–spring season (80–100 kg N; 40–50 kg P_2O_5; 25–30 kg K_2O); summer–autumn season (70–80 kg N; 40–50 kg P2O5; 25–30 kg K_2O) (Phung et al., 2014).

organic phosphorus and carbamates in pesticides, of whom, 21% had symptoms of chronic poisoning. The household survey by Toan *et al.* (2013) found that household-level pesticide management remains suboptimal in the MKD, and a wide range of pesticide residues was found in the water, soil, and sediments throughout the monitoring period. Further, the human and environmental health awareness is limited, as evidenced by improper pesticide storage and waste disposal during pesticide handling and application (Chau *et al.*, 2015). Owing to pesticide pollution, the authors failed to identify a clean water source in the MKD.

To reduce the excessive use of chemical fertilizers and pesticides, the Vietnam Ministry of Agricultural and Rural Development (MARD) has encouraged farmers to apply a farming technology known as climate smart agriculture (CSA), which is aimed at promoting sustainability in rice cultivation. First, following the framework of a crop management technology designed by the International Rice Research Institute (IRRI), the “Three Reductions, Three Gains” (3R3G) program was developed to reduce production costs, improve farmers’ health, and protect the environment when rice-production areas in the MKD are irrigated (Huan *et al.*, 2005). Later, based on 3R3G, “One Must Do, 5 Reductions” (1M5R) technological package was developed during Phase IV of the IRRI’s Consortium and promoted by the World Bank’s Agricultural Competitiveness Project. Farmers who apply this technique are urged to use certified seeds (One Must Do) and reduce the seed rate, use of fertilizers and pesticides, irrigation cost, and post-harvest losses (Five Reductions). In particular, this advanced technology is expected to be the best practice for intensive rice production in the MKD, and includes benefits, such as reducing production costs, increasing paddy yield, improving rice grain quality, enhancing farm profit, saving water and natural resources, reducing greenhouse gas emissions, and protecting the community’s health (Phung et al., 2014). 1M5R has been recognized by the Department of Crop Production as technical progress, according to Decision No. 532/QD-TT-CLT, dated November 7, 2012. Therefore, MKD’s agriculture sector urgently requires a formal assessment of the benefits of 1M5R application for rice producers. The most recent study by Connor *et al.* (2020) explores the factors that influence farmers’ decision to apply the 1M5R package in two MKD provinces: An Giang and Can Tho. It concluded that, while all farmers meticulously met the requirements for certified seeds, pesticides, and post-harvest loss reduction, they still had difficulties reducing their fertilizer use, water use, and seed rate. Other studies have measured the difference between farmers applying 1M5R and other groups of conventional farmers (Chi *et al.*, 2013; Son *et al.*, 2013; Tin *et al.*, 2015). These studies compared descriptive statistics to draw conclusions regarding the higher profitability for households participating in 1M5R, compared to traditional households. However, making conclusions on the differences in potential outcomes, without considering the observed sociological factors of the two household groups, may lead to self-selection bias. Therefore, using the propensity score matching (PSM) method, this study aims to i) identify the factors that influence farmers’ decision to join 1M5R and ii) assess the impact of the 1M5R technique on the economic performance of rice smallholders in the Vietnamese MKD. The empirical results of this study have implications for policymakers and local authorities, regarding the causal effects of such an important rice farming technique. Some potential suggestions to improve the economic benefits of 1M5R for rice smallholders and, simultaneously, protect the surrounding natural environment in the region are suggested.

The remainder of this chapter proceeds as follows. Section 2 introduces the methodology and data used in this study. Section 3 presents the results and discussions. The last section concludes the study and presents policy recommendations for enhancing the economic welfare of 1M5R rice farming in MKD.

4.2. Methodology and Data

4.2.1. Methodology

Household sampling for climate smart farming techniques, such as 1M5R, cannot be random. The survey and interviews of rural households must be based on the geographical location, ecological region, rice cultivation characteristics, and consultation with local authorities. As such, this causes, first, “selection bias,” when sampling participants for analysis. Second, bias may arise from the unobserved characteristics in rice households. For example, these households may participate in the 1M5R technique because of their personal preferences, abundant capital resources, and motivation to experience new technology, among other reasons. In such cases, controlling for these types of biases requires an instrument that can explain the participation of farmers in 1M5R, based on their observable socioeconomic characteristics, before subsequently explaining the difference in rice production outcomes.

To date, many studies have used PSM to eliminate non-randomization bias and, simultaneously, calculate the causal effects of a program or project on smallholders in the agricultural sector. Recently, PSM was used to calculate the impact of CSA and climate change adaptation on smallholder rice farmers' technical efficiency (TE) (Ho and Shimada, 2019). The results indicate that both climate change adaptation and CSA application affect the rice growers’ TE score. More specifically, climate change adaptation increases the TE scores for rice-producing households by 13–14% compared to conventional households. CSA also helps households increase TE by about 5–6%, compared to households that do not apply it. Duong and Thanh (2019) also use the PSM–DID approach to examine the economic impact of adopting modern rice varieties in Vietnam, using a dataset derived from the Vietnam Access to Resources Household Survey in 2012 and 2014. The empirical results reveal that only large farms can improve their productivity by adopting modern varieties, and that the impact of the adoption on the value-added, in terms of profit and based on different farm sizes, is insignificant. Concerning the Pakistan agricultural sector, Ali *et al.* (2014) used PSM to establish the impact of a direct sowing technology on rice production. This technique, with the essence of a water-saving technology, saves a considerable amount of irrigation water, compared to the traditional transplanting method, thereby helping adopters to reduce production and labor costs, and simultaneously increase rice and corn yields in the same cultivated area, compared with conventional households. Wu *et al.* (2010) also used PSM to conclude that adopting the improved upland rice technology has had a significant positive effect on farmers' well-being in rural China, which is measured by increased household income and reduced poverty incidences. The incomes for households that apply science and technology to production are expected to be approximately 1.53, 1.32, and 1.26 times higher in 2000, 2002, and 2004, respectively, compared to those of households that do not apply science and technology. With increased income and reduced poverty incidences considered as possible outcomes, PSM was used effectively by Mendola (2006) to estimate the impact of adopting agricultural technology on households in rural Bangladesh. Adopting a high-yielding variety (HYV) was found to have a robust and positive impact on household income, which in turn contributes to poverty alleviation in rural Bangladesh.

PSM was first defined by Rosenbaum and Rubin (1983) and supplemented by Khandker *et al.*, in 2010. PSM constructs a statistical comparison group, which is based on a model of the probability of participating in treatment T and is conditional on observed characteristics X or the propensity score, $P(X) = Pr(T = 1|X)$. Two important assumptions need to be followed to estimate the causal effects of a program. These include (i) the conditional independence assumption (CIA) and (ii) the presence of common support or overlap condition. Under these two assumptions, matching on $P(X)$ is as good as matching on X, according to Rosenbaum and Rubin (1983).

The CIA posits that given a set of observable covariates X, which are not affected by treatment, potential outcomes Y are independent of treatment assignment T (Khandker *et al.*, 2010). Hence, in the first PSM step, a probit model is used to identify the determinants of farmers' decisions to participate in the 1M5R package (T) and to calculate the propensity scores, using a set of covariates (X_i). The main purpose of the propensity score estimation is not to predict selection into treatment but to balance all covariates (Caliendo and Kopeinig, 2008). The probit model is specified as

$$y\,(0,1) = \beta_0 + \beta_1 X_1 + \ldots + \beta_{12} X_{12} \qquad (4.1)$$

where $y\,(0,1)$ is the status of farmers' participation in 1M5R ($y = 1$ participating in 1M5R; $y = 0$ not participating in 1M5R/conventional farmers), and β_0 to β_{12} are the regression coefficients. The covariates are chosen following the assumption that only variables that are unaffected by participation (or related anticipation) should be included in the model. If these variables are measured before participation, it must be guaranteed that they are not influenced by the anticipation of participation (Caliendo and Kopeinig, 2008). The data for participants and non-participants should also be obtained from the same sources (same questionnaires). As such, the independent variables in equation (1) are as follows: X_1 is the age of household head, X_2 is the gender, X_3 is education level, X_4 is the years of experience, and X_5 is the family members. Further, X_6 is the paddy land size, X_7 is the number of land plots, X_8 is the credit status of households, X_9 is the prior participation in training classes, X_{10} is the off-farm (non-agricultural activities), X_{11} is the cooperative membership, and X_{12} is the membership of Farmers' Association. The details for these covariates are described in detail in Section 2.3 (Table 1).

Subsequently, the common support region, where the propensity score distributions for the treatment and comparison groups overlap, $0 < P\,(T_i = 1|X_i) < 1$, need to be defined. Therefore, treatment units have to be similar to non-treatment units, in terms of observed characteristics that are unaffected by participation. The common support region was assessed by examining a graph of propensity scores across the treatment and comparison groups (Figure 4.1). Some of the non-participant observations, which fall outside the common support region, are excluded at this stage. In addition to overlapping, there should be a similar distribution ("balance") in the treatment and comparison groups within each of the five quintiles to ensure that the mean propensity score is equivalent (Imbens, 2004). Therefore, a balancing test should be performed on individual covariates (Dehejia and Wahba, 2002), to check if $\hat{P}(X \mid T = 1) = \hat{P}(X \mid T = 0)$ (Khandker *et al.*, 2010). No rule states the extent to which imbalance is acceptable in a propensity score, and the proposed maximum standardized differences for specific covariates range from 10% to 25% (Stuart *et al.*, 2013; Garrido *et al.*, 2014).

Because of the overlap of propensity scores between treatment and comparison groups, due to CIA, the average treatment effect on the treated (ATT) can be written as

$$ATT_{PSM} = E_{P(X)|T=1}\{E[Y_1 \mid T=1, P(X)] - E[Y_0 \mid T=0, P(X)]\} \tag{4.2}$$

where T refers to the treatment and is equal to 1 if the farmer is a 1M5R participant, Y_1 is the participant's outcome, Y_0 is the non-participants' outcome, and X is a vector of the control variables. The ATT in this study represents the average difference between the observed outcomes of the two groups of farmers: participants and non-participants, in the 1M5R technical package. The outcome variables used in this study are paddy yield, output price, production cost, gross income, and return on investment (ROI) ratio.

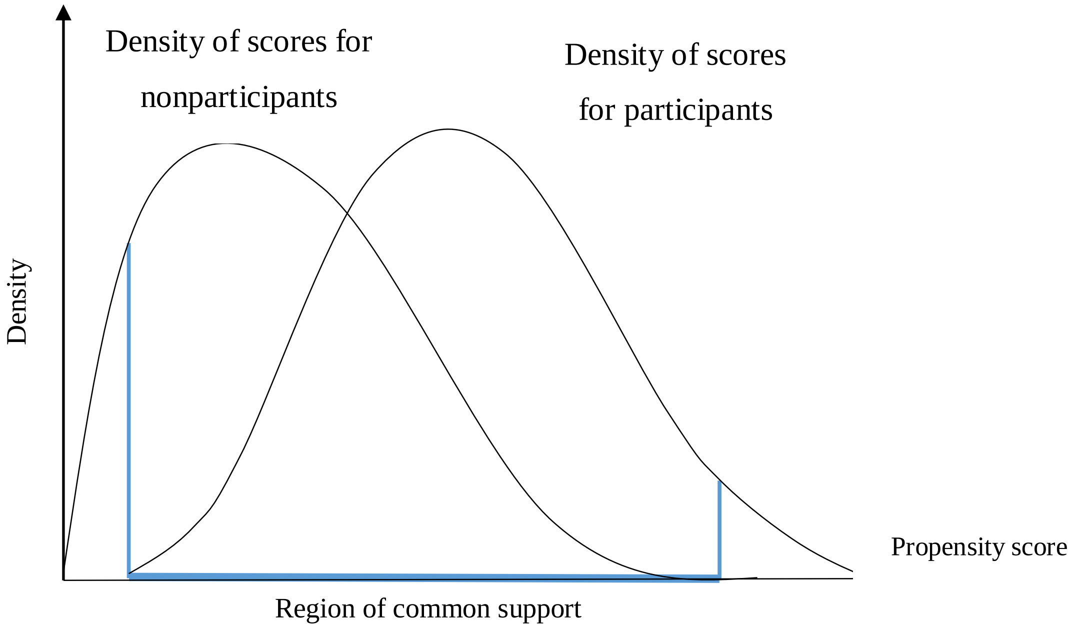

Figure 4.1. Example of common support (Khandker et al., 2010)

After the propensity scores were generated, and the balancing test passed, participants and non-participants with similar propensity scores were matched using different matching algorithms, including nearest neighbor, caliper or radius, stratification or interval, kernel matching, and local linear matching. Without a clearly superior propensity score weighting or matching method (Garrido *et al.*, 2014), we used two extensively applied methods: nearest neighbor matching (NNM) and kernel matching (KM). NNM is one of the most popular techniques, in which each treatment unit is matched to the comparison unit with the closest propensity score. One can also choose the number of nearest neighbors *n* (usually *n = 5)* and match it, with or without replacement (Khandker *et al.*, 2010). KM and local linear matching are nonparametric matching estimators that use the weighted averages of (nearly) all individuals in the control group, depending on the choice of the kernel function, to construct the counterfactual outcome (Caliendo and Kopeinig, 2008). In addition, KM maximizes precision (by retaining sample size) without worsening bias (by placing greater weight on better matches) (Garrido *et al.*, 2014); therefore, it is more favorable than NNM (Powell-Jackson and Hanson, 2012).

