Environmental Efficiency Analysis of Thai Rice Farming

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Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged

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Abstract

The overarching objective of this research is to provide insight into how Thailand can sustainably intensify its rice production. To achieve this aim, this research develops an innovative approach for measuring agricultural environmental efficiency, which is called "the directional nutrient surplus efficiency measure", which takes place within the theoretical context of directional distance function. Thus, the study determines optimal rice output and the combinations of inputs used for rice production that will minimise the nutrient surplus. This is done using cross-sectional secondary data from 1,112 rice farms which were divided into 9 categories for observation for the crop year 2008/09.

In order to estimate the technical efficiency of the 9 observed groups of Thai rice farmers, the directional distance function was used, with different directions of improvement towards the production possibility frontier. The results indicate that measuring technical efficiency is robust in the context of the model choice for the technically efficient farms, implying that different TE measurements (i.e. different directional vectors) do not change the status of the technically efficient farms in the observation. 70%, 26%, 55%, 55%, 64%, 40%, 46%, 78%, and 34% of the total observations of jasmine rice North, jasmine rice Northeast, jasmine rice Central, non-jasmine rice North, non-jasmine rice Northeast, non-jasmine rice Central, non-jasmine rice South, glutinous rice North, and glutinous rice Northeast, respectively, produce on the PPF. The results also indicate that Thai rice farmers have average TE scores ranging from 84.1% to 99%, depending on which directional vector is chosen.

Directional nutrient surplus efficiency measures with the directional vectors towards the nitrogen and phosphorus surplus minimum points were applied to measure the nitrogen and phosphorus surplus efficiency of Thai rice farming systems. The results indicate that the amount of NS discharged into the environment by the observed Thai rice farmers averages from 20.1 to 50.7 kg/ha, and the PS discharged into the environment averages from 11.0 to 28.7 kg/ha. The best practice farms of the 9 observed groups, according to this study, can earn higher profits by using fewer inputs, especially inputs detrimental to the environment like nitrogen and phosphorus fertilisers, than the average farms in their respective groups; this also results in lower amounts of NS and PS being discharged into the environment, compared to the average farms in their respective groups. Thus, the environmental problems caused by Thai rice farming systems can be solved by adopting the methods of the best practice farms, and imposing policies for environmental taxation and site-specific soil nutrients testing.

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List of Abbreviations and Acronyms

AE: Allocative Efficiency

AIE: Allocative Inefficiency

BCC: Banker Charnes Cooper

BPF: Best Practice Farm

CCR: Charnes Cooper Rhodes

CE: Cost Efficiency

CRS: Constant Returns to Scale

DDF: Directional Distance Function

DDF1: The directional distance function measure with the direction towards observed farm's individual inputs used holding output fixed (Input-oriented DEA)

DDF2: The directional distance function measure with the direction towards observed farm's individual output produced holding all inputs fixed (Output-oriented DEA)

DDF3: The directional distance function measure with the direction towards observed farm's individual inputs used and output produced

DDF4: The directional distance function measure with the direction towards profit maximisation benchmark

DEA: Data Envelopment Analysis

DMU: Decision Making Unit

DRS: Decreasing Returns to Scale

EE: Economic Efficiency

IRS: Increasing Returns to Scale

K: Potassium

MBC: Material Balance Condition

N: Nitrogen

NESDP: National Economic and Social Development Plan

NESDB: The Office of the National Economic and Social Development Board

NAE: Environmental Allocative Efficiency

NE: Environmental efficiency

NDRS: Non-Decreasing Returns to Scale

NIRS: Non-Increasing Returns to Scale

NS: Nitrogen surplus

NSMM: Nitrogen Surplus Minimisation Model

OAE: The Office of Agricultural Economics

P: Phosphorus

PPS: Production Possibility Set

PPF: Production Possibility Frontier

PS: Phosphorus Surplus

PSMM: Phosphorus Surplus Minimisation Model

RTS: Returns to Scale

SE: Scale Efficiency

SFA: Stochastic Frontier Analysis

TBPFs: Technical Best Practice Farms

TE: Technical Efficiency

TE_{CRS}: Technical Efficiency under assumption of constant returns to scale

TE_{VRS}: Technical Efficiency under assumption of variable returns to scale

TIE: Technical Inefficiency

VRS: Variable Returns to Scale

Chapter 1

Introduction

1.1 Implications of agricultural intensification

Agricultural ecosystems are important for both humans and animals as they provide food, forage, bioenergy, and medicines (Power, 2010). The majority of global land and fresh water is used for agriculture (Power, 2010). Nearly 40% of the world's surface is used for agriculture (FAO[1], 2009, cited in Power, 2010 p. 2959). Two major constraints on agricultural production are the scarcity of farmland and water resources. Inorganic fertiliser and pesticides have become important factors in increasing agricultural productivity. However, the intensive use of chemical fertiliser and pesticides not only increases agricultural production, but also increases the cost of production and generates severe environmental problems, especially pollution, biodiversity loss, and changes to the ecosystem (Luh and Liao, 2001; Tilman et al., 2011). Inorganic fertiliser can harm environmental services such as biological pest control, crop pollination and protection of soil fertility (Geiger et al., 2010; Power, 2010). Geiger et al. (2010) also indicate that populations of some wild plant and animal species have declined, with some becoming extinct, and the functioning of ecosystems have been changed regionally and nationally due to agricultural intensification. The global population is projected to be 9.1 billion by 2050 (34% higher than today), which will result in increased demand for food (FAO, 2009), and Tilman et al. (2011) project that global crop demand will increase 100% - 110% from 2005 to 2050. Thus, the challenge for the future growth of agricultural systems is to simultaneously produce enough food to accommodate the demand of future growth and reduce the negative impacts on the environment. This implies that crop production systems need to achieve higher yields with lower impacts on the environment.

Sustainable intensification of agriculture has been proposed as a solution to meet the challenge of the increasing food demand of a growing global population in an environment constrained by factors such as the scarcity of agricultural land and water resources, and dangers posed by climate change, agricultural pollution, and biodiversity loss (Godfray and Garnett, 2014; Buckwell et al., 2014; Gadanakis et al., 2015; Barnes et al., 2016). The concept of sustainable intensification is known as the need to simultaneously increase yields on existing agricultural land (without the cultivation of more land), increase input use

[1] FAO stands for the Food and Agriculture Organization of the United Nations.

efficiency, and reduce the negative externalities of farming systems on the environment in order to sustainably use the limited resources for agriculture and ensure food production in the future (Pretty et al., 2011; Garnett and Godfray, 2012; Godfray and Garnett, 2014; Buckwell et al., 2014; Gadanakis et al., 2015; Barnes et al., 2016). Thus, sustainable intensification of agriculture requires the improvement of agricultural ecosystems that rely on ecosystem services, including biological pest control, crop pollination, maintenance of soil structure and fertility, nutrient cycling, and hydrological services (Power, 2010). Power (2010) states that agricultural ecosystems are essential to human wellbeing, because they provide food, bioenergy, and medicines for humans.

The three leading global food crops are rice, wheat, and maize (Loftas et al., 1995; GRiSP[2], 2013), which supply more than 42% of all calories consumed by the global population (GRiSP, 2013). Of these three food crops, rice is the main staple food for people in Asia and Africa (GRiSP, 2013), areas where the FAO (2009) predicts the highest growth in the world population will occur. Global rice consumption is projected to increase from 450 million tonnes in 2011 to about 650 million tonnes by 2050 (Rejesus et al., 2012). Thailand is the world's leading rice exporter and the sixth largest rice producing country in the world after China, India, Indonesia, Bangladesh, and Vietnam (FAO, 2016), and rice is an important crop for Thailand across both social and economic dimensions. The majority of Thai people consume rice three times a day with an average consumption of 133 kilograms of milled rice per person per year in 2009 (GRiSP, 2013). Rice is also a major crop for Thai farmers. In 2015, the population in Thailand was approximately 65.7 million people, while the agricultural population was approximately 25.1 million people, around 38% of the whole population. Approximately 60% of the agricultural population are rice farmers (OAE[3]). Hence, the majority of Thai people are involved in rice production, either as producers or consumers. The total land area of Thailand is 51.3 million hectares, which are divided into 16.3 million hectares of forest, 23.9 million hectares of agricultural land, and 11.1 million hectares of non-agricultural land (OAE). 11.2 million hectares, which accounts for 46.9% of total agricultural land, are used to cultivate rice. Each year Thailand produces approximately 22 million tonnes of milled rice, of which 10 million tonnes is exported and this brings high revenue to the country (OAE, 2015). The top ten importers of rice from Thailand are China,

[2] GRiSP stands for Global Rice Science Partnership
[3] OAE stands for the Office of Agricultural Economics, Thailand

the U.S.A., the Philippines, Benin, Nigeria, South Africa, Malaysia, Hong Kong, Cote d'Ivoire, and Japan (OAE, 2015).

1.2 Problem statement

Environmental challenges for Thailand are dominated by the negative effects of rice farming practices on water and land resources. Tirado et al. (2008) indicate that the problem of water pollution caused by nitrogen and phosphorus surplus from rice fields is becoming more serious in Thailand. Nitrogen surplus causes nitrate contamination of the surface and groundwater, while phosphorus surplus causes eutrophication of surface water. Evidence of the negative effects of nitrogen and phosphorus surplus from rice cultivation in Thailand is reviewed in detail in Chapter 2.

A key solution to reducing water pollution is to decrease the nitrogen and phosphorus surplus from rice cultivation by achieving greater efficiency in the use of nitrogen and phosphorus (Nguyen et al., 2012). Thus, Thai rice farming systems need to achieve greater efficiency in the use of nitrogen and phosphorus in order to reduce their excess and maintain the sustainability of rice-producing environments. Coelli et al. (2007) state that nitrogen and phosphorus efficiency can be monitored and evaluated by adjusting traditional methods of efficiency analysis by integrating environmental concerns into the standard technical and economic efficiency analysis. If Thai farmers apply nitrogen and phosphorus nutrients more efficiently, they can simultaneously reduce the negative effects on the environment and reduce their cost of production, because nitrogen and phosphorus are costly inputs, and reduce adverse health effects on themselves and their consumers. This means that rice farming systems would be more ecologically, economically, and socially sustainable. Moreover, Thailand would be able to produce more rice: an important consideration, since future demand which will increase more than 40% by 2050 (Rejesus et al., 2012).

1.3 Research gap

Some researchers have measured the technical efficiency of rice farmers at farm level using cross-sectional primary data in specific areas in Thailand (Krasachat, 2004; Songsrirote and Singhapreecha, 2007; Kiatpathomchai, 2008; Rahman et al., 2009; Taraka et al., 2010; Ogundari and Awokuse, 2016). These researchers used either the input-oriented Data Envelopment Analysis (DEA) approach (Taraka et al., 2010; Kiatpathomchai, 2008; Krasachat, 2004) or the Stochastic Frontier Analysis (SFA) approach (Ogundari and Awokuse, 2016; Rahman et al., 2009; Songsrirote and Singhapreecha, 2007) for their efficiency analysis. The efficiency analyses in these six studies are reviewed in Chapter 3. None of the empirical studies of efficiency measurement of rice production in Thailand has addressed efficiency analysis for Thai rice farming at farm level for the whole country, or investigated the technical efficiency of Thai rice farming using output-oriented DEA and directional distance function (DDF). Moreover, only one of these studies (Kiatpathomchai, 2008) has investigated the environmental efficiencies of Thai rice farmers by incorporating nitrogen-leaching and nitrogen-emission in the input-oriented DEA model as input variables. Further, none of empirical studies of the efficiency measurement of rice production in Thailand refers to the "material balance condition" (Coelli et al., 2007) in its environmental efficiency analysis. The material balance condition is defined by Reinhard and Thijssen (2000, p. 169) as "the nutrients in desirable output and the discharge of those nutrients equal the nutrients in inputs". This implies that the amount of nutrients (N-Nitrogen, P-Phosphorus, and K-Potassium) that farmers apply to their crops during cultivation periods should equal the amount of nutrients absorbed by plants and discharged into the environment.