4.2.2. Study site

This study uses data of the household survey in Can Tho, An Giang, Dong Thap, and Bac Lieu provinces, from the "Market Oriented Smallholder Value Chains" (MSVC) project in 2018. The MSVC project is a public–private partnership (PPP) between the Federal Ministry for Economic Cooperation and Development (BMZ) through Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) and Olam International Limited. The study site chosen by stratification sampling technique represents four out of six agro-ecological sub-regions of the MKD, including An Giang province (Long Xuyen Quadrangle), Dong Thap province (Dong Thap Muoi area), Can Tho city (the riverside of Tien and Hau rivers), and Bac Lieu province (coastal area) (Figure 4.2). The paddy area and production for these four provinces accounted for 38.11% and 39.98% of the entire MKD region and production in 2018, respectively.

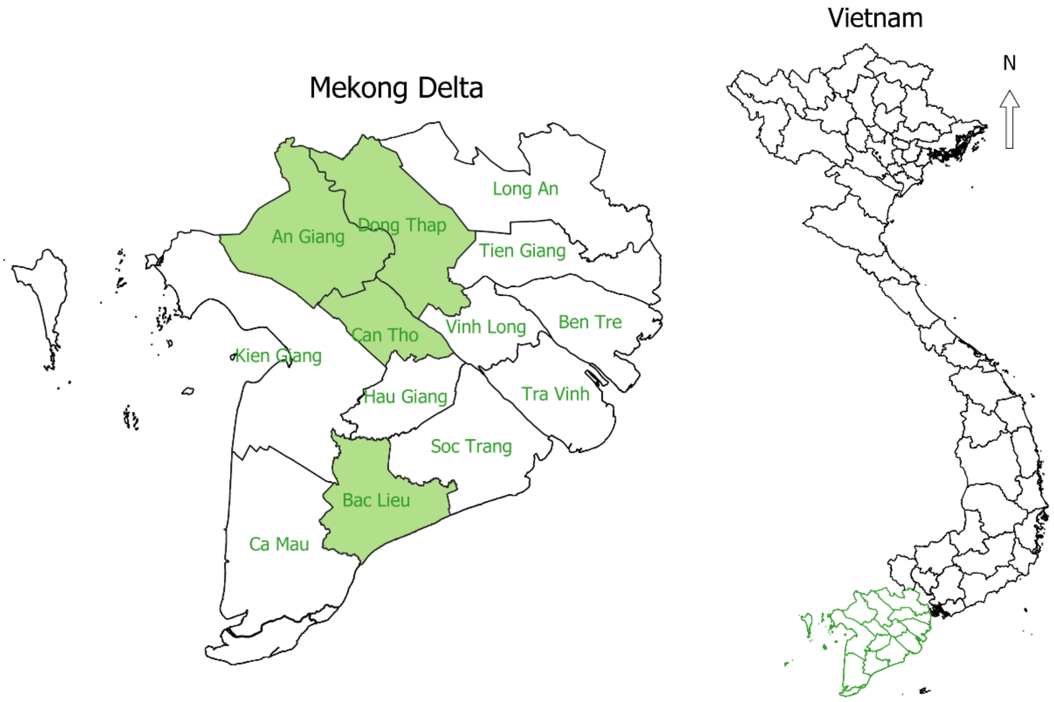

Figure 4.2. Map of Mekong Delta and study site

Source: Authors' compilation, using GIS mapping

4.2.3. Data collection

After the study site was identified, primary data were collected using the convenience sampling method in the two seasons Summer-Autumn and Autumn-Winter in the crop year 2018. Each province has 100 paddy producers, who were interviewed on the following: households demographic information (age, gender, farming experience, family members, number of family labour, cultivated land size, number of plots, credit status, training class attendance, memberships of cooperatives and farmer associations); information regarding production activities(production cost items, paddy yield, selling price, gross income, and net profit); the experience and application of smart rice cultivation techniques (1M5R, 3R3G, integrated pest management – IPM, alternative wet and drying – AWD). Specifically, households who practice 1M5R must follow the six elements of the technical package. These elements include: households must use certified seeds,[7] reduce the seed sown density to the range 80–100 kg/ha, reduce the amount of nitrogen fertilizer applied to less than 130 kg/ha,

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[7] Certified seed varieties are defined according to the national technical standards on the quality of rice seeds QCVN 01-54: 2011/BNNPTNT, issued by the Ministry of Agriculture and Rural Development.

reduce the amount and frequency of pesticide use, reduce the amount of irrigation water, and finally reduce the post-harvest loss by using combine harvesting machines. To meet the study objectives, the authors conducted PMS analysis on extracted data from the 380 households, which included 140 1M5R adopters 240 non-adopters/individual rice producers. These two groups of farmers have similar farming areas, weather conditions, and climate conditions for comparison.

4.2.4. Explanation of variables used in the model

The treatment variable represents participation of households in the 1M5R farming technique for the four provinces. The treated group (participants) comprises farmers who practiced 1M5R for at least three seasons on their farms. The untreated group (non-adopters, non-participants, and control group) include those who use their own traditional techniques to cultivate paddies (conventional farmers).

The independent variables used in the probit model to compute trend scores are shown in Table 4.1. The most recent study on the determinants of 1M5R adoption in the MKD indicates that all farmers met the requirements, which include the use of certified seeds, pesticide reduction, and post-harvest loss reduction. However, farmers found it difficult to reduce their fertilizer use, irrigation water, and especially the seed sown density. All six elements of the technical package are adopted owing to the ease of implementation, education, satisfaction, and non-rice income (Connor *et al.*, 2020). In existing studies, household demographic factors, such as gender, age (Tran *et al.*, 2020), education level (Dung, 2020; Abegunde *et al.*, 2020), farming experience (Abegunde *et al.*, 2020), cultivated area (Abegunde *et al.*, 2020; Ho and Shimada, 2019; Dung, 2020), formal credit access (Mwungu, 2018; Dung, 2020); technologies and the cost of implementation (Khatri-Chhetri *et al.*, 2017), and memberships in agricultural organization (Tran *et al.*, 2020; Abegunde *et al.*, 2020) were found to have significant impacts on farmers' decision to join climate smart agriculture (CSA) in developing countries and in Vietnam. Based on previous studies, the authors included variables, such as participation in agricultural training and membership of local Farmer's Associations (FAs). There has been no large correlation between these independent variables in the probit model.[8]

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[8] There is significantly moderate correlation between age and experience (Pearson correlation coefficient = 0.4266); total farm size and plots (Pearson correlation coefficient = 0.3766). The other variables show weak correlation between each other with the coefficients smaller than 0.3.

Table 4.1. Covariates used in the probit model to generate the propensity scores

Variable	Description	Mean	S.D
T: 1M5R participation	Treatment-Dummy, receives 1 value if households practice 1M5R package on their farms, 0 otherwise.	0.37	0.48
Age	Age of the household heads (year)	49.46	10.64
Gender	Dummy, receives 1 value if household heads are male, 0 otherwise.	0.94	0.23
Educational level	Number of years in school of the household heads	6.97	3.53
Farming experience	Number of years of rice farming experience	26.17	19.14
Household size	Number of family members	4.46	1.43
Rice land	Total area of rice farmland, measured in hectare	2.77	3.35
No. of rice plots	Number of plots in that rice farmland	2.10	1.80
Credit	Dummy, receives 1 value if households had a loan for agricultural production from banks, 0 otherwise.	0.19	0.40
Training	Dummy, receives 1 value if households did participate in training classes for 1M5R, 0 otherwise	0.71	0.46
Off-farm	Dummy, receives 1 value if households have non-agricultural job that can create income, 0 otherwise	0.14	0.35
Cooperative membership	Dummy, receives 1 value if household heads are rice cooperative members, 0 otherwise	0.69	0.46
Farmer's Association	Dummy, receives 1 value if household heads are members of farmer associations, 0 otherwise	0.26	0.44

Source: Authors' calculation based on household survey

Among these variables, farmer characteristics, such as education level, production experience, membership of cooperatives or FAs, and training participation are expected to have positive impacts on the decision to adopt the 1M5R package. Farmers with higher education levels and much more experience could achieve better understanding when trained on, or consulted about, the technical requirements. FA membership and production groups could also help farmers obtain incentives for input materials and agricultural mechanization to apply modern farming technology. The statistical information and mean difference of these covariates between participants and non-participants are presented in Table 4.2, Section 3.1.

Regarding the outcome variables, some studies have used economic indicators to estimate the causal effect of a program or agricultural technology on smallholders. Bidzakin *et al.* (2019) used yield and gross margins as outcomes to investigate the importance of contract farming in rice production. Ma and Abdulai (2017) examined the impact of agricultural cooperative membership on output price, gross income, farm profit, and ROI. Ali *et al.* (2015) estimated the impact of direct seeding, using the rice sowing technology, on rice and wheat crop yields and farmers' incomes. Wu *et al.* (2010) utilized households' incomes and poverty gap as outcome variables to assess the impact of improved upland rice technology on farmers' well-being. Based on the advantages of adopting the 1M5R package, indicated in the guidebook of MARD (Phung *et al.*, 2014), this study uses production cost, paddy yield, output price (per kg), farm's income, and the ROI ratio as the outcome variables for comparison. Since 93% of the paddy products is acquired by individual traders and 75% of farmers sell wet paddy at the harvest time, the price was subject to flexible arrangements between farmers and traders (The Anh et al., 2020). In this case, traders visit and negotiate the farm-gate price with farmers. 1M5R products will display more advantages than normal products since traders could sell them to local millers or exporters with a better price.

The input data mentioned in this study is the average values of the two seasons. Farm's net profit was calculated by deducting total production cost from the gross income. The gross income was computed by fresh paddy (wet paddy) yield multiplying with farm-gate selling price reported by each household. Total production cost included all the costs for seeds, fertilizers, pesticides, herbicides, fungicides, hired labor and machinery for all steps including land preparation, irrigation, seeding, fertilizing, pesticides spraying and harvesting. The return on investment ROI was calculated by (Returns – Investment/Investment). Using ROI as an indicator to measure farm performance is preferred because it not only introduces the farm's income from rice production, but it also considers the profitability of agricultural investments (Ma and Abdulai, 2017; Böhme, 2015; Kleemann *et al.*, 2014).

4.3. Results and discussion

4.3.1. Descriptive statistics

General information regarding the two groups of rice farmers is presented in Table 4.2. Compared to conventional farmers, farmers who participate in 1M5R comprise younger and more educated heads of households. Specifically, there is a significant difference between the heads of households in the treated and control farms, in terms of their participation in previous agricultural technical training and their agricultural cooperatives' memberships. In addition, farmers who choose to apply the 1M5R technique also have more experience in paddy cultivation; however, this difference is not statistically significant. The difference in other characteristics, such as household size, rice land area, number of plots, credit status, and non-agricultural activities, is not significant. This indicates similarities in the sociological characteristics of the interviewees.

Table 4.2. Main characteristics of rice farms by 1M5R participation status

Characteristics	Participants (1) (140)	Non-participants (2) (240)	Diff. (1)–(2)
Age	49.40	49.50	0.10
Gender	0.94	0.94	0.00
Educational level	7.73	6.51	1.22 ***
Farming experience	28.22	24.96	3.26
Household size	4.55	4.41	0.14
Rice farmland	2.94	2.68	0.26
Rice plots	2.07	2.11	– 0.04
Credit	0.21	0.18	0.03
Training	0.87	0.60	0.27 ***
Off-farm activities	0.14	0.13	0.01
Cooperative membership	0.85	0.60	0.25 ***
Farmer’s association	0.23	0.27	– 0.04

Source: Authors' calculations, based on household surveys. *** *indicates 1% significant level.*

Regarding the inputs required for the cultivation steps, Table 4.3 shows the difference in physical materials used by the two groups of rice households. It is clear that households who practice 1M5R use significantly fewer seeds, which are sown at 121 kg/ha, compared to households who do not practice 1M5R. While this amount is still high, compared to the technical recommendation (seed density should be from 80 to 100 kg/ha regarding to the broadcasting technique using a manually-pulled drum seeder) (Phung *et al.*, 2014), it still indicates the farmers’ effort in seed reduction compliance. Seed rate reduction is the first important step in the 1M5R technical package. Reducing the amount of seeds to 80–100 kg/ha reduces the pest infestation, compared to a strong seeding density. For this reason, farmers can reduce the amount of pesticides and nitrogen fertilizers and save irrigation water. As described in Table 3, households participating in 1M5R used nitrogenous fertilizers N, P_2O_5, and K_2O[9] at 95, 64, and 50 kg/ha, respectively, while ordinary households with larger amounts of seeds used more fertilizer at 117, 79, and 58 kg/ha, respectively.

A significant difference is noted in almost all types of costs between 1M5R participants and non-participants. Following the instructions of the technical package, participants can reduce their seed cost by an average of 23.59 USD/ha. Consequently, this group could also reduce their fertilizer and pesticide expenses by 38.01 and 30.99 USD/ha, respectively. Using tractors combined with laser technology for land leveling,[10] before each season, not only helps farmers to reduce the amount of seeds but also to reduce the water pumping cost[11] (Phung *et al.*, 2014; Aryal *et al.*, 2015). Moreover, applying the AWD technique mentioned in the guidebook can effectively help 1M5R adopters to reduce irrigation costs by 6.44 USD/ha. Regarding the harvesting step, the 1M5R group was promoted to harvest paddy using a combine harvesting machine. This sharing activity in renting machinery helps 1M5R farmers to lower their harvesting costs by 5.75 USD/ha, compared to individuals who hire labor to complete their harvests. The data also show that the total production cost and the cost per kg of 1M5R fields are lower by 110.55 USD/ha and 0.01 USD/kg, respectively, compared to those of ordinary households. Except for spraying pesticides, fertilizing, and hired labor costs, all 1M5R fields' cost items are significantly lower than those for traditional fields are. The rice yield of the treated fields (5.90 ton/ha) was lower than that of the control fields (6.24 ton/ha) by 340 kg/ha. However, with a significantly higher output price, at 0.25 USD/kg, 1M5R households achieve much better profitability at 849.84 USD/ha. Therefore, the calculated profitability ROI ratio of participants in CSA was 31% higher than that of regular households in MKD provinces. Generally, it is shown that the values of the four, out of five, outcome variables are higher for 1M5R adopters than they are for non-adopters, and the mean differences are statistically significant at the 1% level. However, this comparison, based on the t-test, is only descriptive; to obtain the true effects of the 1M5R technical package on farms' economic outcomes, a potential selection bias needs to be considered.

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[9] Farmers in this study used inorganic Urea (contains 60% N), DAP (18% N and 46% P_2O_5), NPK_1 (20% N and 20% P_2O_5 and 15% K_2O) and NPK_2 (16% N and 16% P_2O_5 and 8% K_2O), KCL (60% K_2O) commercial fertilizers.

[10] Laser land leveling (LLL) is a laser-guided technology used to level fields by removing soil from their high points and depositing it in their low points. LLL reduces greenhouse gas emissions by saving on energy, reducing cultivation time, and improving input-use efficiency. In a level field, water is distributed evenly, thus, reducing the amount of time and volume of water needed for irrigation (Mitigation technologies, IRRI).

[11] The empirical results from the study by Aryal (2015) indicated that laser leveling in rice fields reduced irrigation time by 47–69 h/ha/season and improved yield by approximately 7 %, compared with traditionally leveled fields.

Table 4.3. Mean difference in rice production cost and outcome variables between 1M5R participants and non-participants in MKD

	Adopters (140) (1)	Non-adopters (240) (2)	Diff. (1)–(2)
Inputs quantity (kg/ha)			
Seeds	121 (25.86)	187 (34.40)	-66^{***}
N	95 (30.27)	117 (46.16)	-22^{***}
P_2O_5	64 (30.67)	79 (38.63)	-15^{***}
K_2O	50 (32.80)	58 (37.01)	-8^{*}
Cost items (USD/ha)			
Seeds	69.60 (19.66)	93.19 (21.67)	-23.59^{***}
Fertilizer	167.69 (55.48)	205.70 (81.15)	-38.01^{***}
Pesticides	152.14 (79.29)	183.08 (79.34)	-30.94^{***}
Land preparation	58.12 (23.32)	72.20 (34.18)	-14.07^{***}
Irrigation	37.03 (23.43)	43.47 (28.73)	-6.44^{**}
Fertilizing, spraying	67.26 (79.79)	57.13 (56.49)	10.13
Harvesting	80.03 (19.92)	85.78 (21.31)	-5.75^{***}
Others	3.51 (5.39)	5.27 (10.13)	-1.76^{*}
Total cost	687.56 (156.34)	798.11 (185.10)	-110.55^{***}
Cost per kg	0.12 (0.29)	0.13 (0.28)	-0.01^{***}
Outcome variables			
Rice output (ton/ha)	5.90	6.24	-0.34^{***}
Output price (USD/kg)	0.25 (0.02)	0.23 (0.01)	0.01^{***}
Revenue (USD/ha)	1,537.39 (269.88)	1,545.82 (239.56)	– 8.42
Profit (US/ha)	849.84 (269.18)	747.71 (247.80)	102.13^{***}
ROI	1.32	1.01	0.31^{***}

***, **, *and* * *significant at 1, 5, and 10% probability level, respectively*
Standard deviation in the parentheses
1 US Dollar in Vietnamese Dong is 23,288.98 for 11/11/2018
Source: Authors' calculation based on household survey

4.3.2. Estimating the effect of 1M5R package on economics performance of rice smallholders

The result of the probit model, presented in Table 4.4, indicates the correlation between participation in 1M5R and households' demographic characteristics. More specifically, the decision to adopt this CSA is positively correlated with the education of household heads, their 1M5R training class attendance, and cooperative membership. Household heads with higher education are more likely to participate in the 1M5R. It is understandable that farmers with better education will understand cultivation techniques, and they can benefit in their production and natural environments if the amount of seeds and chemical fertilizer are reduced. This result supports the findings of previous studies on households' decisions to engage in CSA (Dung, 2020; Connor *et al.*, 2020; Abegunde *et al.*, 2020). Farmers who had previously participated in 1M5R technical training prefer to join 1M5R, as they were officially and technically aware of the importance of this farming technique and its benefits to production and to the environment. Finally, for cooperatives memberships, the institutional factor has a significantly positive impact on the implementation of the 1M5R technique, at the 1% significance level. Similar conclusions are also indicated by Abegunde *et al.* (2020) and Tran *et al.* (2020). These results emphasize the importance of information distribution to farmers through training classes and the support of cooperatives/farming groups in providing seed supply, fertilizer, agricultural machinery, and irrigation systems during dry seasons.

Table 4.4. Determinants of farmers' participation in 1M5R package

	Coef.	Std. error
Age	– 0.013	0.010
Gender	0.286	0.314
Educational level	0.036 *	0.022
Farming experience	0.011	0.010
Household size	0.041	0.052
Rice land	0.022	0.022
No. of rice plots	– 0.010	0.043
Credit	0.127	0.182
Training	0.768 ***	0.177
Off-farm	0.091	0.213
Coop. membership	0.532 ***	0.171
Farmers Assoc.	– 0.148	0.165
_cons.	– 1.692	0.608
Number of observations		364
Log-likelihood		– 212.724
Prob > chi^2		0.000
Pseudo R^2		0.116

***, **, and * significant at 1, 5, and 10% probability level, respectively

Source: Authors' calculation based on household survey

The propensity score distributions of the two groups are shown in Figure 4.3. The estimated propensity scores for the entire sample range between 0.035 and 0.999, with a mean score of 0.374 (SD = 0.178). The propensity scores for members vary between 0.058 and 0.999 and have a mean score of 0.462 (SD = 0.150). The propensity scores for non-members vary between 0.035 and 0.717, with a mean score of 0.321 (SD = 0.171). Thus, the common support region for the distribution of the estimated propensity scores of members and non-members would range between 0.058 and 0.717. Those households whose propensity scores lie outside this range are excluded from the sample. The final number of households in the common support region is 364, including 136 participants and 228 non-participants in the 1M5R package.

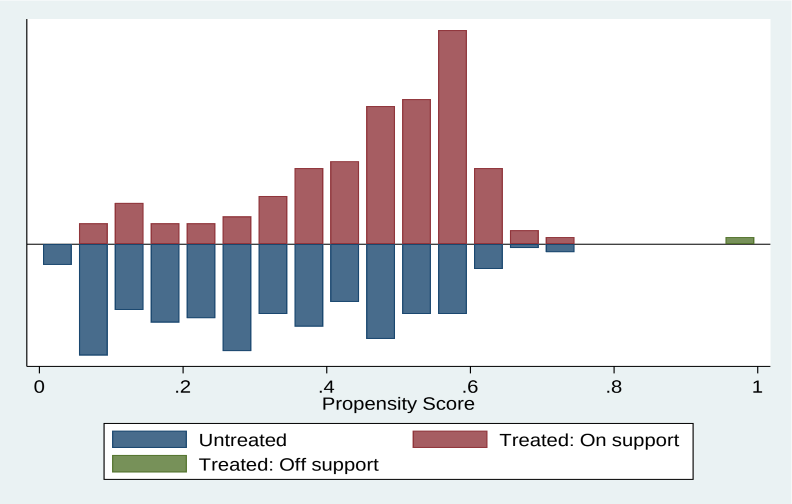

Figure 4.3. Distribution of the propensity score for 1M5R participants (treated group) and non-participants (untreated group)

Source: Authors' compilation

The next important step is checking for selection bias and the quality of the matching algorithm used in this study. The results of the balancing test for all covariates between the 1M5R participants and non-participants are presented in Table 4.5. Before matching, the mean standardized bias for all variables used in the probit model was 17.8%. After matching, using NNM (n = 5) and kernel algorithms, the mean bias between these covariates was significantly reduced to 4.3% and 2.2%, respectively. The large bias values of educational level and training activity between the two groups were greatly reduced to values smaller than 10%. The balancing test's result, through KM and NNM, presents a good matching quality, which can be used to draw conclusions regarding the treatment effect and to provide further implications of the 1M5R package.

Table 4.5. Balancing test with unmatched and matched samples

Variable	Unmatched				NNM (n = 5)				Kernel			
	Treated	Control	% bias	T	Treated	Control	% bias	T	Treated	Control	% bias	T
Age	49.40	49.45	– 3.9	– 0.36	48.99	48.41	5.4	0.46	48.99	48.83	1.5	0.13
Gender	0.95	0.94	2.4	0.22	0.96	0.96	0	0	0.96	0.95	1.6	0.14
Educational level	7.63	6.52	33.1***	3.01	7.61	7.35	7.8	0.67	7.61	7.43	5.5	0.47
Farming experience	28.22	25.10	14.6	1.50	25.99	26.08	– 0.5	– 0.08	25.99	26.35	– 1.7	– 0.28
Household size	4.56	4.44	8.2	0.75	4.57	4.69	– 8.5	– 0.72	4.57	4.57	– 0.1	– 0.01
Rice land	2.95	2.61	9.9	0.96	2.96	2.68	8	0.7	2.96	2.77	5.5	0.46
No. of rice plots	2.09	2.12	– 1.7	– 0.15	2.09	2.19	– 5.8	– 0.54	2.09	2.16	– 3.7	– 0.34
Credit	0.21	0.18	7.7	0.72	0.21	0.18	6.4	0.52	0.21	0.19	3.4	0.28
Training	0.85	0.62	52***	5.77	0.87	0.88	– 1.4	– 0.15	0.84	0.84	0	0.02
Off-farm	0.88	0.60	65.4	0.34	0.14	0.13	2.6	0.21	0.87	0.87	0.2	– 0.13
Cooperative memberships	0.14	0.13	3.7***	4.63	0.84	0.84	1	0.1	0.14	0.15	– 1.6	0
Farmers Assoc.	0.24	0.29	– 11.3	– 1.04	0.24	0.22	4.7	0.41	0.24	0.24	– 1.8	– 0.15
Mean standardized bias (%)			17.8				4.3				2.2	

Note: *** *significant at the 1% probability level*; *NNM = nearest neighbor matching*

Finally, the economic impact of 1M5R on household performance is presented in Table 4.6. Overall, applying 1M5R can help reduce the total production cost by more than 80USD/ha. For adopters, the cost per kg is lower by 0.007 USD/kg through kernel matching, compared to that for ordinary farmers, which is still a very modest figure. Regarding the outcome variables, households following 1M5R package have lower rice yields, compared to households using normal amount of inputs, which are equivalent to 0.37 tons/ha and 0.28 tons/ha with NNM and Kernel matching, respectively. Households who practice 1M5R grow aromatic and high quality rice to provide for both export and domestic markets. In the season Summer-Autumn, the weather was very humid and there was high risks of pests and disease. Meanwhile, 1M5R adopters had to reduce seeds, fertilizers and pesticides spraying. Therefore, the yield of 1M5R participants was lower which might be caused by the reduction of inputs. It would be ideal that paddy yield could maintain or slightly increase as mentioned in previous studies when Vietnamese farmers practiced the reductions in seeds, fertilizers and pesticides application (Huan et. al, 2005; Tin et. al, 2008), however our empirical results shows that higher yield has not yet realized and lower yield may be inevitable in the short-run. Paddy products from 1M5R households are purchased by traders at a higher average price of 0.011 and 0.010 USD/kg, respectively, thanks to the operation of cooperatives as agencies in selling products and making contracts with traders· The total revenue of the 1M5R household group decreases slightly due to lower paddy output; however, owing to the relative cost reduction, the net profit is higher by 62.28 USD/ha and 77.63 USD/ha with NNM and KM, respectively. This result is in line with the findings from other studies (Alexander et. al, 2018; Tin et. al, 2008; Huan et. al, 2005) that the improved farming technique (mainly cutting down excessive input items activities) significantly helped applicants to reduce production cost and increase their net income. Finally, the technical package 1M5R proves to be effective in helping participants improve economic performance when their ROI is higher by 0.24, which is statistically significant at the 1% level. In conclusion, the technical package 1M5R does not ensure paddy yield, but achieves its primary objective of reducing the production costs and improving households' earnings in treatment fields. Hence, the advantageous ROI ratio not only presents the 1M5R adopters' benefits from rice production but also introduces their effective investments into agricultural activity by following the reduction strategies. The practical results of this study could encourage farmers in other areas to join in and be convinced about both the economics and environmental impacts of 1M5R technical package to paddy smallholders. Through the benefits brought to rural life, scaling up the 1M5R in every province of the MKD is very promising.