1.4 Objectives and research questions

The overarching objective of this research is to provide insights into how Thailand can sustainably intensify its rice production. To this end, this research develops an innovative approach to measuring agricultural environmental efficiency by incorporating the material balance condition into production efficiency analysis: as mentioned above, this has not been part of previous analyses of Thai rice production efficiency. Thus, the study determines optimal rice output and the combinations of inputs used for rice production that will minimise the nutrient surplus. This is done using cross-sectional secondary data from 1,112 rice farms which were divided into 9 categories for observation for the crop year 2008/09. If Thai rice farmers use inputs more efficiently, an identical amount of rice output can be produced by using a lower amount of inputs, implying that nitrogen and phosphate emissions will be reduced. As a result, environmental degradation will be reduced and consequently, the health of farmers and consumers should improve. In addition, farmers' production costs will also be reduced.

Hence, the main focus of this research is the evaluation of the technical and environmental efficiency of rice farming systems at a farm level in Thailand. The environmental efficiency analysis emphasises minimising the nitrogen and phosphorus surplus arising from the rice farming systems by improving efficiency in the use of nitrogen and phosphorus nutrients. If farmers improve the efficiency of their use of these nutrients, they can simultaneously achieve their economic and environmental objectives (De Koeijer et al., 1999 cited in De Koeijer et al., 2002, pp. 9-10).

More specifically, this thesis will address the following research questions and their main objectives.

Research question 1: To what extent do Thai rice farmers use an efficient combination of inputs for producing rice? Sub-question: What are the existing technical efficiency levels of rice production in Thailand?

This research question is addressed through a comparison of the technical efficiency of Thai rice farmers using the input-oriented DEA, output-oriented DEA, and DDF approaches. For each group of Thai rice farmers, a contemporaneous production possibility frontier is constructed to estimate and compare the performance of Thai rice farmers across the group. The estimation of efficiency scores reveals how many farms in the group produce on the production frontier and how far the inefficient farms fall short of this frontier. The input-oriented DEA model reveals to what extent inputs can be reduced whilst still producing the same level of rice output. This implies that an inefficient farm can reduce the quantity of each input to produce the same level of rice output and thus achieve higher efficiency. The output-oriented DEA allows the determination of the extent to which rice output can be expanded by using the same level of inputs. This implies that an inefficient farm can manage to achieve a higher output by using the same level of inputs and thus be more efficient. The DDF model explores to what extent production can be increased and inputs reduced simultaneously, implying that an inefficient farm can adopt more efficient strategies that will produce more rice while reducing the quantity of all inputs. More generally, the inputs used by the efficient farms or the technical best practice farms (TBPFs) can be used as benchmarks to improve the technical efficiency of Thai rice farming.

Research question 2: How can an efficiency analysis of rice farming systems in Thailand be developed to accommodate and explore the problem of excess nutrient application on rice fields? Sub-question: How can the environmental impact of rice cultivation be assessed?

The main activity undertaken is the development of an approach for measuring agricultural environmental efficiency by adjusting traditional methods of technical efficiency analysis through incorporation into the model of environmental concerns (nutrient surplus). The nutrient surpluses from rice cultivation that cause environmental problems are nitrogen and phosphorus surplus. Hence, this study focuses on the evaluation of the nitrogen and phosphorus surplus efficiency of Thai rice farmers during the environmental efficiency analysis. Using the concept of the material balance condition, the nitrogen surplus (phosphorus surplus) discharged to the environment is equal to the total amount of nitrogen nutrient (phosphorus nutrient) that farmers apply to rice fields minus the total amount of nitrogen nutrient (phosphorus nutrient) that is absorbed by the rice plants. There are three possible strategies to reduce the nitrogen surplus (phosphorus surplus) arising from rice cultivation. Firstly, the nitrogen surplus (phosphorus surplus) can be minimised by minimising the total amount of nitrogen nutrient (phosphorus nutrient) in inputs while fixing the same level of rice outputs. This implies that the estimation of environmental efficiency analysis can be done by adjusting the input-oriented DEA analysis through the incorporation of the material balance condition into the model. This environmental efficiency measure approach has been proposed by Coelli et at. (2007) and is reviewed in Chapter 3. It has been used by Hoang and Coelli (2011), Hoang and Alauddin (2012), and Nguyen et al. (2012) in different country settings. Secondly, nitrogen surplus (phosphorus surplus) can be minimised by using the same amount of nitrogen nutrient (phosphorus nutrient) in inputs but producing more rice output. This implies that the estimation of environmental efficiency analysis can be done by adjusting the output-oriented DEA analysis, again by incorporating the material balance condition into the model. A review of the literature shows that adjusting the nutrient surplus into the output-oriented DEA has not to date been undertaken. Finally, nitrogen surplus (phosphorus surplus) can be minimised by simultaneously reducing the amount of nitrogen nutrients (phosphorus nutrients) in inputs and expanding rice output. In this case, the estimation of environmental efficiency analysis can be done by adjusting the DDF analysis by incorporating the material balance condition (i.e. nitrogen and phosphorus surplus) into the model. Again, a review of the literature suggests that this has not been undertaken to date.

Thus, this research will propose the measurement for nutrient surplus minimisation within the theoretical context of the DDF, using the nutrient surplus minimum point direction, known as the “directional nutrient surplus efficiency measure”, to evaluate the environmental efficiency of Thai rice farmers. The concept underlying this measure, and its application, will be introduced in detail in Chapter 4, Section 4.9.

Research question 3: What scope is there for Thai farmers to produce the same or higher rice output using fewer inputs, particularly environmentally damaging inputs? Sub-question: What is the current nitrogen and phosphorus use efficiency of Thai rice farmers?

The main activities for research question 3 are as follows: a) measurement of the efficiency of farms relative to a benchmark in which the lowest possible amount of nitrogen surplus is produced using the directional nutrient surplus efficiency measure; b) measurement of the efficiency of farms relative to a benchmark in which the lowest possible amount of phosphorus surplus is produced using the directional nutrient surplus efficiency measure; c) comparison of the results of technical and environmental inefficiencies of Thai rice farming; and d) exploration of the implications for policies designed to improve the technical and environmental efficiencies of Thai rice farming.

For each group of Thai rice farmers, a contemporaneous nitrogen surplus minimising frontier is constructed to estimate and compare the nitrogen surplus efficiency or environmental efficiency of Thai rice farmers across the group. Farms that discharge the minimum nitrogen surplus into the environment compared to the other farms in the group will create the nitrogen surplus minimising frontier. Then the nitrogen surplus inefficiency level of each farm in the group is estimated relative to this frontier. Likewise, a contemporaneous phosphorus surplus minimising frontier is constructed to estimate and compare the phosphorus surplus efficiency or environmental efficiency of Thai rice farmers across the group. Farms that discharge the minimum phosphorus surplus into the environment compared to the other farms in the group will create the phosphorus surplus minimising frontier. Then the phosphorus surplus inefficiency level of each farm in the group is estimated relative to this frontier. The nitrogen surplus and phosphorus surplus inefficiencies of each farm in the group are estimated using the directional nutrient surplus efficiency measure. This measure ascertains the current level of nitrogen and phosphorus surpluses, arising from the Thai rice farming system, which cause negative impacts on the environment. Simultaneously reducing the excessive use of nitrogen and phosphorus nutrients in rice cultivation and increasing yield, or reducing the excessive use of nitrogen and phosphorus nutrients in rice cultivation and maintaining an acceptable yield by improving nitrogen and phosphorus nutrients use efficiency, is critical for the success of the sustainable intensification of Thai rice farming in the 21st century. Furthermore, the inputs used and rice output produced by the nitrogen surplus best practice farms can be used as a benchmark to improve the nitrogen surplus efficiency of Thai rice farming. At the same time, the inputs used and rice output produced by the phosphorus surplus best practice farms can be used as a benchmark to improve the phosphorus surplus efficiency of Thai rice farming. Consequently, the results of this study will enable policy makers to create a sustainable rice policy in order to improve the standard of living of Thai people, especially rice farmers, who are the majority of the agricultural population. This will allow Thailand to retain its position of the world largest rice exporter. More importantly, the negative impacts of rice farming systems on the environment will be automatically reduced.

1.5 Outcomes

The analysis and findings generated by this thesis contribute to three key areas of agricultural policy-making in Thailand. First, the input used by the technical best practice farms (TBPFs), which are estimated on the basis of efficiency scores, can be used as a benchmark to improve the technical efficiency of Thai rice farming. Secondly, the input used by the nitrogen surplus best practice farms (BPFs) and phosphorus surplus BPFs, which are estimated on the basis of their efficiency score, can be used as a benchmark to improve the nitrogen and phosphorus use efficiency of Thai rice farming. Finally, policy implications for technical and environmental efficiency improvement of Thai rice farming are suggested.

1.6 Structure of research

This research is organised into seven chapters. Chapter 1 presents the background and the objectives of the study. Chapter 2 presents a review of the history of Thai rice cultivation, taking into account the evolution of Thai agricultural development policies, and the negative environmental effects of overuse of chemical fertiliser in rice farming.

Chapter 3 presents a comprehensive review of previous empirical studies on technical and environmental efficiency measurements of rice farming system, the environmental efficiency of other crops, and the application of the directional distance function.

Chapter 4 has two main objectives: 1) to introduce the relevant efficiency theory, focusing on technical efficiency and its estimation using the DEA and DDF, and 2) to introduce the directional nutrient surplus efficiency measure, which incorporates nutrient surplus into the conventional DDF in a similar manner to that in which price information is normally incorporated in the directional profit efficiency measure (Zofio et al., 2013). The directional nutrient surplus efficiency measure is used to assess the environmental performance of Thai rice production. Furthermore, the basic concepts of the directional profit efficiency measure, the material balance condition, the data cloud method, and the non-parametric tests of returns to scale are also explained.

Chapter 5 describes sources of data, how to build the data analysed in this analysis, data cleaning, and the descriptive statistics used for this research. Moreover, the source of nitrogen and phosphorus content in inputs and outputs of the observed sample data, and the calculation of nitrogen and phosphorus surplus from the observed sample data based on the concept of the material balance condition followed by Coelli et al., (2007) are determined and presented.

Chapter 6 consists of four main objectives: 1) to evaluate the technical inefficiency of Thai rice farming, 2) to evaluate the nitrogen surplus inefficiency of Thai rice farming, 3) to evaluate the phosphorus surplus inefficiency of Thai rice farming, and 4) to compare the technical and environmental inefficiencies of Thai rice farming. This chapter starts by presenting and discussing the empirical results of the efficiency analysis of the performance of 9 observed groups of Thai rice farmers using the DDF models with four different directional vectors. The input-oriented DEA and output-oriented DEA models, with the assumption of constant returns to scale (CRS) and variable returns to scale (VRS), are employed to estimate scale efficiency (SE). Furthermore, the input-oriented DEA and output-oriented DEA models, with the assumption of non-increasing returns to scale (NIRS), are used to investigate the scale of operation, i.e. whether farms operate at optimal size (CRS), larger than the optimal farm size (DRS), or below the optimal scale (IRS). Then the application of the empirical results of the nitrogen surplus minimisation and phosphorus surplus minimisation models to the measurement of the environmental efficiency of 9 observed groups of Thai rice farmers is presented and discussed. Furthermore, the groups of Thai rice farmers are compared in terms of, the improvement of rice output produced and the combination of inputs used per hectare of the average farm, if it produces on the production, profit efficiency, nitrogen surplus efficiency, and phosphorus surplus efficiency frontiers. Lastly, after a comparison of rice output produced and the inputs used by Best Practice Farms, Technical Best Practice Farms, and the most profitable farms, the farm with the best practice in each group of Thai rice farmers will be revealed.

Finally, Chapter 7 addresses the implications of the findings. It discusses the possible direction of future research and the potential implications of a policy to improve the technical and environmental efficiency of Thai rice farming.

Chapter 2

Recent History of Rice Cultivation in Thailand

2.1 Introduction

The main objective of this chapter is to present a comprehensive review of the history of Thai rice cultivation, taking into account the evolution of Thai agricultural development policies, and the negative environmental externalities of overuse of chemical fertiliser in rice farming.

The chapter is organised as follows. Section 2 reviews the evolution of agricultural development policies, especially rice policies, in Thailand, and documents the changes in Thai rice production over the past five decades. Section 3 presents the negative effects on the environment of overuse of fertiliser in Thai rice cultivation, followed by Section 4, which provides explanations from the literature as to why this overuse has taken place. In conclusion, Section 5 addresses the importance of environmental aspects for Thai rice farming.

Rice is a staple food for many countries including Thailand, and the majority of Thai people consume rice three times a day. Rice is also a major crop for Thai farmers, and a major agricultural export which brings high revenue to the country; consequently, Thailand is one of the world's largest rice producers and exporters (FAOSTAT, 2016; USDA[4], 2016a). This is not only because Thailand has an abundance of land resources and a suitable climate for rice cultivation, but also because, thanks to its domestic rice policy, it has retained its position as the world's leading rice exporter (Forssell, 2009). The largest rice producer in the world is China, followed by India and Indonesia, while Thailand is the 6th largest rice producing country in the world (FAOSTAT, 2016). In 2014, Thailand produced 32.6 million tonnes of paddy (21 million tonnes of milled rice) or approximately 4.4% of world production, which amounted to 478 million tonnes of milled rice (USDA, 2016b). Of this, it exported 11 million tonnes of milled rice (USDA, 2016a) or approximately 25% of the world exports (USDA, 2016b).

[4] USDA stands for the United States Department of Agriculture.

2.2 History of Thai rice policy from the 1960s to the present

For developing countries, including Thailand, agriculture and agricultural policy play an important role in the economy (Kasem and Thapa, 2012). The agricultural sector can provide food at low and stable prices for its population and raw material for the industrial sector. In addition, agriculture can help in financing the development of industry, create markets, stimulate demand for the products of the manufacturing sector, and earn foreign exchange if crops are exported (Rock, 2002, cited in Forssell, 2009, p. 485). Since rice is important crop for Thai society and its economy, the creation of an effective rice policy has been important for the Thai government. It is necessary in order to improve the standard of living of Thai people, especially rice farmers who are the majority of agricultural population, and for Thailand to retain its position as the world largest rice exporter. The evolution of rice policies in Thailand is discussed in the next section.

2.2.1 Conventional agricultural development policies since 1960 to 1991

The main goal of agricultural policies since the first National Economic and Social Development Plan (NESDP) of Thailand, implemented in 1961 and lasting until the sixth NESDP period (1987 – 1991), was increased rice production for domestic consumption and export (NESDB[5], 1961). During the 1960s and 1970s, the Thai government focused only on improving agricultural production, especially production of rice, through the promotion of Green Revolution technology, both in terms of quantity and quality. This was in order to accommodate the rising demands of domestic and international consumption: from the 1960s onwards, the growth of the world population led to an increasing demand for food. The government focused on extending rice cultivation areas, the development of physical infrastructures (e.g. expanded irrigation areas, power, and transportation), the use of chemical fertilisers and pesticides, the use of modern farm machineries, and improved high yielding varieties (HYVs) seed and livestock breeds (NESDB, 1961; NESDB, 1967). The government also provided credit to farmers through the Bank for Agriculture and Agricultural Cooperatives (BAAC) to enable them to buy modern technologies and build facilities for their agricultural activities (NESDB, 1972; NESDB, 1977).

As a result, agricultural production, specifically that of rice, significantly increased (Figure 2.1) and Thai agriculture gradually changed from subsistence to semi-subsistence and commercial agriculture, and domestic market-oriented agriculture to export-oriented

[5] NESDB stands for the Office of the National Economic and Social Development Board, Thailand.

(Kasem and Thapa, 2012). As a result of these policies, Thailand has been the largest rice exporter in the world market since 1981 (Figure 2.2). Moreover, Thailand has become the only country in Asia that has been in the position of a "net food exporter" since the beginning of the 1960s (NESDB, 1982, p. 43). The annual growth rate of the national economy during the 1960s and early 1970 was 5.7%; thus agriculture became the main engine of Thai economy (Poapongsakorn et al., 2006 cited in Kasem and Thapa, 2012, p. 102).

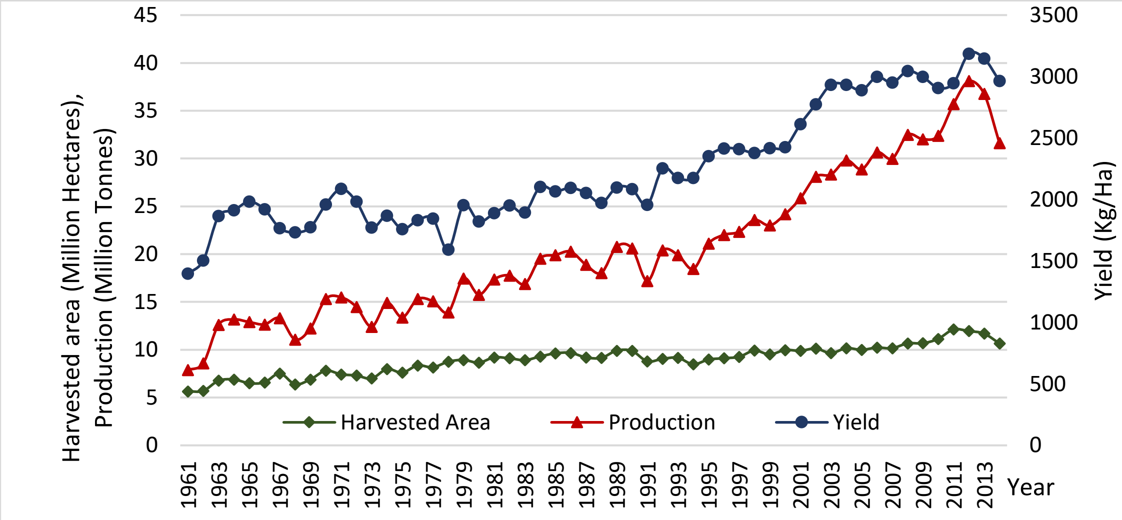

Figure 2.1 Production, harvested area, and yield of rice in Thailand, 1961 – 2014 (Data source: the Office of Agricultural Economics (OAE), 2016).

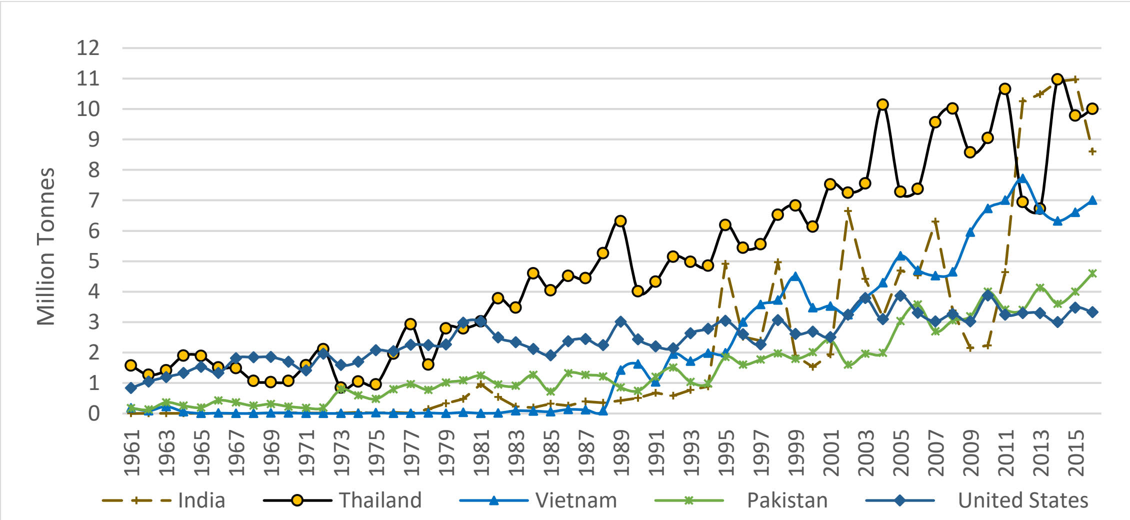

Figure 2.2 Top 5 rice exporters in the World, 1961 - 2015 (Data source: FAOSTAT (2016), 1961 – 2000, USDA (2016a), 2001 – 2015).

However, this success was associated with extensive exploitation and destruction of natural resources, especially land, forest, water, fish, and minerals. Inefficient natural resources management has contributed to relatively rapid deterioration and depletion of natural resources (NESDB, 1982, p. 7; Kasem and Thapa, 2012; Chansarn, 2013). The Office of the National Economic and Social Development Board (1982, p. 44) indicates that the productivity of major crops, especially rice, has increased slowly at 0.5% per year, while most increase in production has been due to area increases. The “expansion of cultivated areas” has increased by approximately 4% per year since the 1960s and reached 23.5 million hectares in 1982. This consists of 13.4 million hectares (57% of the total cultivation area) of paddy fields, and 10.1 million hectares (43% of the total cultivation area) of cash crops and perennial crops. The low productivity of rice from the 1960s to the 1980s was due to the fact that the use of high yield seeds, fertilisers, and pesticides was still very low. The Office of the National Economic and Social Development Board (1982) indicates that the use of high yielding rice seeds was only 12% of the total rice cultivation area, and the fertiliser application rate was 11.9 kilograms/hectare (kg/ha), while other Asian countries used over 31.3 kg/ha.

Thai agriculture had to face the problems of the limitations of land, as suitable land for agriculture began to run out and water and forest resources were used inefficiently from the 1960s to the 1980s without any conservation efforts (NESDB, 1982). Agricultural development policies during the 1980s and 1990s (NESDB, 1982; NESDB, 1987) changed from “extensive agriculture” to “intensive agriculture”, with the target to “raise agricultural productivity”. The Thai government encouraged farmers to improve their productivity rather than expand cultivation areas. To achieve this strategy, the government provided improved HYVs seed by exchanging seeds, provided increased access to chemical fertilisers by subsidising transportation costs for rice farmers in rain-fed areas, and encouraged farmers to produce organic fertilisers (NESDB, 1982). Furthermore, the government also encouraged farmers to use new technologies, such as chemical fertilisers and improved HYVs seed, by providing credit extension to farmers through the BAAC (NESDB, 1982).

By the end of the sixth NESDP (1987-1991), the share of the agricultural sector in GDP gradually declined to 11.5% in 1991, while the industrial and service sectors continued to grow at a very high rate (NESDB, 1992). The agricultural sector was still important to the Thai economy, since the agricultural employment share remained as high as 64% of total national employment (NESDB, 1992). Unfortunately, despite the success of increasing agricultural productivity through the policies mentioned above, soil fertility and water resources gradually deteriorated due to the intensive use of chemical fertilisers and pesticides (Kasem and Thapa, 2012). Besides, farmers were also faced with the problems of adverse health effects from agrochemicals, and heavy indebtedness since they relied on credit for purchase of inputs (Kasem and Thapa, 2012). Consequently, the Thai government has changed its policies towards sustainable agricultural development policies since the seventh NESDP (1992 – 1996) (NESDB, 1992; Kasem and Thapa, 2012).