Table 4.6. Treatment effect of 1M5R on farm’s performance with Nearest Neighbor Matching and Kernel algorithms

	Variables	Sample	Adopters	Non-adopters	Diff.	T-stat
NNM (n = 5)	Cost/kg (VND/kg)	Unmatched	0.119	0.128	–0.010	–3.21
		ATT	0.118	0.124	–0.006	–1.54
	Total cost (thousand VND/ha)	Unmatched	691.398	793.353	–101.955 ***	–5.51
		ATT	692.243	773.071	–80.828 ***	–3.63
	Yield (ton/ha)	Unmatched	5.91	6.24	–0.33 ***	–3.39
		ATT	5.92	6.29	–0.37 ***	–3.11
	Output price/kg (VND/kg)	Unmatched	0.247	0.237	0.011 ***	5.43
		ATT	0.247	0.237	0.011 ***	4.38
	Revenue (thousand VND/ha)	Unmatched	1537.369	1546.782	–9.412	–0.35
		ATT	1540.742	1559.292	–18.550	–0.56
	Farm’s profit (thousand VND/ha)	Unmatched	845.971	753.428	92.543 ***	3.37
		ATT	848.498	786.221	62.277 ***	1.82
	ROI	Unmatched	1.31	1.03	0.28 ***	4.97
		ATT	1.32	1.08	0.24 ***	3.48
Kernel	Cost/kg (VND/kg)	Unmatched	0.119	0.128	–0.010 ***	–3.21
		ATT	0.118	0.126	–0.007 **	–2.09
	Total cost (thousand VND/ha)	Unmatched	691.398	793.353	–101.955 ***	–5.51
		ATT	692.243	772.363	–80.120 ***	–3.83
	Yield (ton/ha)	Unmatched	5.91	6.24	–0.33 ***	–3.39
		ATT	5.92	6.20	–0.28 ***	–2.57
	Output price/kg (VND/kg)	Unmatched	0.247	0.237	0.011 ***	5.43
		ATT	0.247	0.237	0.010 ***	4.4
	Revenue (thousand VND/ha)	Unmatched	1,537.369	1,546.782	–9.412	–0.35
		ATT	1,540.742	1,543.233	–2.491	–0.08
	Farm’s profit (thousand VND/ha)	Unmatched	845.971	753.428	92.543 ***	3.37
		ATT	848.498	770.870	77.628 ***	2.45
	ROI	Unmatched	1.31	1.03	0.28 ***	4.97
		ATT	1.32	1.08	0.24 ***	3.64

***, **, *and* * *significant at 1, 5, and 10% probability level, respectively*

1 US Dollar in Vietnamese Dong is 23,288.98 for 11/11/2018

Source: calculated from household survey in 2017

4.4. Conclusion

The 1M5R package has become one of the most important techniques for paddy producers to adopt in Vietnam and the MKD, since 2011. The empirical results from this study indicate that educational level, training class attendance, and cooperative membership are the key factors driving households' decision to practice the 1M5R technique in their fields. The PSM results are also consistent with the objectives of the 1M5R application, which helps farmers to reduce production costs, have better output prices, and enhance profit per hectare. However, the rice yield was not maintained, but was slightly lower in the treatment fields due to the decrease in seed density and chemical fertilizer usage. PSM is found to be effective in estimating the treatment effects of the important 1M5R technique on the economic performance of smallholders, after eliminating the selection bias problem. With the significant reduction in seed sown density and chemical inputs, it is possible to conclude that 1M5R is a climate-smart practice that contributes not only to rice producers' economic performance but also to the sustainable environment of the MKD region.

Some policy implications are suggested through the main findings of this study. First, participating in cooperatives and farming groups could provide better access to irrigation, mechanization, and after-harvest storage for farmers because of the available input supply and output contracts associated with rice enterprises. Second, agricultural training courses should emphasize and encourage paddy producers to continue reducing the seeds sown, to meet the recommended amount, which is 80–100 kg/ha. When seeds density is reduced, the other inputs like N fertilizer, pesticides and irrigation will also be cut down consequently. As a result, the environment will be protected and household's income will increase. By visiting fields that implement 1M5R in local areas successfully, traditional producers could understand and practice input reduction on their own farms. In addition, the government could encourage rice enterprises to expand their paddy areas, and grant certificates to 1M5R products for both domestic and export demands.

Chapter 5 Rice variety and sustainable farming in the Vietnamese Mekong Delta

Abstract

This chapter measures the overall efficiency (OE) and input slacks of rice production in the Vietnamese Mekong Delta (MKD) and to consider low-emission rice farming. Using the primary survey data of 380 households, the slack-based super-efficiency measure (SBM) in data envelopment analysis (DEA) was employed to calculate the efficiency scores and the non-radial slacks of each farm household. The results indicated that both aromatic rice (AR) and high-quality rice (HR) groups achieve their higher OE in the Autumn-Winter (AW) season compared to Summer-Autumn (SA) season. In addition, OE also increases with paddy farm greater than 2 hectares and households that have cooperative membership and climate smart agriculture (CSA) application. Regarding the input reduction strategies based on slacks, each rice group needs to reduce the seed density with the amount ranging from 29 to 45 kg/ha. The slacks of nitrogen (N) fertilizer are still high at over 30 kg/ha for all three types of variety. Among the adaptation strategies, households that practice CSA techniques like “One must do, five reductions” (1M5R) and Alternative Wetting and Drying (AWD) have smaller slacks of N fertilizer and irrigation. Low-emission paddy sector development in the MKD is fully potential with AR and HR, if the CSA techniques are continuously promoting and strictly monitored by the Vietnamese government for sustainable farming.

5.1. Introduction

Agriculture accounts for an estimated 11-15% of greenhouse gases (GHGs), which mainly come from agricultural soils (39%), enteric fermentation (38.7%) and rice cultivation (9%) (International Fertilizer Association-IFA, 2018). Approximately a third of emissions from agricultural sector comprises nitrous oxide (N_2O) which has a global warming potential 265 times that of carbon dioxide (CO_2) over a 100-year lifespan (The Intergovernmental Panel on Climate Change - IPCC, 2014). N_2O production in agricultural soil occurs predominantly through the microbial transformations of inorganic nitrogen (7N) fertilizer (Robertson and Groffman, 2007) and the potential to emit N_2O increases with the increasing availability of N (Bouwman *et al.*, 1993). IPCC estimated that emissions will increase by 35 to 60% by 2030 and CH_4 by 60% (IPCC, 2007).

A significant source of GHG emissions comes from the manufacture of synthetic N fertilizers consumed in crop production processes. And the application of N is recognized as the most important factor contributing to direct N_2O emissions from agricultural soils (Chai *et al.*, 2019). In the study of Zhang *et al.* (2014) in Shanghai, China, cumulative N_2O emissions of 23.09, 40.10, and 71.08 mg N_2O/m^2 were observed over the growing season in 2011 under the three levels of N application at low-150kg/ha, moderate-210kg/ha and high-300 kg/ha, respectively. Thus, reducing the high rate of fertilizer application is a feasible way of attenuating the global warming potential (GWP) while maintaining the optimum yield for the paddy fields (Snyder *et al.*, 2009; Zhang *et al.*, 2014).

Zou *et al.* (2007) with their on-field assessment concluded that seasonal total N_2O was equivalent to 0.02% of the nitrogen applied in the continuous flooding (CF) paddy farm. N_2O emissions increased with N fertilizer applied in rice fields that are under the water regime of flooding – drainage and reflooding. Moreover, study of Yan *et al.* (2005) also indicated that organic amendment and water regime in the rice-growing season were the top two controlling variables that significantly affected CH_4 emissions. Regarding the climate smart strategies for paddy cultivation, controlled irrigation or Alternative Wetting and Drying (AWD) technique are believed to be effective for mitigating the CO_2 equivalents of CH_4 and N_2O emissions from fields (Linquist *et al.*, 2015; Yang *et al.*, 2012). Multiple drainage (MD), a simplified form of AWD, has also been practiced in An Giang province in Vietnam, where full dike systems are prevailing, in the Mekong Delta (MKD). Uno *et al.* (2021) evaluates the effects of MD on rice yield and emissions of CH_4

and N_2O to point out the conclusions that MD can increase rice yield and decrease CH_4 emissions in paddy fields in An Giang province if it is adequately implemented. Specifically speaking, rice yield was significantly increased by 22% in MD fields relative to continuous flooding fields. Seasonal total CH_4 emissions were significantly reduced by 35% in MD plots, but no difference was found in N_2O emissions.

In 2013, agricultural production in Vietnam emitted 89.41 $MtCO_2$, which represented 34.51% of total national GHG emissions, including land use, land-use change, and forestry. Rice production alone emitted 44.61 $MtCO_2$, which accounted for 50.5% of total agricultural GHG emissions in 2010 (Ministry of Natural Resource and Environment - MONRE, 2014). The MKD is the main rice production region that contributes 55.63% of the national rice output (General Statistics Office - GSO, 2018). Simultaneously, the GHG emissions contribution from paddy cultivation of the MKD is in a similar proportion (Vo *et al.*, 2018). Among priori strategies of the Vietnam's agricultural restructuring policy, it is urgent to identify and develop the climate-adapted rice varieties that consume less chemical fertilizers, help reducing input costs and lead to a low-emission agricultural system on a large scale in the MKD (Decision No. 3434/QD-BCT, 2017).

For the above reasons, understanding about the overall efficiency and the potential for contributing to the mitigation of the effects of climate change of rice production in the MKD becomes meaningful and necessary. Increasing efficiency in the use of resources (i.e. producing more of a given output using less of a given input), is thus the key to reduce emissions intensity per kilogram of output and to improve food security and the environment. Furthermore, the overall efficiency of the agricultural sector can be enhanced by improving these following constituent components: the resilience, adaptive capacity and the potential for contributing to the mitigation of the effects of climate change and variations. Indeed, by improving the overall efficiency of agricultural production, emissions can be reduced and sequestration capacity enhanced (FAO, 2013). In the past, some of the studies use data envelopment analysis (DEA) with the radial approach to explore the technical efficiency (TE) of rice smallholders, including studies of Watkins (2014); Linh *et al.* (2015); Le *et al.* (2017); Krasachat (2004); Khosroo *et al.* (2013); Islam *et al.* (2011); Dhungana *et al.* (2004); Li *et al.* (2018); Brázdik (2006). There has to date not been a study that analyzes the overall efficiency and identifies the input excessive usage in rice production in the MKD. The radial approach of DEA used in previous studies, including Charnes, Cooper, and

Rhodes (CCR) and the Banker, Charnes, and Cooper (BCC) models, assumes that all inputs and outputs can be simultaneously changed without altering the proportions in which they are utilized. Despite of its useful and plentiful applications, its shortcoming is that it neglects the non-radial input/output slacks (Tone *et al.*, 2020). The slack-based measure (SBM) model proposed by Tone (2001), which is a non-radial DEA approach will capture the drawbacks of radial DEA and takes the slacks into consideration and allows inputs and outputs to change in different scales (Tone *et al.*, 2020). Therefore, this study aims to calculate the overall efficiency (OE) and input slacks, especially N fertilizer and irrigation slacks, of major rice variety groups and to consider low-emission rice farming in the MKD region. This work differs from the existing literature, as it extends the application of the SBM model by the super-efficiency SBM model which is able to rank efficient units (households). Through the comparison of efficiency and input slacks between rice variety groups and CSA adoption, valuable practical reference for the sustainability of rice sector in the MKD will be given.

The structure of this chapter is as follows. Section 2 explains the methodology and data used in the study. Section 3 presents results and discussions. The last section concludes, with policy recommendations towards a sustainable and low-emission rice sector in the MKD.

5.2. Methodology and data

5.2.1. Methodology

Data envelopment analysis (DEA) is a nonparametric linear programming (LP) approach for measuring the relative efficiency among a set of decision making units (DMUs). This tool originated from Farrell (1957), but the term “data envelopment analysis” became more popular following the works of Charnes et al (1978) and Banker et al (1984). A DEA model can be input-oriented (minimizing inputs while maintaining the same level of outputs) or output-oriented (increasing outputs with the same level of inputs).

Super efficiency

The term "super efficiency" relates to an amended DEA model in which DMUs can obtain efficiency scores greater than one because each DMU to be evaluated is not permitted to use itself as a peer. This method was originally proposed by Andersen and Petersen (1993), who used the method to provide a ranking system that would help them discriminate between efficient DMUs.

That is, a DMU with a super-efficiency score of 1.2 is better than one with a score of 1.05 because the former is further ahead of its peers. An illustration of this technique is provided in Figure 5.1, where five DMUs *(A, B,* C, *D, E)* use two inputs to produce a particular output. When the standard DEA model is applied to these data, the DMUs *B,* C and *D* form the frontier and, hence, each of these DMUs have an efficiency score of 1. However, if we apply the super-efficiency DEA methods, it is possible for these frontier DMUs to obtain super efficiency scores that are greater than 1. For example, consider the case of *C,* when measuring its super-efficiency score it will no longer form part of the frontier and, hence, the new frontier involves only two DMUs (*B* and *D)* and, therefore, its projected point will be *C*'. The super-efficiency score for DMU *C* will be *OC'/OC,* which is approximately 1.2. This indicates that *C* could increase input usage by 20% and still be within the technology defined by the other DMUs in the sample. Other non-frontier DMUs including *A* and *E* did not form part of the original DEA frontier, so their original efficiency scores do not change when the super-efficiency method is applied. The super efficiency method has subsequently been used in a number of alternative ways including sensitivity testing, identification of outliers, and as a method of circumventing the bounded-range problem in a second stage regression method so that standard ordinary least squares regression methods can be used instead of Tobit regression.