2.2.2 Sustainable agricultural development policies from 1992 to the present

Conventional agricultural development policies since 1960 to 1991 have focused on expansion of agricultural land areas, especially areas for rice cultivation, expansion of irrigation areas for agriculture, and use of agrochemicals to increase productivity. This has created severe environmental problems such as deforestation, natural resource exploitation, environmental degradation, and pollution (Kasem and Thapa, 2012; Chansarn, 2013). In order to solve these environmental problems, the Thai government has implemented policies which concentrate on sustainable agricultural development by restructuring the agricultural production system in order to reduce deforestation; increasing sustainable farming practices by promoting crop diversification and mixture crops; reducing the use of agrochemicals by promoting organic agriculture and farming that utilises both organic and inorganic inputs; and focusing on food safety through the adoption of Good Agricultural Practice (GAP) by encouraging farmers to use organic fertilisers and bio-pesticides. The rationale for these strategies is that they can reduce the environmental and human health problems resulting from agricultural practices that employed a greater quantity of agrochemicals. They can also increase agricultural productivity and product quality, as well as increasing farmers' income by reducing production costs, since the price of agrochemicals is high (Kasem and Thapa, 2012).

Nevertheless, many Thai rice farmers still prefer to monocrop and rely on chemical fertilisers and pesticides to maintain productivity and product appearance, and are less concerned about environmental degradation. Farmers have increased the use of chemical fertilisers, as can be seen in Figure 2.3, because of lack of soil fertility resulting in a decline in agricultural output (Tirado et al., 2008). The increase in chemical pesticide use is a result of many factors including insect resistance, the resurgence of pests, the industrialisation of crop production, switching from low value added to high value added agricultural production, and changing to off-season crop production to satisfy market demand and earn higher prices (Tirado et al., 2008; Panuwet et al. 2012). The reasons why farmers overuse chemical fertiliser will be discussed in Section 2.4.

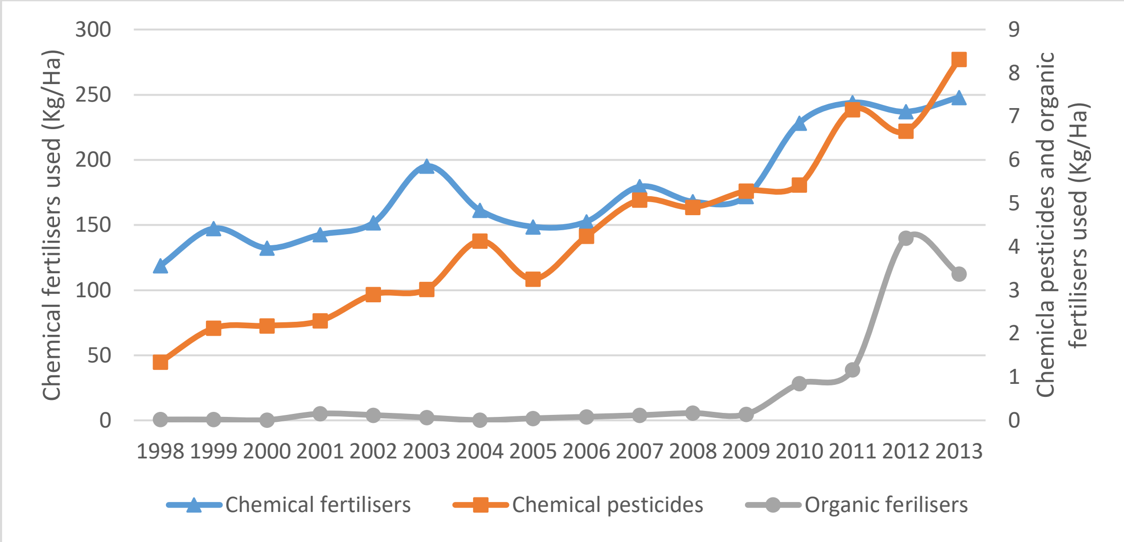

Figure 2.3 Quantity used per hectares of organic fertilisers, chemical fertilisers and pesticides (Data source: OAE, 2014).

The use of chemical fertiliser and pesticide[6] by farmers in Thailand continued to increase in both quantity and intensity (the amount of fertiliser and pesticide used per hectare) between 1998 and 2013, while the use of organic fertiliser per hectare was low and remained so between 1998 and 2009 (Figure 2.3). The use of organic fertiliser per hectare also increased dramatically between 2009 and 2012, with a slight decrease in 2013. However, its use remains low compared to chemical fertiliser (Figure 2.3). In 2010, N and P used for rice cultivation accounted for 45% and 28% of total nutrients imported[7], respectively (Heffer, 2013).

The average inorganic fertiliser application rates per hectare of the top 10 largest rice producing countries in the world between 1961 and 2013 are shown in Figure 2.4. Of these ten countries, the rank of application rate of inorganic fertiliser of Thai rice farmers is seventh, but Thailand has the lowest yields (Figure 2.5). The average yield in China is more than double of the average yield of Thailand. This is driven in part by China's average fertiliser application rate, which is more than double of that of Thailand (Ricepedia, 2013). Moreover, nearly all China's rice cultivation areas are irrigated, and their adoption of hybrid seed is widespread (GRiSP, 2013). Rice yields in China, at greater than 6.5 tonnes per hectare, were the highest in Asia since 2009. In contrast, in Thailand, only 25% of the rice cultivation area is irrigated (OAE). In addition, Thai farmers prefer to plant high quality jasmine rice[8] (i.e. Khao Dawk Mali 105 variety) to obtain a premium price in both domestic

[6] Most of the chemical fertilisers and pesticides used in Thailand are imported (OAE).
[7] Total N and P imports are 1.3 and 0.3 million tonnes of nutrients, respectively (Heffer, 2013).
[8] Jasmine rice is called "Khao Hom Mali" in Thai.

and world markets (GRiSP, 2013). Although this is one of Thailand's improved seed varieties, it has a low yield of approximately 2.3 tonnes per hectare (Rice department, 2010). Further major constraints on rice production for major season crops are rainfall variability, flood, drought, and poor soil fertility (GRiSP, 2013).

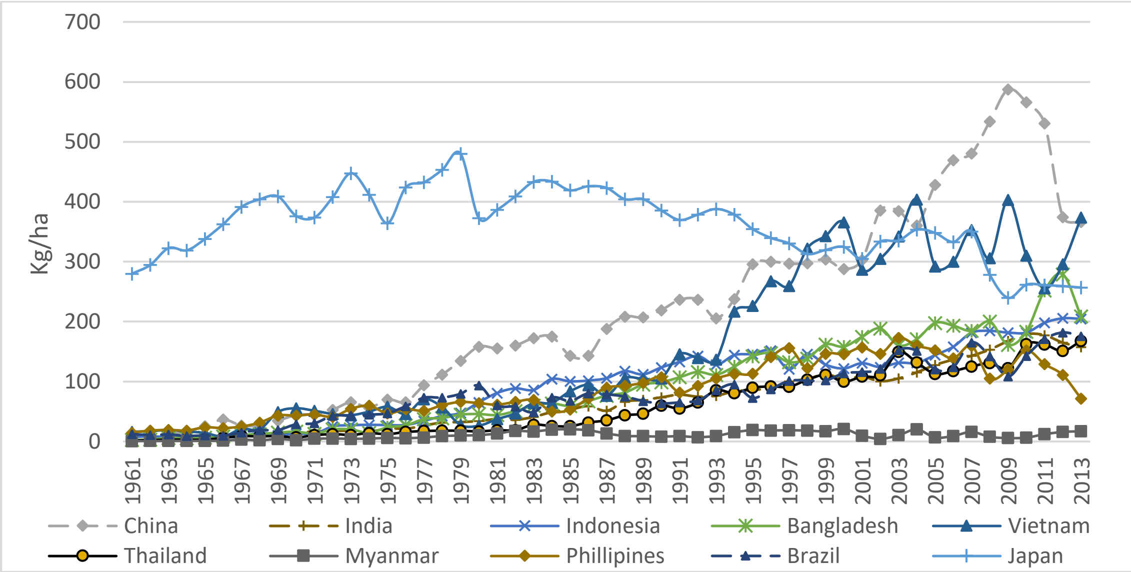

Figure 2.4 Fertiliser application rate (NPK) of top 10 largest rice producing countries in the World, 1961 –2013 (Data source: Ricepedia, 2013).

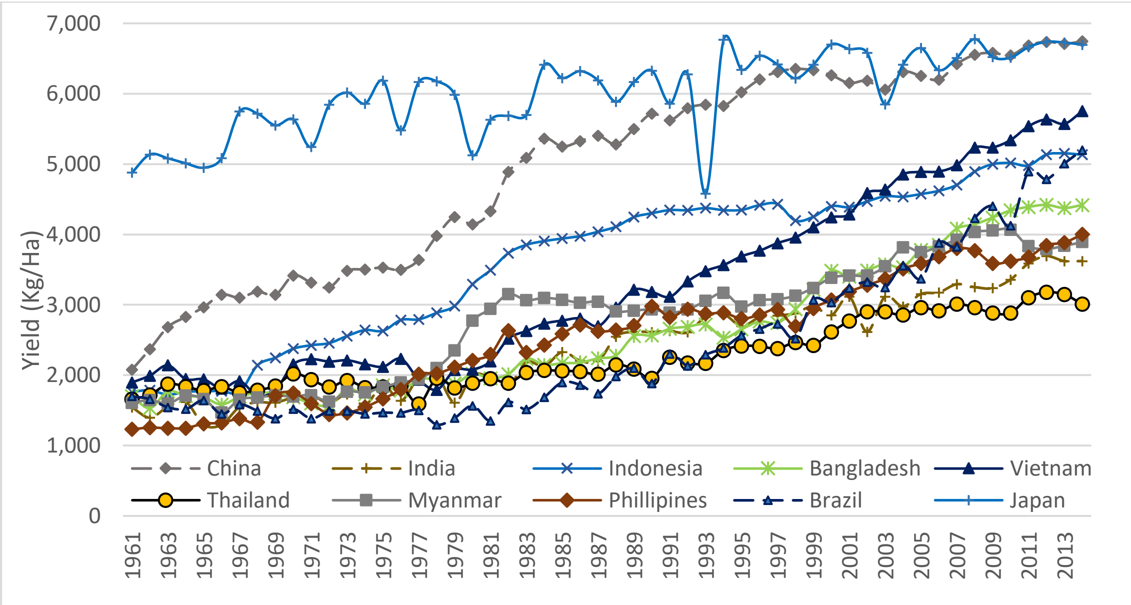

Figure 2.5 Rice yield of top 10 largest rice producing countries in the World, 1961 – 2014 (Data source: FAOSTAT, 2016).

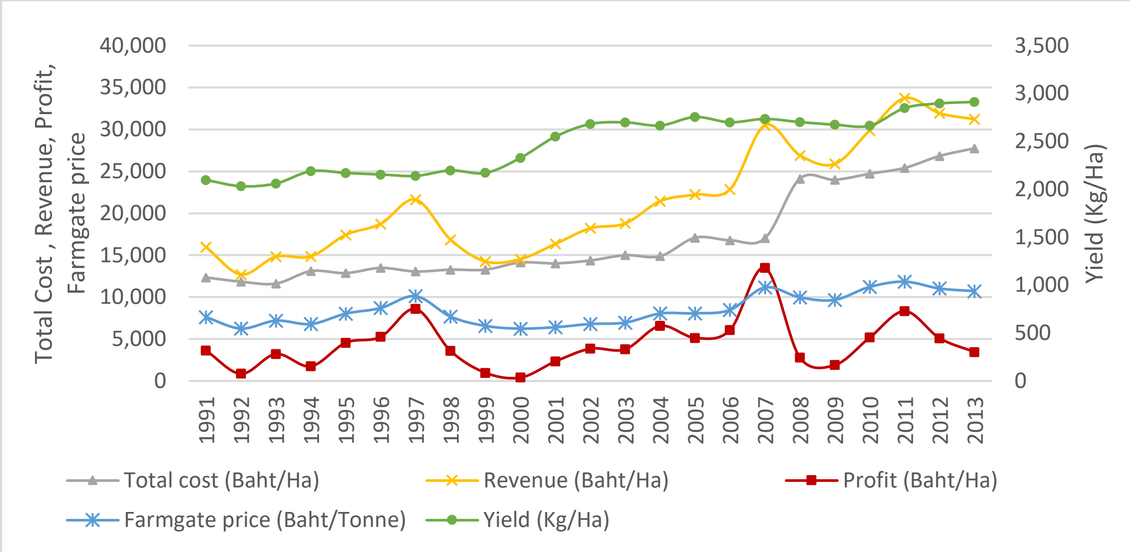

Figure 2.6 Total cost, total revenue, profit, farm-gate price, and yield of Thai rice 1991 - 2013 (Data source: OAE).

Greater use of chemical fertilisers and pesticides leads to higher production costs. Some farmers have been faced with increased debt due to the purchase of these inputs, as well as health damage from their intensive use (Suksri et al. 2008). Figures for the average cost, revenue, profit, farm gate price and yield of major rice production in Thailand are presented in Figure 2.6. This price data has been adjusted for inflation by use of the consumer price index (CPI, 2011 is the base year), retrieved from the Bank of Thailand (BOT, 2017). The total cost of rice production increased from 1991 to 2013 due to the increasing cost of all inputs, especially labour and fertiliser (OAE). While the farm gate price increased slightly, the total cost of production rose sharply. Consequently, Thai farmers have been facing high production costs and earning low profits because their output per hectare is low and selling prices are not sufficiently high to outweigh the high costs and low yields.

2.3 Evidence of negative effects of the overuse of fertiliser on the environment

After the promotion of Green Revolution technologies in many countries, including Thailand, agricultural practices created undesirable outputs such as increased water pollution, air pollution, and greenhouse gas emissions during the production process. Agricultural intensification using agrochemicals can harm environmental services (Geiger et al., 2010; Pretty, 2008). Chansarn (2013) stated that Thailand is very successful in creating economic growth following the National Economic and Social Development Plan from 1961 to 2011, but this success comes together with various environmental problems such as deforestation, natural resource exploitation, environmental decadence, and pollution. These environmental problems caused by economic activities have been an important topic for political and public debate in recent years (Nguyen et al., 2012).

Nitrogen surplus (NS) and phosphorus surplus (PS) from rice fields caused by overuse of chemical fertiliser and manure are key environmental issues for rice production (Linquist et al, 2014; Tirado et al., 2008; Schaffner et al., 2011). Some of the nutrients applied are absorbed by rice, but the excess discharges into groundwater, rivers, and finally coastal areas. This problem of water pollution caused by NS and PS from rice fields is becoming more serious in Thailand (Tirado et al., 2008). NS brings about nitrate contamination of the surface and groundwater, which are the most important sources of drinking water, while the NS that evaporates as ammonia to the atmosphere causes acid rain (Reinhard et al., 2000). PS leads to the problem of eutrophication of surface water which harms fish and plant life (Reinhard et al., 2000). Pathak et al. (2004) found that the percentages of total N fertiliser outflow from Thai rice fields to the atmosphere, and surface and groundwater were 13.6% and 19.02%, respectively. This is equivalent to N loss from rice fields to the atmosphere of 80,240 tonnes per year and N leaching to groundwater and surface of 112,218 tonnes per year[9].

Tirado et al. (2008) suggest that water pollution with nitrates from rice fields caused by fertiliser runoff is more widespread in Thailand than previously thought. More than 40% of surface water and about 33% of coastal water in Thailand have been found to be “poor” and “very poor” in quality (The Pollution Control Department cited in Tirado et al., 2008, p. 3). Furthermore, Tirado (2007) found that the drinking water from deep wells in Kanchanaburi province and Suphanburi province in Thailand, where farmers’ intensive rice farming makes higher than average use of chemical fertilisers, have levels of nitrates above the WHO drinking water safety limit of 50 mg/l NO_3^-. They also stated that water polluted with nitrates poses risks for human health, particularly for children. People who eat products with high levels of nitrate or drink water from contaminated wells could be vulnerable to the long-term effects of nitrates such as various types of cancers (Greer et al., 2005 cited in Tirado et al., 2008, p. 15). “The greatest risk of nitrate poisoning is considered to be *the blue baby syndrome or methemoglobinemia*[10], which occurs in infants given nitrate-laden water, and

[9] The estimated quantity of N-fertiliser use by Thai rice farming in 2010-2010/11 is 590,000 tonnes of nutrients (Heffer, 2013).
[10] “The blue baby syndrome occurs when the hemoglobin in the blood losses its capacity to carry oxygen and this can ultimately cause asphyxia and death” (Tirado et al., 2008, p.15).

affects particularly babies under 4 months of age," (Greer et al., 2005 cited in Tirado et al., 2008, p. 15).

Eutrophication of river, lakes, coastal and marine ecosystems can also have a negative impact on both human health and the natural populations of fish and other aquatic fauna through ecological changes, such as massive growth of harmful algal blooms that produce toxins (Robertson and Swinton 2005 cited in Tirado et al., 2008, p. 15). Human consumption of shellfish that ingest these algae may cause conditions such as neurological disorders, amnesia, paralysis, and diarrhoea, and may result in death. Tirado et al. (2008) refer to case studies related to the problem of eutrophication from Thai rice cultivation which are as follows.

Firstly, algal blooms producing the potent liver toxin microcystin were found in "the Mae Kuang Udomtara Dam reservoir in Chiang Mai province" (Peerapornpisal et al., 1999 and Chanttara et al. 2002, cited in Tirado et al., 2008, pp. 12-13). Further, these algal blooms were also found in "the Bang Phra reservoir in Nakhon Pathom Province" (Wang et al., 2002 cited in Tirado et al., 2008, p.13). Secondly, the increasing occurrence of algal blooms in the Gulf of Thailand over the last decades resulted in the death of fish, and paralysis and death of humans who consumed contaminated seafood, especially shellfish (Singhasaneh, 1995, Menasveta, 2001, and Cheevaporn and Menasveta, 2003, cited in Tirado et al., 2008, p.13). Finally, the density of benthic faunas and fish in 2005 in Pranburi Irrigation Project area in Prachuab Khiri Khan province was less than half of the section downstream of the paddy fields compared to that in the upstream section, which was far from the impact of rice cultivation (Tirado et al., 2008, p.11).

2.4 Reasons that Thai farmers overuse chemical fertiliser

Understanding why farmers overuse chemical fertiliser and manure is necessary to enable policy makers to design effective agro-environmental policies in which farmers use fertiliser efficiently (Sheriff, 2005). Policies need to help farmers to grow rice by using less fertiliser, but still maintain their yields and profits, while also reducing environmental degradation. Key reasons why Thai farmers over-apply chemical fertiliser and manure are discussed in the next sections.

2.4.1 Lack of information on soil quality

Farmers lack information on soil quality or are uncertain about the quality of soil in their fields (Sheriff, 2005). Nutrients that allow plants to grow, such as N, P, and K, originate from soil (DeJoia, 2015), but soil in some areas is naturally low in these nutrients, while in other areas, soil has become depleted due to continuous monocropping (Homenauth, 2013). Romig et al. (1995) state that farmers learn how to identify soil quality from experience by looking at soil appearance (e.g. dark coloured and crumbly); plants' appearance (e.g. dark green leaves, tall stems, and a large spreading root system); animals' health (e.g. higher production, and less disease); and water quality (ground and surface water). The authors also suggest that soil quality can be identified by tillage. Healthy soil is easy to till as the soil breaks down faster with less traction, while unhealthy soil is harder to till, requiring more time and horsepower to make a suitable cultivation area. However, though farmers may know which soil is healthy or unhealthy and what nutrients plants lack, they do not know exactly how much of each nutrient needs to be added to the soil.

Rice plants will suffer from nutrient deficiency and stop growing if nutrients in the soil are lacking. Therefore, farmers have to apply nutrients to their fields using manure or chemical fertiliser to maintain soil fertility or improve soil quality. "Fertilisers are simply plant nutrients applied to agricultural fields to supplement required elements found naturally in the soil" (DeJoia, 2015, p. 1). However, because farmers typically do not know which nutrients in the soil are lacking and how much of each nutrient needs to be added to the soil, they may apply too little fertiliser to the soil, so that crops will not grow as well as they should, resulting in low yields (DeJoia, 2015). On the other hand, if they apply too much fertiliser to the soil, or apply it at the wrong time, the excess will run off from their fields and cause the pollution of streams and groundwater (DeJoia, 2015). Farmers bear the costs of low yields through reduced profits if they apply too little fertiliser, whilst they are not penalised for the environmental costs of applying too much, suggesting an incentive to over apply. If farmers were able to send a soil sample to a laboratory to test its nutrients, they would know which were lacking and how much should be applied to the soil. However, this procedure is complicated and costly and so rarely happens (LDD[11], 2012). Moreover, farmers would have to wait for the soil sample results, which could come too late for planting. As a result, farmers are likely to reach their decisions about fertiliser rates by calculating how much they can afford, or by drawing on previous experience, which leads

[11] LDD stands for the Land Development Department, Thailand.

them to use similar amounts to those they used before. They may also try to reduce their risk of a poor harvest and low profits by using the same amount as neighbouring farmers (Sheriff, 2005; Babcock, 1992).

2.4.2 Uncertainty of the weather

Farmers face uncertain weather during the rice farming season. Unexpected bad weather can reduce the capacity of plants to absorb nutrients (Sheriff, 2005). This is a problem as the optimal application rates for fertiliser under mean growing conditions may differ from those under uncertain growing conditions (Sheriff, 2005). Specifically, crop nutrient uptake is higher in years with good growing conditions and lower in years with bad growing conditions (Babcock, 1992). Thus, if a farmer applies the optimal amount of fertiliser for mean growing conditions, and the conditions prove to be better than expected, there will be too little fertiliser because crop nutrients uptake is higher than mean growing conditions. If growing conditions are worse than expected, there will be too much fertiliser because crop nutrients uptake is lower than mean growing conditions. This is illustrated by Sheriff (2005, p. 545 – 546), who states that a "risk-neutral farmer applies fertiliser at a higher rate as long as the expected gain in profit from the increased yield in a good growing condition is higher than the expected loss in profit from wasted fertiliser in the bad growing condition." On the other hand, the application rate of fertiliser for a risk-averse farmer will depend on whether the farmer considers fertiliser as a risk-enhancing or risk-reducing input (Sheriff, 2005). If a risk-averse farmer considers fertiliser as a risk-enhancing input, the fertiliser application rate will be lower than that of risk-neutral farmers (Just and Pope, 1979 cited in Sheriff, 2005, p. 547). If a risk-averse farmer considers fertiliser as a risk-reducing input, the fertiliser application rate will be higher than the application rate in the mean growing conditions (Sheriff, 2005).