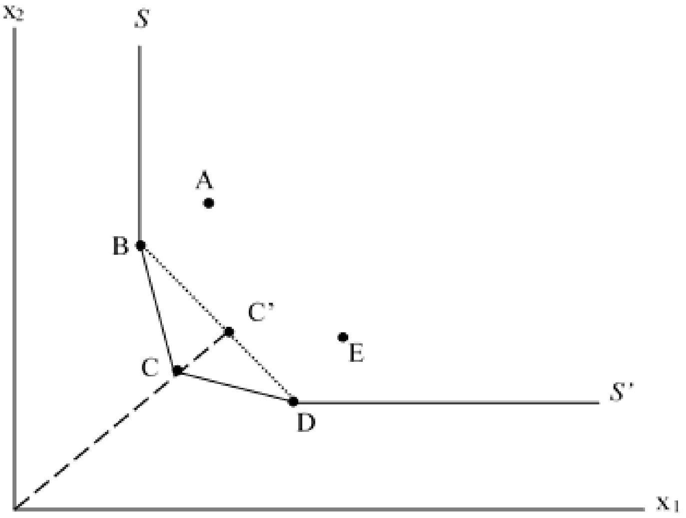

Figure 5.1. Super efficiency (Coelli, 2005)

Traditional CCR and BCC models in DEA reflect the common proportional maximum reduction of all types of input. However, in the reality, especially in the rice sector, not all of the inputs will be presented in the proportional way (like labor, material, capital, etc.). If we want to consider the efficiency scores as the only index to evaluate the performance of households, the radial approaches may mislead the decision since they neglect these important slacks in reporting the efficiency scores (Tone, 2001 and Tone, 2015). The slacks-based measure (SBM) is a non-radial measure that takes into consideration both the radial and non-radial slacks (Tone, 2001). It considers the overall efficiency of rice DMUs, put aside the assumption of proportionate changes in inputs and directly calculate the slacks of each DMU. The SBM model can divide the set of observations into two mutually exclusive and collectively exhaustive sets: efficient and inefficient. The SBM model has three variations, namely input-, output- and non-oriented. The non-oriented model is both input- and output-oriented. An input-oriented SBM approach sets a goal to reduce the input levels as much as possible while at least maintaining the present output levels.

In particular, the number of SBM and super SBM applications in agriculture, especially in paddy production is limited (Dong *et al.*, 2018; Kocisova *et al.*, 2018; Kuhn *et al.*, 2020). Since Vietnamese rice sector which mainly relies on limited resources, an input-orientated DEA model is more appropriate to measure efficiency scores than an output-oriented model. The assumption of variable returns to scale (VRS) is better than that of constant returns to scale (CRS) because not all farmers operate at optimal scales (Masuda, 2018). The following brief description of SBM and super-SBM models are cited from Tone (2017).

The SBM model

Let the set of DMUs be $J = \{1, 2, \ldots, n\}$, each DMU having m inputs and s outputs. We denote the vectors of inputs and outputs for DMU_j by $x_j = (x_{1j}, x_{2j}, \ldots, x_{mj})^T$ and $y_j = (y_{1j}, y_{2j}, \ldots, y_{sj})^T$, respectively. We define input and output matrices X and Y by (Tone, 2017):

$$X = (x_1, x_2, \ldots, x_n) \in R^{m\times n} \text{ and } Y = (y_1, y_2, \ldots, y_n) \in R^{s\times n} \qquad (5.1)$$

We assume that all data are positive, that is, $X > 0$ and $Y > 0$. The production possibility set is defined using a non-negative combination of the DMUs in the set J as:

$$P = \{(x, y) \mid x \geq \sum_{j=1}^{n} \lambda_j x_j, 0 \leq y \leq \sum_{j=1}^{n} \lambda_j y_j, \lambda \geq 0\} \qquad (5.2)$$

where $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_n)^T$ is called the intensity vector.

The inequalities in (5.2) can be transformed into equalities by introducing slacks as follows:

$$x = \sum_{j=1}^{n} \lambda_j x_j + S^-$$

$$y = \sum_{j=1}^{n} \lambda_j y_j - S^+ \qquad (5.3)$$

$$S^- \geq 0, S^+ \geq 0$$

where $s^- = (s_1^-, s_2^-, ..., s_m^-)^T \in R^m$ and $s^+ = (s_1^+, s_2^+, ..., s_s^+)^T \in R^s$ are called the input and output slacks, respectively.

Input-oriented SBM

In order to evaluate the relative efficiency of DMU$_h$ = (x$_h$, y$_h$), we solve the following linear program. This process is repeated *n* times for *h* = 1,…, *n*:

[SBM-I-C] (Input-oriented SBM under constant-returns-to-scale assumption)

$$\rho_h^* = \min_{\lambda, S^-, S^+} 1 - \frac{1}{m} \sum_{i=1}^{m} \frac{S_i^-}{x_{ih}}$$

subject to

$$x_{ih} = \sum_{j=1}^{n} x_{ij} \lambda_j + S_i^- (i = 1, ..., m) \qquad (5.4)$$

$$y_{rh} = \sum_{j=1}^{n} y_{rj} \lambda_j - S_r^+ (r = 1, ..., s)$$

$$\lambda_j \geq 0(\forall_j), S_i^- \geq 0(\forall_i), S_r^+ \geq 0(\forall_r)$$

ρ_1^* is called the SBM-input efficiency. A DMU$_h$ = (x$_h$, y$_h$) is called SBM-input-efficient if ρ_1^* = 1. This means s^{-*} = 0, that is, all input slacks are zero. However, output slacks may be non-zero. Using an optimal solution $\left(\lambda^*, s^{-*}, s^{+*}\right)$, we define a projection of DMU$_h$ = (x$_h$, y$_h$) by

$$(\overline{x_h}, \overline{y_h}) = (x_h - S^{-*}, y_h + S^{+*}) \qquad (5.5)$$

The projected DMU is SBM-input-efficient. The SBM-input-efficiency score is not greater than the CCR efficiency score (Tone, 2001).

However, SBM model fails to provide more details about efficient DMUs, which reveals the lack of discrimination power in the SBM model (Tone *et al.*, 2020). Super SBM can solve the problems of traditional SBM method, which cannot rank multiple effective DMUs. Efficiency scores are obtained from super-SBM by eliminating the data for the DMU$_h$ to be evaluated from the solution set. This can result in values which are regarded as according DMU$_h$ the status of being "super-efficient".

Input-oriented super-SBM

We solve the following program for an efficient DMU$_h$ = (x$_h$, y$_h$) to measure the minimum ratio-scale distance from the efficient frontier excluding the DMU$_h$ (x$_h$, y$_h$). The input-oriented model under the constant-returns-to-scale assumption is described by the following scheme:

$$\text{[Super SBM-IC] } \delta^* = \min 1 + \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ih}}$$

$$x_h + s^- = \sum_{j=1, j\neq h}^{n} X_j\lambda_j \tag{5.6}$$

$$y_h - s^+ = \sum_{j=1, j\neq h}^{n} y_j\lambda_j$$

$$\lambda \geq 0, s^- \geq 0, s^+ \geq 0$$

This model is under the constant returns-to-scale assumption. If we add the following condition, we can get the variable-returns-to-scale (VRS) model:

$$\sum_{j=1, j\neq h}^{n} \lambda_j = 1 \tag{5.7}$$

The super efficiency scores will be larger than 1. The higher values of super SBM score that a farm obtains, the more efficient that farm is. Large values of super-efficiency (such as 4 or higher) indicate that the respective households are of impact on the production possibility set and should be treated as outliers (Zimkova, 2014). Therefore, the ranking of efficient paddy farms coupling with rice varieties information, will provide useful reference for policy implications in the MKD region.

5.2.2. Study site and data collection

Study site

The MKD region can be classified into six agro-ecological zones, including: the Freshwater Alluvial zone (FAZ), the Plain of Reeds (PRZ), the Long Xuyen Quadrangle Zone (LXZ), the

Trans-Bassac Depression Zone (TBZ), the Coastal Zone (CZ), the Ca Mau Peninsula Zone (CPZ) (Xuan and Matsui, 1998; Duong *et al.*, 2005). We conducted the survey on these following provinces: An Giang province (LXZ), Dong Thap province (PRZ), Can Tho city (FAZ), and Bac Lieu province (CZ) (see Figure 4.2 in chapter 4). The paddy areas of An Giang, Dong Thap, Can Tho and Bac Lieu provinces in two seasons Summer-Autumn (SA) and Autumn-Winter (AW) in the crop year 2018 were 388, 314.7, 154.8 and 102.9 thousand ha, respectively. Regarding total paddy volume, An Giang ranked the first with 2.19 million tons, followed up by Dong Thap with 1.89 million tons. Can Tho and Bac Lieu provinces produced 835.4 and 596.7 thousand tons of paddy, respectively (GSO, 2018).

Data collection

Primary data were collected using the structural questionnaires. We interviewed 100 paddy producers in each province on the following: households' demographic information, paddy production activities, application of climate smart agriculture (1M5R, 3R3G, integrated pest management-IPM, alternative wet and drying-AWD). Summer–Autumn (SA) and Autmn-Winter[12] (AW) are the two main crop seasons in the production structure in these localities. To meet the study objectives, the authors conducted / among the sample units. The output is defined by the total plain rice yield (ton/ha) for a crop season. The ten inputs comprises four inputs with physical unit, including seed sown density, N, P_2O_5 and K_2O in kilograms per ha. The remaining six inputs in monetary unit are expenditures of pesticides and herbicides, irrigation, hired labor, land preparation and finally harvesting. The family labor for rice farming activities is measured by number of working hour/ha in each season. Some previous studies that employed DEA to analyze the efficiencies of agricultural farms with data per land unit (Nandy and Singh, 2020; Ullah et al., 2019; Masuada, 2016. Bolandnazar et al., 2014). After dropping some households with lacking information on production steps and extremely low output, we conducted the analysis on the sample of 380 paddy households from 4 provinces: An Giang, Dong Thap, Can Tho and Bac Lieu.

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[12] In the MKD, the Summer-Autumn (SA) season is from March/April to July/August and the Autumn-Winter is from August/September to November/December depending on the local recommendation of each province.

5.3. Results and discussion

5.3.1. Descriptive statistics

Vietnamese government has recently set up the strategy for rice production in the period of 2020 and 2030 by reducing the export volume and focusing on the quality of products. In this agricultural restructuring policy, the proportion of AR, HR and MR will account for approximately 25%, 40% and 10% of the total farming area by the year 2030, respectively (Decision No. 3434/QD-BCT, 2017). The important HR varieties for export like OM5451, OM6976, OM7347 and OM4900 should account for 50 to 60% of the total cultivated area. Also, there should be a restrictive breeding of sticky rice and MR varieties like IR50404 or OM576. However, bridging the economics benefits and environmental issues of these rice groups is still an open question.

In the study area, farmers produce three categories of rice varieties including aromatic rice (AR), high quality rice (HR) and medium quality rice (MR) (Table 5.1). AR group has good quality characterized by long slender grains, intermediate amylose, intermediate gelatinization temperature, high elongation ratio and strong aroma (Cruz and Khush, 2000). In SA season, there are 49.74% of farmers who choose to plant this rice group, including Dai Thom 8, Nang Hoa 9, Jasmine 85 and RVT varieties. This figure increases to 65% of the total producers in AW season. The two AR varieties that have a major proportion in this study are Dai Thom 8 and Nang Hoa 9. Dai Thom 8 variety has a low amylose content of 16.29%. Its cooked rice has soft and fragrant taste. This variety is adaptable to many ecological zones, including aluminum and saline areas. Nang Hoa 9 variety has been bred from Jasmine85 and AS996 varieties. It is disease resistant and tolerant to acid sulphate soil. Rice product of Nang Hoa 9 is soft and has sweet taste with a pineapple leaf aroma.

The next rice group is HR that accounts for 48.42% and 30.78% of the sample in SA and AW season, respectively. This is a group of rice varieties that are selected, bred and released by the Mekong Delta Rice Research Institute (formerly O Mon Rice Institute, hence these varieties are called OM). These OM rice varieties are commonly grown in the MKD, with high yield and good quality. They also widely adapts to different agro-ecological zones, tolerates acidic and saline soils. OM varieties have long grain rice, and very nice appearance for export. In our study, OM5451 is the most widely cultivated HR by farmers. The final group of varieties has medium quality with sticky rice CK92 and chalky grain IR50404, accounts for only 1.84% and 4.21% of the producers in the two seasons. IR50404 variety originated from the International Rice Research Institute (IRRI) and was imported into Vietnam in the early 1990s and released in 1992. The variety is popularly grown in the MKD. Due to the high amylose content and chalkiness degree, IR50404 is not suitable for international tastes and has very low commercial value. The main use of this variety is for making rice flour. In Figure 5.2, the proportion of these varieties cultivated in the four provinces of the study site is presented. In SA season, farmers in An Giang province mainly produce OM5451 and DT8 while Bac Lieu's farmers focus on aromatic DT8 and NH9 production. The similar proportion also happens with households in Dong Thap province. There is 91% of farmers in Can Tho city cultivates OM5451 for domestic and export demands thanks to its high quality and the resilience to pest and diseases. In AW season, when the more advantageous weather comes, some households in the study site switch their production from HR to AR. Particularly, farmers in An Giang and Can Tho change from OM5451 to DT8. Bac Lieu province's production does not change much since farmers mainly produce aromatics DT8 and NH9. The proportion of varieties of Dong Thap province seems to stay similarly to SA season. However, these information is just for reference and the three main group AR, HR, MR will be used for analysis in the next steps of generating efficiency scores for comparison.