2.4.3 Farmers' belief in agronomic advice from government extension officers

A central responsibility of government agricultural extension officers is "providing knowledge for farmers to use agrochemicals safely, in the right amounts, with the best timing" (Nelles and Visetnoi, 2016, p. 229). Farmers' fertiliser application rates may therefore be influenced by their belief in agronomic advice from government agricultural extension officers (Sheriff, 2005; Rajsic and Weersink, 2008; Nelles and Visetnoi, 2016). If farmers believe that the fertiliser application rate recommended by extension advisors is correct, they will apply fertiliser as advised (Sheriff, 2005). If, however, if farmers believe that the extension advisors' recommendations are incorrect, these beliefs could lead to over-application (Sheriff, 2005). This notion is supported by Rajsic and Weersink (2008), who report that farmers tend to apply higher rates of fertiliser than the rate recommended by extension advisors. The main reason for this is the perception that the extension officers recommend general application rates for the whole region which are not suitable for their soils (Sheriff, 2005; Rajsic and Weersink, 2008). This has led to the suggestion that extension officers should recommend area specific rates for nutrient application rather than a general application rate for the whole region (Yadav et al., 1997). Furthermore, farmers may be unable to compare the difference in profits between using the right amount and a higher fertiliser rate, and may not recognise the negative effects of excessive use of fertiliser on their health and the environment. Even if farmers know there is a cost to the environment, this is an externality that farmers may not take into account when deciding how much fertiliser to apply. High application reduces the risk of a low harvest; it may be cheaper and more timely than getting soil tested; farmers do not have to pay the externality cost imposed on the environment. Together, these realities are likely to encourage farmers to apply fertiliser at a higher than economically and environmentally optimal rate.

2.5 The environmental aspect

The limited amount of farmland, referred to as scarce land resources, is a major constraint for agricultural production. Chemical fertiliser and pesticide have become important factors of agricultural production because farmers have to increase their productivity and protect their crops if there is no option of expanding the area cropped to rice. However, the intensive use of chemical fertiliser and pesticide not only increases agricultural production, but also increases the cost of production and generates severe environmental problems, especially pollution, biodiversity loss, and changes to ecosystems (Luh and Liao, 2001).

The global population is projected to reach 9.1 billion by 2050, which will result in a rising demand for food (FAO, 2009). A major concern of rice intensification is maintaining the sustainability of rice-producing environments by efficient use of agrochemicals that have negative effects on soil fertility, the environment, and human health. If the use of agrochemicals, that are costly inputs, can be minimised efficiently, the negative effect on the environment, production cost, and adverse health effects on farmers and consumers will be reduced. This means that agricultural systems will be developed economically and socially, and will be ecologically sustainable.

2.6 Summary

Rice is crucial to Thai people for many reasons. It plays an important role in the Thai economy and society and is the cheapest main staple food for a society where levels of income vary greatly. Rice can help in financing the development of industry, create markets, stimulate demand for the products of the manufacturing sector, and even earn foreign exchange. Since the major constraint on rice production and other agricultural production is the limitation of land resources, agrochemicals have become an important input for agricultural practices because farmers aim to boost their productivity and protect their crops. However, the intensive use of chemical fertiliser and pesticide not only increases productivity, but also increases the cost of production, creates severe environmental problems, and has adverse effects on human health. Therefore, the major concern with regard to rice intensification is maintaining the sustainability of rice-producing environments by efficient use of agrochemicals. This is vital in order to produce enough rice to feed the future population when the demand for rice is predicted to increase by more than 40%.

Most of the environmental problems associated with rice cultivation arise from the overuse of agrochemicals. They are costly inputs, and if their use can be minimised efficiently, the negative effect on the environment, the cost of production, and adverse health effects on farmers and consumers will be reduced. This means that agricultural systems will be economically, socially, and ecologically sustainable. Hence, this study focuses on the efficient use of N and P fertilisers because NS and PS from rice fields, caused by overuse of chemical fertiliser and manure, are key environmental issues for rice farming. The key to sustainable intensification development of Thai rice farming in the 21st century is simultaneously reducing excessive N and P fertilisers from rice cultivation and maintaining/increasing an acceptable yield and sufficient profit margin for farmers. This can be achieved by improving the efficiency of the use of N and P fertilisers. Consequently, policy makers can use the results of this study to create a sustainable rice policy in order to improve the standard of living of Thai people, especially rice farmers who are the majority of agricultural population, and enable Thailand to retain its position as the world's largest rice exporter, as well as to help meet the future demand for rice.

Furthermore, the application of chemical fertiliser and manure during rice cultivation periods causes negative effects on the environment. In order to reduce these effects, policy makers should understand why farmers overuse fertiliser. This should help them design effective agro-environmental policies and implement appropriate programmes for the monitoring, assessment and improvement of soil quality. The government could provide fertiliser application rates by area specific rather than a general application rate for the whole region, and encourage farmers to use the right amount of fertiliser at the right time in order to avoid potential harm to the environment. As fertiliser use is very expensive, Thai farmers who learn not to over-apply it will earn more profit since the cost of production will be reduced. When farmers apply fertiliser at the right time, plants can absorb all, or almost all, the nutrients. Consequently, the environmental problems caused by NS and PS from rice fields will be reduced. A review of previous empirical studies on technical and environmental efficiency measurements of the rice farming system, the environmental efficiency of other crops, and the application of the directional distance function are presented in the next chapter.

Chapter 3

Technical and Environmental Efficiency Analysis in the Literature

3.1 Introduction

Data envelopment analysis (DEA) and stochastic frontier analysis (SFA) are popular approaches to measuring the performance of the agricultural sector. DEA is a non-parametric approach which was first introduced by Charnes, Cooper, and Rhodes (CCR) in 1978 and it has subsequently been developed by various researchers (e.g. Banker, Charnes, and Cooper, 1984; Färe et al., 1989). The DEA method has been applied to evaluating the performance of various phenomena, such as hospitals, banks, schools, and agriculture. A number of DEA studies have focused on technical efficiency measurements in the agricultural production of either crops or livestock (Gadanakis, 2014).

The main purpose of this chapter is to present a comprehensive review of previous empirical studies of technical and environmental efficiency measurements of rice farming systems, environmental efficiency in other productions, and the application of the directional distance function.

The remainder of the chapter is organised as follows. Section 2 presents background information, and the advantages and disadvantages of the DEA and stochastic frontier analysis approaches. Section 3 reviews previous studies of efficiency measurement of rice production in Thailand and other countries, followed by a discussion of empirical evidence of environmental efficiency measurement in Section 4. Section 5 presents empirical studies of efficiency measurement using the directional distance function.

3.2 DEA and SFA of production efficiency measurement

The study by Farrell (1957) has been used as a basis for theoretical methods of efficiency measurement (e.g. Coelli et al, 2002; Ogundari and Awokuse, 2016; Zahidul Islam et al., 2011; Watkins et al., 2014). The relative efficiency of a farm is compared with the other farms within a sample group (Farrell, 1957). Farrell (1957) identified three categories for measuring the efficiency of a farm: technical efficiency (TE), price efficiency or allocative efficiency (AE), and overall efficiency or economic efficiency (EE) or cost efficiency (CE). TE measures the potentiality of a farm to produce a fixed amount of output using the minimum possible amounts of inputs (input-oriented TE) or produce the maximum feasible output using a fixed amounts of inputs (output-oriented TE) (Watkins et al., 2014). AE measures the potentiality of a technically efficient farm to proportionately reduce the amount of inputs, thus minimising production costs, given input prices (Watkins et al., 2014). It can be calculated by "the ratio of the minimum costs required by the farm to produce a given level of outputs and the actual costs of the farm adjusted for TE" (Watkins et al., 2014, p. 90). The EE of a farm is equal to "the product of the TE and AE" (Farrell, 1957, p. 255) or "the ratio of the minimum feasible costs and the actual observed costs for a farm" (Watkins et al., 2014, p. 90).

Two approaches that have been applied to evaluate farms' performances are stochastic frontier analysis and DEA. The former method is a parametric approach which contains a random error term in the model (Reinhard et al., 2000; Watkins et al., 2014). It employs a standard production function (i.e. translog function, Cobb-Douglas production function, quadratic function, or normalised quadratic function) to find the relationship between inputs and outputs, and then estimates the parameters of this production function by using statistical techniques such as ordinary least square (OLS), corrected ordinary least square (COLS), and likelihood function estimations (Watkins et al., 2014). The stochastic frontier analysis approach incorporates two components in the error term which are a symmetric component error and a non-negative component error (Reinhard et al., 2000; Watkins et al., 2014). The symmetric component error accounts for statistical noise related to data measurement errors, while the non-negative component error estimates the inefficiency of the production process (Reinhard et al., 2000; Watkins et al., 2014). Stochastic frontier analysis facilitates hypothesis testing and creates the need to determine the distribution of inefficiency terms such as half-normal, truncated-normal, exponential, or gamma-distribution (Umanath and Rajasekar, 2013; Watkins et al., 2014). The technical efficiency of each farm, as estimated by the stochastic frontier analysis approach, will vary over all inputs taken together (Kalirajan, and Shand, 1999).

The DEA is a non-parametric (deterministic) method that does not contain a random error term. This method applies linear programming to construct a piecewise production frontier to envelop the data; it takes the observed input and output data and forms a production possibility set in order to measure the relative technical efficiency of the farms in the sample (Watkins et al., 2014). The technical efficiency of each farm, as estimated by the DEA approach, will vary by inputs (Kalirajan, and Shand, 1999, p. 167). More details of the DEA approach are discussed in Chapter 4.

The advantages of the stochastic frontier analysis approach are that it allows for white noise error or random error which represents influences outside the farmers' control (Omer et al., 2007), and attempts to separate statistical noise effects from technical inefficiency (Reinhard et al., 2000). Stochastic frontier analysis also permits statistical hypothesis testing and confidence interval construction (Reinhard et al., 2000; Wadud and White, 2000; Watkins et al., 2014). However, the major disadvantage is misspecification of the functional forms of both the production function and the distribution of inefficiency term (Reinhard et al., 2000; Wadud and White, 2000; Omer et al., 2007; Watkins et al., 2014). The functional form is sensitive to multicollinearity ($Cov\left(x_i, x_j\right) \neq 0\,; i \neq j$) , and theoretical restrictions (monotonically and curvature) may be violated (Reinhard et al., 2000).

The major advantage of DEA is that it does not require an assumed production function, such as Cobb-Douglas or translog functions, nor does it require the formation of assumptions about the distribution of the inefficiency term, such as half-normal. Furthermore, it does not require assumptions about behaviour decision making units (DMUs) such as cost minimisation or nutrient minimisation (Nguyen et al., 2012). Therefore, it is less sensitive than stochastic frontier analysis to misspecification (Wadud and White, 2000; Coelli et al., 2002; Umanath and Rajasekar, 2013; Watkins et al., 2014). Moreover, DEA can be used to estimate the efficiency of the production frontier for many inputs and outputs (Reinhard et al., 2000; Ahmed et al., 2011; Wadud and White, 2000). It does not have a testing procedure because it satisfies monotonicity and curvature restrictions by construction (Reinhard et al., 2000). In later research by Simar and Wilson (2007), the double bootstrap procedure was proposed: this enables statistical inference within the DEA approach. However, the major disadvantage of DEA compared to the stochastic frontier analysis is that it does not account for random variation in the production function (Tingley and Pascoe, 2005; Ahmed et al., 2011; Watkins et al., 2014); thus, it is unable to distinguish data noise from the inefficiency scores (Nguyen et al., 2012).

3.3 Empirical studies of efficiency measurement of rice production

Efficiency of rice production has been evaluated in several studies which are summarised in Table 3.1. The studies presented measure the efficiency of rice production during the period 2000 to 2016. Fourteen studies employed the DEA approach, six employed the stochastic frontier analysis approach, three employed both DEA and stochastic frontier analysis methods, and only one study employed the directional distance function (DDF) approach. Although most of the studies employing the DEA approach assume the input-oriented TE measurement, Tun and Kang (2015), Balcombe et al. (2008), and Wadud and White (2000) assume the output-oriented TE measurement. These assumptions, regardless of the orientation, depend on the purpose of the research, i.e. whether the researcher would like to maximise output (output-oriented DEA) or minimise input usage (input-oriented DEA). Coelli et al. (2005) state that both DEA and stochastic frontier analysis models can be analysed in terms of TE, AE, EE, scale efficiency (SE), and environmental efficiency (NE). The efficiency of each farm can be estimated according to the availability of data. TE requires only data on the quantities of inputs and outputs, while EE requires data on the quantities of inputs and outputs and their corresponding prices, as well as assumptions about producers' priorities (i.e. cost minimisation, profit maximisation, or revenue maximisation).