Table 5.1. Rice varieties structure used by farmers in the study site

Rice varieties	Origin	Year of recognition	SA season (%)	AW season (%)
Aromatic			49.74	65.00
Dai Thom 8	Vinaseed	2019	32.90	42.11
Nang Hoa 9	Hoa Tien Seed Ltd. Co.	2011	14.47	17.90
Jasmine 85	IRRI and CLRRI	1990	0.79	1.58
`RVT	imported by Vinaseed	2011	1.58	3.42
High quality			48.42	30.78
OM5451	CLRRI	2011	44.47	27.37
OM4218		2010	2.37	2.11
OM4900		2009	1.32	0.79
OM7347		2011	0.26	0.26
OM2517		2004	0	0.26
Medium quality			1.84	4.21
IR50404	IRRI	1992	1.05	3.95
Sticky rice CK92	An Giang Rice Breeding Station	1992	0.79	0.26

Notes: Vinaseed - Vietnam National Seed Group Joint Stock Company; IRRI – International Rice Research Institute; CLRRI - Mekong Delta Rice Institute

Source: Household survey in 2018

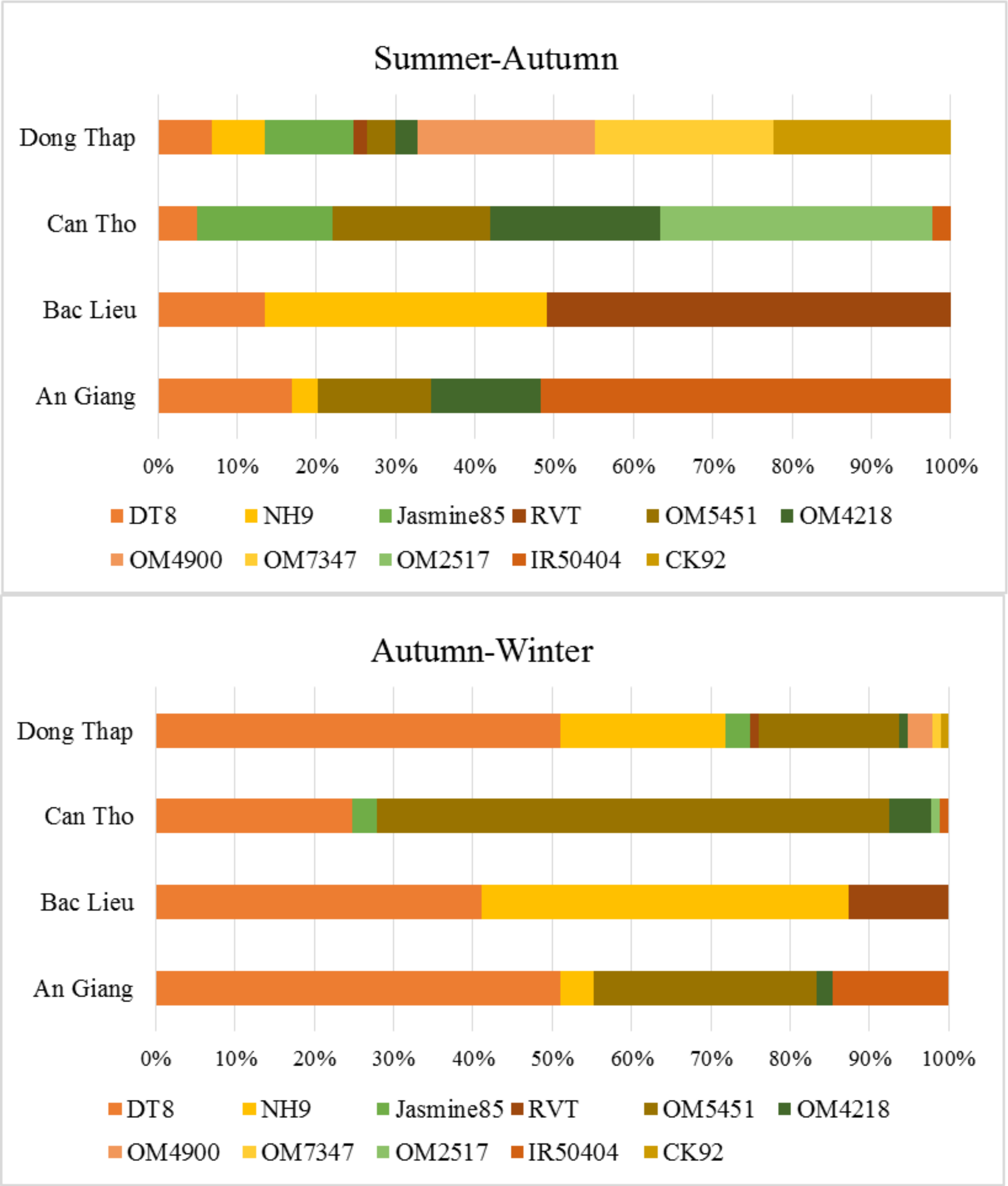

Figure 5.2. The proportion of rice varieties in four provinces and two seasons in the MKD

The descriptive statistics of output and input items used for estimating efficiency scores are presented in Table 5.2. Households in this study have the average land size at 2.77 ha, with the smallest size is just 0.26 ha and the largest one is 35.1 ha. In general, paddy farms obtain about 6.13 ton/ha and 6.11 ton/ha in SA and AW seasons, respectively. HR group gives the highest yield at 6.46 ton/ha in rainy season, meanwhile AR only obtains just 5.83 ton/ha. In AW season, AR group obtain the yield at 6.14 ton/ha, higher than that of HR group by 170kg and lower than medium-quality rice output at 6.55 ton/ha. Regarding the inputs used, the seeds sown density is relatively high in the two seasons, at more than 160kg/ha. AR producers apply seeds at 145 kg/ha in SA and 154 kg/ha in AW season, significantly much lower than the density of high-quality and medium rice. The amount of fertilizers used as nitrogen, phosphorus and potassium is acceptable and similar in the two seasons. In SA season, farmers use a little higher nitrogen fertilizer. The other nutrients' quantities are at about 73 kg/ha of phosphorus and 55 kg/ha of potassium. Importantly, when cultivating AR in the wet season, farmers consume significantly less nitrogen (103.46kg/ha) than HR (117.75kg/ha) and MR (117.78kg/ha). As mentioned above, GHG increase when more N fertilizer is consumed on paddy fields (Chai *et al.*, 2019; Zou *et al.*, 2007). Thus, this is a good signal to develop aromatic rice varieties that at the same time achieve high yield, obtain good selling price and mitigate with GHG thanks to its less consumption of N fertilizer. AR households also use significantly less potassium than the other two groups in the SA season. Among production cost items measured, pesticides and herbicides purchase is the costliest with the average of 178 and 168 USD/ha in SA and AW seasons, respectively. Being aware of the high risks of pest and disease, AR farmers have to pay more for pesticides than HR and MR. Paddy farms consume much higher irrigation cost, which includes pumping and drainage activities, in AW season at 49.7 USD/ha when compared to SA wet season at 33 USD/ha. The opposite situation happens with the land preparation cost. Harvesting cost calculated by lump sum is cheaper in SA season. There is not so much difference in hired labor cost and family labor working hour in the two seasons.

Table 5.2. Summary statistics on the output and inputs used in super-SBM model

Variable	Unit	Summer-Autumn					Autumn-Winter				
		Whole sample	Aromatic	High quality	Medium quality	F-stat	Whole sample	Aromatic	High quality	Medium quality	F-stat
Output											
Rice yield	ton/ha	6.13	5.83	6.46	5.92	***	6.11	6.14	5.97	6.55	*
Inputs											
Seed density	kg/ha	164.17	144.52	182.56	211.43	***	162.93	154.36	177.07	191.90	***
N	kg/ha	110.64	103.46	117.75	117.78	***	107.85	105.34	114.15	100.55	
P_2O_5	kg/ha	73.49	69.44	77.53	76.38		72.83	73.17	73.41	63.26	
K_2O	kg/ha	55.95	45.95	66.10	58.92	***	54.82	51.40	61.72	57.14	**
Pesticides	USD/ha	177.27	189.02	166.24	149.77	**	167.47	175.36	156.87	123.17	***
Irrigation	USD/ha	32.84	28.65	37.15	32.49	***	49.70	45.15	54.93	81.66	***
Hired labor	USD/ha	61.18	63.22	59.25	56.80		60.13	62.12	55.46	63.59	
Land preparation	USD/ha	67.83	61.70	74.45	59.07	***	66.74	65.21	69.24	72.14	
Harvest	USD/ha	83.56	85.83	81.39	79.06		84.44	87.42	77.56	88.71	***
Family labor	hour/ha	6.07	6.50	5.77	2.48		5.96	6.84	4.66	1.81	

F-stat is used for comparison of mean value between rice groups.

***, **, *and* * *significant at 1, 5, and 10% probability level, respectively.*

Source: Calculated from household survey in 2018; 1 USD = 23,195 VND at 31/12/2018.

5.3.2. Overall efficiency of rice production in MKD

The result of input-oriented super-SBM model under variable returns to scale is presented in Table 5.3. Overall efficiency of paddy farms in the MKD is high, and AW season shows a more efficient estimation at 0.915 than SA season at 0.875. It is shown that, households which grow MR varieties in SA season achieve highest SBM score at 1.045 when compared to AR and HR. However, MR's score decreases slightly to 0.911 in the AW season. In AW season, some households switch from HR to AR rice production and the efficiency scores of these two rice segments increase from 0.914 to 0.917 and from 0.830 to 0.909, respectively. This increase in overall efficiency happens thanks to the advantageous climate condition with drier weather and less humidity.

Table 5.3. Super-SBM scores of rice production in MKD by rice groups

Rice segment	SBM-IV	Std. Dev.	n	F-stat
Summer-Autumn				
Aromatic	0.914	0.582	189	
High quality	0.830	0.544	184	0.2813
Medium	1.045	1.226	7	
Total	0.875	0.580	380	
Autumn-Winter				
Aromatic	0.917	0.682	247	
High quality	0.909	0.874	117	0.9952
Medium	0.911	0.525	16	
Total	0.915	0.740	380	

Source: Calculated from household survey in 2018.

In Table 5.4, super-SBM scores are presented by some of farms' characteristics including farm size, cooperative's membership, 1M5R and AWD farming practice. In SA season, paddy farms greater than 2 ha achieve significantly higher score (98.1%) than those smaller than 2 ha (84.8%). Households which have cooperatives' membership also have significantly higher efficiency at 92.3% compared to non-member ones at 76.9%. There are certain advantages when being cooperative members than individual producers such as technical training support, agricultural extension service, pilot and pioneering CSA programs and projects participation. Paddy cooperatives also have contract with input suppliers and machinery services like tractors or combine harvesters in local area. Therefore, cooperatives members will have the opportunity to operate their production efficiently and manage the inputs use better. Also in this season, farmers who practice CSA technology like obtain significantly higher efficiency scores. In which, 1M5R adopters have super SBM score at 97.8% compared to conventional farmers at 81.6%, meanwhile the score of AWD adopters is 1.085 and non-adopters is 0.835, respectively. Although the application rate of CSA is still low at 36.8% with 1M5R and 16.05% with AWD practices, it still indicates the positive differences in the efficiency of two farmers groups thanks to the inputs reduction strategies.

Table 5.4. Super-efficiency scores by farms' characteristics

Households' characteristics	n	Super-SBM	Std. Dev.	diff	t-stat
		Summer-Autumn			
Farm size					
> 2ha	153	0.979	0.505	0.173*	–2.8901
<= 2ha	227	0.805	0.665		
Cooperative's membership					
Yes	264	0.923	0.608	0.154**	–2.3971
No	116	0.769	0.498		
1M5R practice					
Yes	140	0.978	0.475	0.163***	–2.6544
No	240	0.816	0.627		
AWD practice					
Yes	61	1.085	0.486	0.250***	–3.1142
No	319	0.835	0.907		
		Autumn-Winter			
Farm size					
> 2ha	153	0.949	0.537	0.058	–0.7561
<= 2ha	227	0.890	0.785		
Cooperative's membership					
Yes	264	0.928	0.664	0.046	–0.5625
No	116	0.882	0.890		
1M5R practice					
Yes	140	0.993	0.474	0.125	–1.5989
No	240	0.868	0.854		
AWD practice					
Yes	61	1.144	0.721	0.274***	–2.6724
No	319	0.870	0.793		

****, **, and * significant at 1, 5, and 10% probability level, respectively.*

Source: Calculated from household survey in 2018.

Thus, it can be concluded that cooperatives and advanced farming package positively lead to more efficient fields of members/participants in the disadvantageous weather conditions of SA season. Although only 16% of households practice AWD, this technique proves to be effective for paddy producers to reach higher efficiency score at 1.144 in the AW season. The similar circumstance of other groups happens, however those figures are not statistically significant in AW season. Difficulties for farmers in 1M5R and AWD application still exit including: the surface of rice field was not leveling, there is inefficient operation of irrigation systems and water management for small households who are far away from canals.

In addition to SBM scores, the information on input slacks is much important to be well-understood since it presents the excessive usage of inputs and how well the farmers manage their resources in production in order to reach the most efficient status. The slacks of main input components by rice groups are shown in Table 5.5. Firstly, in SA season, the largest and smallest slacks of seeds density belong to HR at 45.46kg/ha and AR group at 29.70kg/ha, respectively. When coming to the AW season, farmers decide to reduce the amount and not to waste on seeds. The seeds slack of AR group seems to be unchanged at about 29kg/ha. MR group now can generate equal slack of seeds at 30.21 kg/ha to AR, meanwhile this figure of HR group is till high at 38.24 kg/ha although it has reduced by 7 kg/ha compared to SA season. The largest slacks of N, P_2O_5 and K_2O fertilizers are shown in the HR group in the SA season, follow up by MR and the AR groups. In AW crop, farmers overuse N at 35kg/ha with the AR varieties. Due to the high risk of pest and disease in SA season, farmers want to spray much more pesticides and herbicides and this lead to the larger slacks in every rice variety group. Irrigation slacks between AR, HR and MR in AW season are much higher than those in SA season. Producers have to pay for water pumping-in and out of the field to keep the continuous flooding (CF) status for rice plants. Between the categories, MR cultivating requires irrigation cost about 1.78 times higher than that of AR. In AW season, it is feasible to apply multiple drainage (Uno *et al.*, 2021) or AWD technique to reduce water use (Carrijo *et al.*, 2017; Chidthaisong *et al.*, 2018; Linquist *et al.*, 2015; Yan *et al.*, 2005) and, at the same time, reduce the global warming potential (GWP) of CH_4 emissions (Chidthaisong *et al.*, 2018; Linquist *et al.*, 2015; Yan *et al.*, 2005).

Table 5.5. Input slacks of rice production in the MKD by rice variety group and by season

Variables	Unit	Summer-Autumn				Autumn-Winter			
		Aromatic	High	Medium	F-stat	Aromatic	High	Medium	F-stat
N = 380		n = 189	n = 184	n = 7		n = 247	n = 117	n = 16	
Seeds	kg/ha	29.70	45.46	41.39	***	29.13	38.24	30.21	*
N	kg/ha	29.72	35.63	33.95		35.03	31.08	31.82	
P_2O_5	kg/ha	31.89	39.99	38.09	*	24.68	20.98	10.75	
K_2O	kg/ha	17.36	20.58	13.68		21.89	22.88	32.57	
Pesticides	USD/ha	65.54	78.73	67.17		57.45	62.57	40.23	
Irrigation^{b}	USD/ha	17.03	20.48	22.22		27.15	33.29	48.34	**

***, **, *and* * *significant at 1, 5, and 10% probability level, respectively.*
Source: Calculated from household survey in 2018; 1 USD = 23,195 VND at 31/12/2018.

Following the assumptions of the System of Rice Intensification Program (SRI), water-saving irrigation and field drying will reduce CH_4 emissions, while reducing the use of chemical fertilizers (N) will reduce N_2O emissions from rice cultivation (MONRE, 2017). In addition, the same conclusions were drawn from studies of Linquist *et al.*, (2015); Snyder *et al.*, (2009); Yang *et al.*, (2012) and Zhang *et al.*, (2014) that reducing the flooding status in paddy fields by applying AWD and N fertilizer management will help households mitigate GHG emissions. Therefore, information on input slacks by CSA practice is important to be understood and presented in Table 5.6. Regarding N fertilizer use, the 1M5R adopters have significantly smaller slacks than non-adopters in the two seasons by 13.27 kg/ha and 12.84 kg/ha, respectively. In addition, CSA practice is also effective in reducing the waste of water use, proving by smaller slacks of irrigation cost of 1M5R and AWD adopters. In SA season, the difference in excessive irrigation cost between 1M5R and conventional farmers is about 7.66 USD/ha while this figure between AWD adopters and non-adopters is 6.38 USD/ha. In AW season, although the slacks are all larger than in SA season, 1M5R and AWD are still efficient when the participants have significantly smaller slacks than non-participants. Managing nitrogen and irrigation slacks more efficiently by practicing 1M5R and AWD, farmers can better adapt to climate change, sequester more carbon in the soils and reduce the emissions of GHGs such as N_2O emission intensity.

Table 5.6. Input slacks of rice production in the MKD by season and CSA practices

CSA application	n	Slack seeds (kg/ha)		Slack N (kg/ha)		Slack irrigation (USD/ha)	
		Mean	diff.	Mean	diff.	Mean	diff.
Summer-Autumn							
1M5R practice							
Yes	140	19.24	–9.55**	24.28	–13.27***	13.98	–7.66***
No	240	28.79		37.55		21.60	
AWD practice							
Yes	61	23.79	–1.76	30.94	–2.05	13.44	–6.38**
No	319	25.55		32.99		19.82	
Autumn-Winter							
1M5R practice							
Yes	140	22.87	–14.41***	25.56	–12.84***	17.78	–19.25***
No	240	37.28		38.40		37.03	
AWD practice							
Yes	61	27.90	–4.85	33.25	–0.50	22.70	– 8.62*
No	319	32.75		33.75		31.32	

***, **, and * significant at 1, 5, and 10% probability level, respectively.

Source: Author's calculation based on household survey in 2018

When not absorbed by plants, the excessive N is mobile, hard to contain in the field and susceptible to loss. N can be lost as nitrate to groundwater or as the gases N_2O, dinitrogen (N_2) or ammonia (NH_3) (Millar *et al.*, 2014; Woodbury and Wightman, 2017). N_2O emissions are especially high when N fertilizer is applied at rates greater than crop need. Since N_2O emissions increase exponentially with increasing fertilizer N rate, farmers can greatly reduce N_2O emissions from their fields by more precisely estimating fertilizer N needs and reducing the N slack in production steps (Millar *et al.*, 2014). Based on the manual to address data requirements for developing countries in estimating the GHG emissions in agriculture (FAO, 2015), we try to connect the GHG mitigation with the reduction strategy of N. GHG emissions from synthetic N fertilizer consist of direct and indirect N_2O emissions (see Annex). In which, direct N_2O emissions is taken place at the addition site and indirect N_2O emissions is produced from atmospheric deposition of N, volatilized from managed soils. Since there has been no regional N_2O emission factor (EF) for paddy cultivation in the MKD, China's direct N_2O EF (0.003-0.012) (Smith and

Braatz, 2001) for rice production and FAO (2015) N_2O EF (0.010) are available for reference. However, China EF does not provide indirect EF for rice production. Thus we use FAO (2015) N_2O EF for synthetic fertilizer use for both direct and indirect emissions. Table 5.7 presents the possible reduction of N_2O emission by rice groups when the slacks of N fertilizer are reduced by 100% and 50%. In SA season, it is estimated that if the slacks of N are possibly reduced by 100%, AR, HR and MR households can mitigate N_2O emission by 62, 74.2 and 70.7kg/km^2, respectively. In AW season, although the N application rate is similar to SA season, AR group has larger slack of N. Thus, there is no need to apply about 100kg of N per ha for AR production in AW season. If it is possible to minimize 100% of N slacks, paddy producers will be successful in lessening the amount of N_2O at 73, 64.7 and 66.3kg/km^2 in respect of AR, HR and MR groups. Regarding mitigation strategies, it is important to apply nitrogen fertilizer following these four main management factors: Right source at the Right rate, Right time, and Right place (4R). These 4Rs should be used all together in a comprehensive plan appropriate for the cropping system, and accounting for all sources of nitrogen input to crop fields. If 4Rs are practiced and monitored well, they will increase crop yield and profitability, while also greatly reduce GHG emissions (Snyder *et al.* 2009).

Table 5.7. Potential reduction of N_2O emissions when reducing synthesis N fertilizer slacks

Items	Summer-Autumn			Autumn-Winter		
	Aromatic	High	Medium	Aromatic	High	Medium
N use (kg/ha)	103.46	117.75	117.78	105.34	114.15	100.55
Slack of N (kg/ha)	29.72	35.63	33.95	35.03	31.08	31.82
Direct N_2O (1) (kg/km^2)	46.70	56.00	53.36	55.04	48.83	50.01
Indirect N_2O (2) (kg/km^2)	15.18	18.20	17.34	17.89	15.87	16.25
N_2O emission = (1) + (2) (100% slack reduction) (kg/km^2)	61.88	74.20	70.70	72.96	64.70	66.26

Source: Calculated from household survey in 2018 based on FAO (2015).

The information on the most 20 super-efficient paddy farms is presented in Table 5.8. AW season with the advantageous weather conditions help households reach much higher super efficiency scores. Those households with super-SBM scores > 4 (BL032, BL028, CT037, CT019, BL036) are super-efficient DMUs and could be considered as outliers in the sample. There are households that appear to be super-efficient in the two seasons with their un-changed AR and HR varieties, including BL032, BL034 and BL036 with Nang Hoa 9 variety; AG078 and DT032 with OM5451 variety; BL028 and DT100 with Dai Thom 8 variety. BL032, BL034 and BL036 are cooperative members and this is the reason why they are confident enough with the support from cooperatives when producing AR in the wet and rainy season. Although both AG078 and DT032 produce the same OM5451 variety, their products are sold at very different price in the two season. AG078 sell their paddy to traders with the price at 0.21 USD/kg and 0.22 USD/kg in SA and AW seasons, respectively. DT032 with the farming contract beforehand can obtain much higher price at 0.26 and 0.27 USD/kg in the two seasons. Moreover, AG078, DT032, BL028 and DT100 all belong to local paddy cooperatives.

In addition, some households prefer to change their rice varieties when the AW season begins. They are: AG062 and CT027 change from OM5451 to Dai Thom 8; BL081 changes from Nang Hoa 9 to Dai Thom 8; BL047 changes from Dai Thom 8 to Nang Hoa 9; and CT019 from sticky rice CK92 to Dai Thom 8. Among those households that has the variety switching and are still super-efficient, household CT019 produces sticky rice CK92 in the SA season and is even more successful when changing to AR Dai Thom 8 in the AW season with super-SBM scores at 3.77 and 6.48, respectively. This is such a very good result of efficient farming thanks to the cooperative's membership and 1M5R package application on field. Household BL047 changes from Dai Thom 8 in SA season to Nang Hoa 9 in AW season since there is a contract farming between the enterprise and farmer. Thus, the selling price of paddy is also very high at 0.27 USD/kg and 0.31 USD/kg in SA and AW seasons, respectively. Households AG062 and CT027 change from OM5451 to Dai Thom 8 since they want to obtain higher output price from individual traders at harvest.

The appearance of Dai Thom 8 and OM5451 varieties in the list of super-efficient households confirms their super-efficiency when being grown in different ecological zones in the MKD. Especially, aromatic Dai Thom 8 and Nang Hoa 9 varieties which are cultivated by households in Bac Lieu province (the CZ) appear to be strongly adaptive to the environment and still fully overall efficient. Thus, producing AR and HR applying CSA techniques could not only bring economics benefits to farmers but also protect the environment and mitigate to GWP through reducing GHG. The farming area and quantity of MR should follow strictly to the Government's recommendation. Vietnamese government has a plan to develop and scale up ecosystem-based and community-based climate change adaptation models for the period 2021-2030 (Decision No. 1055/QD-TTg dated July 20, 2020). So far, while field trials in other countries indicate that the lower input, more efficient systems have reduced emissions by 20% to 62% (Neate, 2013), there are very few studies have been conducted in Vietnam as well as the MKD on the effects on CH_4 and N_2O emissions. The results of this study could be valuable for local government and researchers to evaluate the benefits that CSA systems brought to smallholder farmers in terms of yields, long-term resilience by reducing the amount of N fertilizer and water use and climate change mitigation. Further studies could focus on mitigation capacity of AR and HR production areas for export in the freshwater alluvial and coastal areas in the MKD.

Table 5.8. Super-SBM scores and ranking of the most 20 efficient paddy farms by season

Summer-Autumn						Autumn-Winter					
Rank	Score	DMUs	Ecological sub-region	Variety	Category	Rank	Score	DMUs	Ecological sub-region	Variety	Category
1	5.339	BL032	2	Nang Hoa 9	aromatic	1	8.660	CT037	3	OM5451	high quality
2	5.181	BL028	2	Dai Thom 8	aromatic	2	6.487	CT019	3	Dai Thom 8	aromatic
3	3.777	CT019	3	Glutinous CK92	medium quality	3	4.528	BL032	2	Nang Hoa 9	aromatic
4	3.661	AG062	1	OM5451	high quality	4	4.060	BL036	2	Nang Hoa 9	aromatic
5	3.010	DT032	4	OM5451	high quality	5	3.879	AG078	1	OM5451	high quality
6	2.961	CT084	3	OM5451	high quality	6	3.454	DT100	4	Dai Thom 8	aromatic
7	2.603	AG078	1	OM5451	high quality	7	3.222	CT027	3	Dai Thom 8	aromatic
8	2.500	DT017	4	OM5451	high quality	8	2.842	AG062	1	Dai Thom 8	aromatic
9	2.467	CT024	3	OM5451	high quality	9	2.443	BL028	2	Dai Thom 8	aromatic
10	2.460	AG040	1	Dai Thom 8	aromatic	10	2.385	DT044	4	Dai Thom 8	aromatic
11	2.412	CT067	3	OM5451	high quality	11	2.371	BL081	2	Dai Thom 8	aromatic
12	2.399	AG086	1	OM5451	high quality	12	2.272	CT043	3	Dai Thom 8	aromatic
13	2.333	CT027	3	OM5451	high quality	13	2.240	AG080	1	Dai Thom 8	aromatic
14	2.063	BL034	2	Nang Hoa 9	aromatic	14	2.097	CT026	3	OM4218	high quality
15	1.992	BL077	2	Dai Thom 8	aromatic	15	2.052	BL034	2	Nang Hoa 9	aromatic
16	1.920	DT100	4	Dai Thom 8	aromatic	16	2.052	DT032	4	OM5451	high quality
17	1.900	CT031	3	OM5451	high quality	17	2.004	AG008	1	IR50404	medium quality
18	1.832	BL081	2	Nang Hoa 9	aromatic	18	1.988	BL041	2	Dai Thom 8	aromatic
19	1.756	BL036	2	Nang Hoa 9	aromatic	19	1.959	BL047	2	Nang Hoa 9	aromatic
20	1.744	BL047	2	Dai Thom 8	aromatic	20	1.950	BL099	2	RVT	aromatic

Ecological sub-region: 1 - Long Xuyen Quadrangle-LXZ; 2 - coastal area-CZ; 3 - the riverside of Tien and Hau rivers-FAZ; 4 - Dong Thap Muoi area-PRZ

5.4. Conclusion

After almost twenty years focusing on the intensive rice farming, Vietnam now has to change the national development strategy for the rice sector. At the present, rice production not only ensures food security in terms of quantity, but also has to adapt to severe climate change and protect the environment. The MKD region, with many advantages in terms of ecological system and climate, contributes to 90% of the national total export volume. Our super-SBM study provides meaningful statistics of overall efficiency and input slacks based on three main rice variety groups, especially the AR and HR for exporting. Having high efficiency score and smaller slacks of seeds and irrigation, AR has a full potential for future scaling up programs since these varieties both bring economic benefits to producers and, at the same time, lead to a low N_2O emissions environment. However, AR cultivators still need to reduce the seeds amount averagely by 29kg/ha in each season. N fertilizer should also be reduced by 33kg/ha and 35kg/ha in SA and AW season, respectively. The recommended reduction of HR group is 45.5 kg/ha of seeds and 38.2 kg/ha of N in SA season. Those figures in AW season should be 38.2 and 31.8kg/ha, respectively. It is estimated that if the slacks of N are reduced by 100%, rice farming can mitigate N_2O emission by 62-74.2kg/km^2 in Summer-Autumn season, and 64.7-73kg/km^2 in Autumn-Winter season respectively. All of the three types of rice need to reduce the irrigation cost in the AW season by applying the AWD technique on field. Super-SBM model is proved to be effective in estimating the overall efficiency and excessive usage of inputs among smallholders. The ranking of paddy farms supports the restructuring policy in forming AR and HR production areas for export in the freshwater alluvial and coastal areas.