All the rice production efficiency studies presented below have undertaken their research in developing countries, except Watkins et al. (2014), who performed their research in the United States (Table 3.1). Nine studies were conducted in Southeast Asian countries, eleven in South Asian countries, one in East Asian countries, and two in African countries. In other words, the majority of rice production efficiency studies have analysed Asian countries because these countries are the main rice-planted areas of the world. Five studies measured TE and SE (Tun and Kang, 2015; Tung, 2013; Taraka et al., 2010; Chauhan et al., 2006; Krasachat, 2004), four measured TE, AE, and EE (Nguyen et al., 2012; Ahmed et al., 2011; Kiatpathomchai, 2008; Wadud, 2003), and six measured TE, SE, AE, and EE (Watkins et al., 2014; Umanath and Rajasekar, 2013; Nkang et al., 2011; Zahidul Islam et al., 2011; Dhungana et al., 2004; Coelli et al., 2002).

The average TE scores reported in these studies range from 0.45 to 0.98. This implies that the mean technical inefficiency for rice production in these studies is between 2% and 55% (Table 3.1). In other words, these empirical studies indicate that rice farmers would be able to reduce their current amount of inputs on average from 2% to 55% to obtain their current levels of rice output. The average AE scores reported in eleven studies range from 0.46 to 0.99 (Table 3.1). This implies that the rice farmers in these studies applied the wrong inputs mix at the given price of inputs, with average cost higher than the cost minimising level by 1% to 54%. The average EE scores reported in ten studies range from 0.38 to 0.91 (Table 3.1). This implies that the rice farmers in these studies can reduce the costs of rice production by 9% to 62% on average, without changing the quantity of rice outputs produced.

Table 3.1 Empirical research on rice production efficiency

Author(s)	Efficiency method	Data	Country	Average efficiency scores
Ogundari and Awokuse (2016)	SFA	Cross sectional data of 252 farmers in 2014	Thailand	TE = 0.93
Tun and Kang (2015)	DEA and SFA	Cross sectional data of 195 farms in 2012	Myanmar	$TE_{CRS-DEA}$ = 0.63 $TE_{VRS-DEA}$ = 0.69 SE_{DEA} = 0.92 TE_{SFA} = 0.78
Watkins et al. (2014)	DEA	Panel data of 158 farms, 2005-2012	U.S.A.	TE_{CRS} = 0.80 TE_{VRS} = 0.88 SE = 0.92 AE = 0.71 EE = 0.62
Tung (2013)	DEA	Panel data of 1,000 households, 1998, 2002, 2004, 2006, 2008, 2010	Vietnam	TE_{VRS} range from 0.53 to 0.70 SE range from 0.90 to 0.94
Umanath and Rajasekar (2013)	DEA	Cross-sectional data of 90 farmers, crop year 2010-2011	India	TE_{CRS} = 0.80 TE_{VRS} = 0.85 SE = 0.95 AE_{VRS} = 0.46 EE_{VRS} = 0.38
Nguyen et al. (2012)	DEA	Panel data , 2003-2007, 480 observations	South Korea	TE = 0.77 AE = 0.72 EE = 0.56 NAE = 0.40 NE = 0.31
Rahman et al. (2012)	SFA	Cross sectional data of 1,360 farms, crop year 2008-2009	Bangladesh	TE = 0.88
Ahmed et al. (2011)	DEA	Cross sectional data of 172 rice farmers, crop year 2007-2008	Bangladesh	TE_{VRS} = 0.98 AE = 0.93 EE = 0.91
Nkang et al. (2011)	DEA	Cross sectional data of 95 farms in 2005	Nigeria	TE_{CRS} = 0.85 TE_{VRS} = 0.92 SE = 0.91 AE_{CRS} = 0.65 AE_{VRS} = 0.81 EE_{CRS} = 0.56 EE_{VRS} = 0.75

Table 3.1 Empirical research on rice production efficiency (Continued)

Author(s)	**Efficiency method**	**Data**	**Country**	**Average efficiency scores**
Khai and Yabe (2011)	SFA	Cross-sectional data of 3,733 households in 2006	Vietnam	TE = 0.82
Bäckman et al. (2011)	SFA	Cross-sectional data of 360 farms in 2009	Bangladesh	TE = 0.83
Zahidul Islam et al. (2011)	DEA	Cross-sectional data of 355 farms in crop year 2008-2009	Bangladesh	TE_{CRS} = 0.63 TE_{VRS} = 0.72 SE = 0.88 AE_{CRS} = 0.62 AE_{VRS} = 0.66 EE_{CRS} = 0.39 EE_{VRS} = 0.47
Taraka et al. (2010)	DEA	Cross-sectional data of 400 farms, crop year 2009-2010	Thailand	TE_{CRS} = 0.517 TE_{VRS} = 0.519 SE = 0.998
Singbo and Lansink (2010)	DDF	Cross-sectional data of 28 farms, crop year 2004-2005	Benin Republic (West Africa)	TIE_{CRS} = 0.09 TIE_{VRS} = 0.35 AIE = 0.01
Rahman et al. (2009)	SFA	Cross-sectional data of 348 farms, crop year 1999-2000	Thailand	TE = 0.63
Kiatpathomchai (2008)	DEA	Cross-sectional data of 247 rice farmers , crop year 2004-2005	Thailand	TE_{VRS} = 0.87 AE_{VRS} = 0.78 EE_{VRS} = 0.68 NE = 0.54
Balcombe et al. (2008)	DEA	Cross-sectional data of 295 observations	Bangladesh	TE_{CRS} = 0.64 TE_{VRS} = 0.59
Songsrirote and Singhapreecha (2007)	SFA	Cross-section in crop year 2005-2006, 330 farms (165 conventional jasmine rice farms, 165 organic jasmine rice farms)	Thailand	Conventional farm $TE_{Input-oriented}$ = 0.45 $TE_{Output-oriented}$ = 0.71 Organic farm $TE_{Input-oriented}$ = 0.72 $TE_{Output-oriented}$ = 0.87
Chauhan et al. (2006)	DEA	Cross-sectional data of 97 farmers, crop year 2000-2001	India	TE_{CRS} = 0.77 TE_{VRS} = 0.92 SE = 0.83

Table 3.1 Empirical research on rice production efficiency (Continued)

Author(s)	Efficiency method	Data	Country	Average efficiency scores
Krasachat (2004)	DEA	Cross-sectional data of 74 farmers in 1999	Thailand	TE_{CRS} = 0.71 TE_{VRS} = 0.74 SE = 0.96
Dhungana et al. (2004)	DEA	Cross-section survey data of 76 farms in 1999	Nepal	TE_{CRS} = 0.76 TE_{VRS} = 0.82 SE = 0.93 AE_{VRS} = 0.87 EE_{VRS} = 0.66
Wadud (2003)	DEA and SFA	Cross-sectional data of 150 farms in 1997	Bangladesh	TE_{SFA} = 0.80 AE_{SFA} = 0.77 EE_{SFA} = 0.61 $TE_{CRS\text{-}DEA}$ = 0.86 $AE_{CRS\text{-}DEA}$ = 0.91 $EE_{CRS\text{-}DEA}$ = 0.78 $TE_{VRS\text{-}DEA}$ = 0.91 $AE_{VRS\text{-}DEA}$ = 0.87 $EE_{VRS\text{-}DEA}$ = 0.79
Coelli et al. (2002)	DEA	Cross-sectional data of 406 farms in 1997 (351 plots surveyed in the Aman season, 422 plots surveyed in the Boro season)	Bangladesh	Aman season TE_{VRS} = 0.66 SE = 0.93 AE_{VRS} = 0.78 EE_{VRS} = 0.52 Boro season TE_{VRS} = 0.69 SE = 0.95 AE_{VRS} = 0.81 EE_{VRS} = 0.56
Wadud and White (2000)	DEA and SFA	Cross-sectional data of 150 rice farms in 1997	Bangladesh	$TE_{CRS\text{-}DEA}$ = 0.79 $TE_{VRS\text{-}DEA}$ = 0.86 TE_{SFA} = 0.79

Note: DEA denotes data envelopment analysis, SFA denotes stochastic frontier analysis, DDF denotes directional distance function, TE denotes technical efficiency, SE denotes scale efficiency, AE denotes allocative efficiency, EE denotes economic efficiency, NAE denotes environmental allocative efficiency, NE denotes environmental efficiency, VRS denotes variable returns to scale, and CRS denotes constant returns to scale.

Ten of the 24 studies reported returns to scale; the scale efficiencies of their sample data are displayed in Table 3.2. Information on returns to scale can be used to identify whether a farmer produces at optimal scale (constant returns to scale (CRS)), below the optimal scale (increasing returns to scale (IRS)), or above the optimal scale (decreasing returns to scale (DRS)). "A farmer is said to operate under CRS, IRS, or DRS if a proportionate increase in all inputs leads to exactly the same, more than, or less than the proportionate increase in outputs, respectively" (Chauhan et al., 2006, p. 1074). This information is useful for indicating the potential redistribution of farming resources, thereby enabling a farmer to attain a higher yield (Chauhan et al., 2006).

The TE score obtained from the DEA model under the assumption of CRS can be decomposed into two components, one due to pure technical inefficiency (obtained from the DEA model under the assumption of variable returns to scale: VRS) and one due to scale inefficiency (Umanath and Rajasekar, 2013). The SE score for a farm can be evaluated by the ratio of its TE score obtained from the CRS assumption and its TE score obtained from the VRS assumption (Umanath and Rajasekar, 2013; Watkins et al., 2014). Since the production possibility frontier (PPF) constructed under the assumption of VRS envelops the data more tightly than the PPF constructed under the assumption of CRS, the TE score obtained from the VRS assumption is greater than or equal to the TE score obtained from the CRS assumption (Dhungana et al., 2004; Krasachart, 2004). Thus, the value of SE will be less than or equal to one ($SE \leq 1$), with SE equal to one (SE=1) when a farmer operates at an optimal scale, and SE less than one ($SE < 1$) when the farm is scale inefficient (a farm operates either above or below the optimal scale) with the scale inefficiency score equal to $1 - SE$ (Watkins et al., 2014).

Although the SE score can indicate whether a farmer is scale efficient or scale inefficient, it cannot identify whether this scale inefficiency occurs from IRS or DRS (Watkins et al., 2014). The IRS or DRS of each farm can be investigated by running the DEA model under the assumption of non-increasing returns to scale (NIRS) or DRS (Coelli et al., 2002; Watkins et al., 2014). A farmer operates under DRS if the TE score obtained from the DEA model under the NIRS assumption is equal to the TE score obtained from the DEA model under the VRS assumption. On the other hand, a farmer operates under IRS if the TE score obtained from the DEA model under the NIRS assumption is unequal to the TE score obtained from the DEA model under the VRS assumption (Coelli et al., 2002).

Table 3.2 shows that the average SEs reported in the ten studies are greater than or equal to 0.90, except one study which reports an average SE of 0.88 (Zahidul Islam et al., 2011). This indicates that the average scale inefficiencies is less than or equal to 10%, which is quite small. The main reasons for the scale inefficiencies of these studies vary. Three studies of rice production in Bangladesh report that the majority of scale inefficiencies result from DRS or farmers operating above the optimal scale (Wadud, 2003; Coelli et al., 2002, for the Boro rice season; Wadud and White, 2000). Two studies report scale inefficiencies resulting almost equally from both IRS and DRS (Umanath and Rajasekar, 2013 for rice production in India; Dhungana et al., 2004 for rice production in Nepal). The remaining studies report that the majority of scale inefficiencies result from IRS or farmers operating below the optimal scale.