Chapter 6 Conclusions and policy implications

This chapter will summarize and conclude the main findings of chapters 3, 4 and 5 of the thesis. Subsequently, policy implications will be suggested with regards to each result of the study. In addition, based on the results found, some future research topics are proposed in order to develop sustainable rice farming in the Vietnamese Mekong Delta.

6.1. Main outcomes, discussion and conclusions

6.1.1. Farm size and the overall efficiency of rice production in the Mekong Delta

Production efficiency of rice production was measured in reference to land size in order to identify excess input uses. While the previous studies in Vietnam used traditional DEA methods to calculate pure technical efficiency of rice production, this chapter provides a new concept of overall efficiency with input slacks using non-radial DEA measures. The four research questions in sub-section 2.6.2 are answered sufficiently. Firstly, production efficiencies including pure, global, scale and mix efficiencies of paddy farms are from moderate to high at 81%, 71%, 83% and 88%, respectively. Meanwhile, overall efficiency, which is calculated through slack-based measure is quite low at 59% due to ineffective inputs use. The results also indicate that paddy farms in MKD have a larger proportion of units that achieved constant returns to scale than farms in other Asian countries. However, about 65% of households operate at increasing returns to scale implies that it is necessary to promote the expansion of operation scale in coming years to achieve an ideal technical efficiency. Importantly, the presence of input slacks through SBM analysis implies that cultivators should cut down approximately 27.81 USD/ha of seeds cost, 60.80 USD/ha of pesticides cost, 77.88 USD/ha of machinery cost and 155.61 kg/ha of the amount of fertilizers that they are using to reach the efficiency frontier. With the second question, it is confirmed that small farms which rely on family labor are facing more disadvantages than large farms which use machinery for production steps. Those farms greater than 2 ha in our study reflect not only higher efficiency scores than small farms but also lower slack of inputs, in which statistical significance of seeds cost, machinery cost, fertilizer quantity and family labor working hour per ha. Regarding driving factors of efficiency, educational level and gender of household heads, family members, farm size, farm size squared, credit status are the key determinants. In which, farm size, the education level, credit status and gender of household heads are positively correlated with scale efficiency. Especially, there is a negative effect of farm size squared on scale efficiency, i.e., inverted-U relationship. In terms of overall efficiency, family members and credit have significantly negative impacts on the efficiency. Meanwhile, an increase of farm size to the optimal scale could enhance efficiency of paddy farms in the MKD. It is clear that Chapter 3 has solved its objectives mentioned in Chapter 2 thoroughly.

6.1.2. The impacts of climate smart agriculture on economic performance of rice smallholders in the Mekong Delta

Since the year 2011, farmers in the MKD has started to practice some climate smart agriculture on their farms to promote a cleaner production process and reduce the input costs. In which, 1M5R technical package is a very famous program. In the framework of our study, propensity score matching was employed with the expectation to eliminate the selection bias when estimating the treatment effect of the 1M5R practice. Firstly, the factors that determine the decision to adopt the decision 1M5R are educational level, training class attendance, and cooperative membership. After propensity scores are generated from the first stage of probit model and the common support range is defined from 0.058 to 0.717, appropriate matching algorithms are used to match 1M5R adopters with non-adopters and define the programs' effect. With the questions about the effect of 1M5R technical package on households' economic performance, the results are consistent with the objectives of the 1M5R application listed in the guidebook. Particularly, 1M5R helps farmers to reduce production costs by more than 80 USD/ha, have better output prices by 0.01 USD/kg, and enhance profit per hectare. The returns on investment – ROI of 1M5R participants is also higher than non-participants by 24%. However, treatment fields obtain a slightly lower yield when compared to conventional fields due to the decrease in seed density and chemical fertilizer usage. Finally, Chapter 4 has successfully achieved its objectives in concluding that 1M5R is a climate-smart practice that both help to enhance economic performance of producers and improve the environment of the MKD.

6.1.3. Rice variety and sustainable farming in the Mekong Delta

In the context of climate change, Vietnamese government has implemented the development strategy for rice production in the MKD region towards improving quality and reducing greenhouse gas emissions. Thus, the proportion of aromatic and high-quality rice production is gradually increasing to satisfy the export market. However, over-reliance on agrochemicals still happens. It is also claimed by some literature that the continuous flooding status in rice cultivation will emit CH_4 and immoderate use of nitrogen (N) fertilizer will emit N_2O significantly. Besides the overall efficiency obtained, the slack-based super-efficiency measure was used to calculate the excessive input use, especially the N fertilizer and irrigation. Particularly, aromatic rice cultivators still need to reduce the seeds amount by 29kg/ha on average in each season. N fertilizer should also be reduced by 33kg/ha and 35kg/ha in summer-autumn (SA) and autumn-winter (AW) season, respectively. The recommended reduction of HR group is 45.5 kg/ha of seeds and 38.2 kg/ha of N in SA season and 38.2 and 31.8kg/ha in AW season, respectively. It is estimated that rice farming can possibly mitigate N_2O emission by 62-74.2kg/km^2 in Summer-Autumn season, and 64.7-73kg/km^2 in Autumn-Winter season respectively. Finally, super-SBM model is effective in estimating the overall efficiency and excessive usage of inputs among smallholders. The ranking of paddy farms also supports the restructuring policy of the government in forming AR and HR production areas for export.

6.2. Policy implications, limitations of the study and future research

6.2.1. Policy implications

Paddy farms with greater advantages in transportation, irrigation, and mechanization could obtain higher efficiency and smaller input slacks. For that reason, the official policies such as Large Field Model, in order to assemble small holders into larger fields/paddy cooperatives, should be promoted and monitored more actively in every province of the MKD. In this program, households could take advantage of economy of scale to apply modern agricultural machinery such as tractors, combine harvesters and thus reduce the production costs. Also, operating at the optimal scale is important for farmers to practice climate smart agriculture techniques such as: One Must Do, Five Reductions, Alternate Wetting and Drying and System of Rice Intensification. More specifically, rice farms in the MKD should prioritize participating in clean farming systems to enhance the quality of products and protect the natural resource environment. Promoting the participation of rice enterprises into the LFM and CSA programs could be such an urgent action of the government.

Technical package 1M5R is confirmed as one of the effective measures to directly reduce the use of inputs and enhance the profit for smallholders in rice cultivation through the results of our study. However, the application rate of this technical package is still modest. It is indicated that households' characteristics such as education level and the training classes' attendance have a positive impact on participation in the implementation of the 1M5R technical package. Besides, the participation to become a member of the cooperative is also a factor that increases the implementation of this technical package. Hence, promoting the operation of paddy cooperatives or farming groups could bring certain benefits to their members and as a consequence, increasing the participation of farmers in climate smart agriculture like 1M5R. Also, granting agricultural loans to cooperatives to improve the irrigation, machines and after-harvest storage could directly help the 1M5R adopters to reduce production costs and ensure the quality of their products. Finally, the role of rice enterprises would be very important in providing training courses and farming contracts to 1M5R participants.

Specialty aromatic rice (AR) varieties and high quality rice (HR) varieties need to be developed more in the future for alluvial soils and especially in coastal areas where conditions are favorable in order to promote the unique qualities of AR. There is a great potentiality of HR or aromatic-organic rice production in the rice-shrimp model. Importantly, the positive operation of paddy cooperatives will also provide rice producers with technical support and contract farming with enterprises. Knowledge about CSA practices are expected to be continuously distributed to every group of farming households by local agricultural departments and rice enterprises. Enhancing the participation of farmers in technical packages such as 1M5R and AWD is also a solution to improve production efficiency, reduce inputs waste and mitigate greenhouse gas emissions.

6.2.2. Limitations of the thesis

The main shortcoming of chapter 3 is the absence of information on farming patterns, physical data of seed sown density and advanced technology application for rice production. Also, there are some unobservable variables that could explain farms' efficiency that the SBM model cannot control like regional agro-ecological patterns, farmers' motivation, farmers' skills, etc. The smooth bootstrap DEA proposed by Simar and Wilson (2000) will be useful since it estimates the bias and the confidence interval for technical efficiency. This should be considered to be practiced in the future studies to reduce the bias of traditional DEA. With chapter 4, the limitation is the absence of post-harvest loss indicator on fields for comparison and the exact wage of family labor for each household. Also there is a possibility of endogenous issue such as self-selection bias for choosing variables such as cooperative participation as explanatory variables. Appropriate strategies should be considered to avoid bias in estimation. Finally, chapter 5 is lack of the information on GHG emissions quantity which are usually measured by on-field experiments. Another limitation in both Chapter 3 and Chapter 5 is that using per ha data is appropriate when the constant returns to scale is assumed. When constant returns to scale is not assumed then it may lead to bias in the efficiency scores. In this case, total input and output data should be used.

6.2.3. Future research

Some further research topics are suggested as follows:

Regarding the farm size and environment, analyzing the impact of the LFMs or climate smart farming systems on production efficiency or environmental benefits of rice farms in the MKD would be a good future research topic. The results of this in-depth research could provide policy makers with the right orientation toward sustainable farming for smallholders in Vietnam in the future.

Some recommendations for future research of CSA's impacts on small holders include examining the difference in TE between 1M5R adopters and traditional fields and estimating the impact of climate smart technologies, such as Laser land Leveling or AWD, on rice production systems in the MKD. Assessing the impact of cooperatives to the application of advanced farming systems could also be interesting and provide useful reference to authorities.

Finally, further research topics relevant to rice variety and sustainable farming include: evaluating rice yields and nitrogen use efficiency with different fertilizers application and water management; or estimating the nitrogen use efficiency of major rice varieties under different water regime in the coastal areas of the MKD. Importantly, adoption of CSA practice will require that they are economically attractive and can be adapted to field scales. Thus, it is also important to simultaneously explore the economic benefits and GHG mitigation capacity that CSAs bring to different targeted rice variety groups and in Vietnam. In addition, further field experiments are necessary to measure the GHG emissions and propose the emission factor under different N application rates and water regimes for AR and HR areas in the MKD.

Acknowledgements

An early version of chapter 3 was presented at the JASRAD (Japan Society of Regional and Agricultural Development) Conference at Hirosaki University, in November, 2019. We would like to thank Professor Yoshifumi Takahashi, from Kyushu University, and Professor Jinhu Shen, from the Division of Natural Resource Economics, Kyoto University, for their valuable comments.

The studies conducted in chapter 4 and 5 was financially supported by the Federal Ministry for Economic Cooperation and Development, Germany in household survey's design and primary data collection. We would like to express our appreciation to the Mekong Delta Development Research Institute's director and the leader of the MSVC project for their consent to acquire and use the dataset for analysis.

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Appendix

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Direct Emission (N_2O)

$$\text{Direct Emission } (N_2O) = N \times \frac{44}{28} \times EF_1$$

Where

Direct emission (N_2O): direct emission N_2O from synthetic nitrogen additions to the managed soils

N = Consumption in nutrients of nitrogen fertilizers, kg N input

EF_1 = 0.01; Emission factor for N_2O emissions from N inputs, kg N_2O–N/kg N input (Table 26A) (FAO, 2015; page 150).

Indirect Emission (N_2O)

$$\text{Indirect Emission } (N_2O) = N \text{ x} \left[\left(FRAC_{GASF} \times EF_4\right) + \left(FRAC_{LEACH} \times EF_5\right)\right] \times \frac{44}{28}$$

Where

Indirect emissions (N_2O) = Indirect N_2O emissions produced from atmospheric deposition of N, volatilized from managed soils.

N = Consumption in nutrients of nitrogen fertilizers, kg N input

$FRAC_{GASF}$ = 0.1; Fraction of applied synthetic N fertilizer materials that volatilizes as NH_3 and NOx, kg N volatilized/kg of N applied (Table 28A) (FAO, 2015; page 150).

EF_4 = 0.01; Emission factor for N_2O emissions from atmospheric deposition of N on soils and water surfaces, kg N–N_2O/kg NH_3-N + NOx-N volatilized (Table 24A) (FAO, 2015; page 149).

$FRAC_{LEACH}$ = 0.3; Fraction of applied synthetic N fertilizer materials that leaches as NH_3 and NO_X, kg N leached/kg of N additions (Table 27A) (FAO, 2015; page 150).

EF_5 = 0.0075; Emission factor for N_2O emissions from N leaching and runoff, kg N_2O–N/kg N (Table 25A) (FAO, 2015; page 149).

Emission (N_2O)

$$\text{Emission } (N_2O) = \text{Direct emission } (N_2O) + \text{Indirect Emission } (N_2O)$$

Where

Emissions (N_2O) = Total N_2O emissions from synthetic nitrogen additions to managed soils, kg N_2O.

Direct emissions (N_2O) = Direct N_2O emissions from synthetic nitrogen additions to managed soils, kg N_2O.

Indirect emissions (N_2O) = Indirect N_2O emissions from synthetic nitrogen additions to managed soils, kg N_2O