Table 3.2 Comparison of average SE and percentage of returns to scale from previous empirical research on rice production efficiency measurement

Author(s)	Observations	Country	Average SE	CRS	IRS	DRS
Watkins et al. (2014)	158	U.S.A.	0.92	26%	49%	25%
Tung (2013)	1,000 (year 2010)	Vietnam	0.90	1%	69%	30%
Umanath and Rajasekar (2013)	90	India	0.95	37%	29%	34%
Nkang et al. (2011)	95	Nigeria	0.91	8%	81%	11%
Zahidul Islam et al. (2011)	355	Bangladesh	0.88	11%	73%	16%
Krasachat (2004)	74	Thailand	0.96	32%	49%	19%
Dhungana et al. (2004)	76	Nepal	0.93	11%	47%	42%
Wadud (2003)	150	Bangladesh	0.95	17%	20%	63%
Coelli et al. (2002)	Aman season 351 plots	Bangladesh	0.93	8%	54%	38%
	Boro season 422 plots		0.95	11%	31%	58%
Wadud and White (2000)	150	Bangladesh	0.92	15%	14%	71%

Note: SE, CRS, IRS, and DRS denote scale efficiency, constant returns to scale, increasing returns to scale, and decreasing returns to scale, respectively.

3.3.1 Empirical evidence of Thai rice production efficiency

Six of the nine studies in Southeast Asian countries have measured the TE of Thai rice at farm level using cross-sectional primary data in specific areas in various provinces in Thailand (Ogundari and Awokuse (2016) for rice production in the Bangplama district in Suphan Buri Province; Taraka et al. (2010) for rice production in Bangkok, Nonthaburi, Pathumthani, Phra Nakorn Si Ayutthaya, Chainat, Lopburi, Saraburi, Singburi, and Angthong provinces; Rahman et al. (2009) for rice production in Chiang Mai, Phitsanulok and Tung Gula Rong Hai provinces; Kiatpathomchai (2008) for rice production in Phatthalung and Songkhla provinces; Songsrirote and Singhapreecha (2007) for rice production in Yasothon province; Krasachat (2004) for rice production in Si Sa Ket, Surin, and Buri Ram provinces). Three studies used the input-oriented DEA model for their analysis (Taraka et al., 2010; Kiatpathomchai, 2008; Krasachat, 2004), while three studies used the SFA model (Ogundari and Awokuse, 2016; Rahman et al., 2009; Songsrirote and Singhapreecha, 2007). None of the researchers investigated the TE of Thai rice using output-oriented DEA and DDF. These analyses measured TE scores of farmers based on either per farm data of rice production (Ogundari and Awokuse, 2016; Krasachat, 2004) or rice output per hectare (Taraka et al., 2010; Rahman et al., 2009; Kiatpathomchai, 2008; Songsrirote and Singhapreecha, 2007). The input variables that have been used for the efficiency measurement of Thai rice production are seed, land cultivated, chemical fertiliser, organic fertiliser, pesticides, human labour, machinery labour, fuel, and other input costs.

The average TE scores obtained from input-oriented DEA models of Thai rice range from 0.52 to 0.87, while the average TE scores obtained from SFA models range from 0.45 to 0.93 (Table 3.1). The highest average TE score across the six studies is 0.93, reported in the study of Ogundari and Awokuse (2016). This is due to the fact that the Bangplama district has the highest rice cultivation area in Suphan Buri province and this province has the highest rice production in Thailand (OAE, 2013 cited in Ogundari and Awokuse, 2016, p. 9). The lowest average TE score across the six studies is 0.45 for conventional jasmine rice farms (input-oriented SFA model) in Yasothon province (Songsrirote and Singhapreecha, 2007). This average TE score is also the lowest average TE score compared to rice production efficiency studies in other countries (Table 3.1). A possible reason is that Thai farmers increased their rice production by the expansion of the area planted rather than by an increased rice output per hectare or yield (Taraka et al., 2010). The average SEs of Thai rice farming reported by Taraka et al. (2010) and Krasachat (2004) are 0.998 and 0.96, respectively (Table 3.1). Krasachat (2004) reports that the main source of the scale inefficiency of Thai rice farmers results from IRS, or farmers operating below the optimal scale (Table 3.2). He suggests that the production efficiency of Thai rice farmers can be improved by adopting the best practices of efficient rice farmers.

Moreover, the factors affecting the technical inefficiency of Thai rice production have been investigated using a two-limit Tobit regression model (Taraka et al., 2010; Kiatpathomchai, 2008; Krasachat, 2004). This model was employed in the second stage of the efficiency analysis because efficiency scores that are dependent variables in the regression model are bound between zero and one (Watkins et al., 2014). Thus, the dependent variable is not a normal distribution, hence ordinary least squares regression is not appropriate (Krasachat, 2004). Taraka et al. (2010) hypothesised that factors affecting technical inefficiency were demographic, socio-economic variables and farm characteristics, agricultural extension, and environmental variables. They found that the key factors affecting technical inefficiency were family labour, certified seed used, extension officer's services, and pest control used to deal with weeds and insects. Kiatpathomchai (2008) hypothesised that factors affecting technical inefficiency were rice variety, farm practices and management, farmer characteristics, and agro-ecosystems. She found that the factors affecting technical inefficiency were soil type and rice variety. Krasachat (2004) found that farm-specific factors, i.e. farm sizes, whether they were irrigated or not (as a dummy variable), and province (as a dummy variable), have no statistical significance effect on TE. However, scale inefficiency of rice farmers in the sample was affected by the provincial differences.

Only Kiatpathomchai (2008) has measured the economic and environmental efficiency of Thai rice farmers. The mean value of EEs or CEs in her study was 0.68, while 2% of sample farms, or 4 out of 247, were economically the best performing farms. This indicates that the farmers in the sample would be able to reduce the current cost of rice production by 32% and still obtain the same rice output. The measurement of NE scores was achieved by incorporating environmental pollution (i.e. nitrogen leaching and nitrogen emission) as input variables into the input-oriented DEA model in order to minimise environmental pollution while fixing the amount of rice output produced. The rationale behind this concept is that environmental pollution will be minimised when environmentally detrimental input (i.e. N fertiliser) is minimised. N-leaching into surface and ground water is calculated as 19% of the total amount of nitrogen applied to the rice field, while N-emission into the atmosphere as a greenhouse gas is calculated as 13.6% of the total amount of nitrogen applied to the rice field (Pathak et al., 2004 cited in Kiatpathomchai, 2008, p. 71). Kiatpathomchai (2008) found that the average values of NE for the sample farms is 0.54, while 2% of sample farms or 5 farms out of 247 farms were environmentally the best practice farms. This implies that average farms could reduce environmental pollution (i.e. N-leaching and N-emission) by reducing N fertiliser application by 46% of its current level and still obtain the current level of output.

3.3.2 Empirical evidence of rice production efficiency in other countries

A two-stage approach has become the standard when DEA is employed to evaluate the performance of farmers, and when factors that influence their efficiency are not under the farmers' control (Singbo and Lansink, 2010). The two-stage DEA approach consists of two steps. First, the efficiency score of a farm is calculated using the DEA model. Then the efficiency score obtained from the first step is used as the dependent variable in a two-limit Tobit regression model, or truncated regression model, to determine factors affecting efficiency levels of farms. Eight previous studies have employed a two-limit Tobit regression in their second step (Wadud and White, 2000; Coelli et al., 2002; Wadud, 2003; Dhungana et al., 2004; Zahidul Islam et al., 2011; Ahmed et al., 2011; Watkins et al., 2014; Tun and Kang, 2015), and two previous studies have employed a truncated regression model in their second step (Balcombe, 2008; Tung, 2013). However, there are three studies that have not examined the factors affecting efficiency levels of farms (Chauhan et al., 2006; Nkang et al, 2011; Umanath and Rajasekar, 2013).

While a number of studies have investigated rice production efficiency in countries other than Thailand using Stochastic Frontier Analysis, DEA, and DDF approaches (Table 3.1), only one study has employed the DDF approach (Singbo and Lansink, 2010), and only one study has measured the environmental efficiency of rice farming systems (Nguyen et al., 2012).

Nguyen et al. (2012) examined the cost and efficiency of nutrient use by 96 rice farmers in South Korea's Gangwon province over the period 2003 to 2007. They also determined the cost of introducing nutrient efficiency operations to farms by employing the theoretical framework proposed by Coelli et al. (2007) which is presented in the next section. In their environmental efficiency analysis, two nutrients applied to rice fields, N and P, were used to calculate the "eutrofying power: EP" by using the constant weight of 1 for N and 10 for P. Thus "$EP = amount\ of\ N + 10 \times amount\ of\ P$". This constant weight has been applied in other environmental efficiency studies such as Coelli et al. (2007), Houng and Coelli (2011), and Hoang and Alauddin (2012). Nguyen et al. (2012) used input-orientated DEA and the Cobb-Douglas production function to confirm that the production technology exhibited CRS. They found that improvements in technical performance would lead to better NE and lower costs of production. However, it is costly for rice farmers to change their current operation to become environmentally efficient: farmers production costs would be increased by 119%, while the eutrofying effect on water would be reduced by 69%. Thus, Nguyen et al. (2012, p. 367) suggest that “agri-environmental policies should be (re)designed to improve both cost and environmental performance of rice farms”. The empirical evidence of Singbo and Lansink (2010) will be discussed in Section 3.5.

3.4 Empirical evidence of environmental efficiency measurement

As a result of increasing concern about environmental problems caused by negative impacts of production activities, many researchers have attempted to incorporate the negative impact of a production process on the environment into the traditional productivity and efficiency analysis methods in order to monitor the environmental performance of DMUs (Coelli et al., 2007). The negative impact was incorporated both in terms of detrimental inputs (e.g. Chung et al., 1997; Reinhard et al., 2000; Shaik et al., 2002; De Koeijer et al, 2002; Areal et al, 2012) and undesirable (bad) outputs (e.g. Färe et al., 1989; Shaik et al., 2002; Färe et al., 2005, Picazo-Tadeo et al., 2005; Macpherson et al., 2010; Färe et al., 2012; Toma et al., 2013) into Stochastic Frontier Analysis, DEA, and DDF approaches.

Reinhard et al. (2000) estimated the NE of an unbalanced panel dataset involving 613 Dutch dairy farms over the period 1991 to 1994 (a total of 1,535 observations) using both Stochastic Frontier Analysis (translog functional form) and DEA (under the assumption of VRS for both input-orientation and output-orientation) methods. They used three environmentally detrimental inputs, nitrogen surplus, phosphorus surplus, and total energy use, to estimate the NE scores. Note that nitrogen (phosphate) surplus is the difference between nitrogen (phosphate) in inputs and nitrogen (phosphate) contained in outputs (i.e. material balance condition). NE is defined as “the ratio of minimum feasible to observed use of multiple environmentally detrimental inputs, conditional on observed levels of output and the conventional inputs” (Reinhard et al., 2000, p.287). Reinhard et al. (2000) treated these three environmentally detrimental variables as additional factors of production (i.e. inputs). This means that a production function was specified by including a vector of the quantity of conventional inputs and these three environmentally detrimental inputs. The minimum feasible multiple environmentally detrimental inputs can be calculated using the DEA model which estimates the performance of a farm in terms of the ability to reduce its environmentally detrimental inputs by fixing the same amount of outputs produced and conventional inputs used (Reinhard et al., 2000). Thus, the NE for each farm can be measured by dividing the minimum feasible multiple environmentally detrimental inputs by its observed amount of multiple environmentally detrimental inputs. Reinhard et al. (2000) found that the average NE score of Dutch dairy farms ranged between 52%-80% depending on the empirical technique used. They claimed that NE scores of their observation could be estimated using both the stochastic production frontier and DEA; however, the estimation of these scores using the stochastic production frontier could be done only in two bad input cases because the three environmentally detrimental input cases (including phosphate surplus) violated monotonicity restrictions. Furthermore, DEA can be used to measure NE for many environmentally detrimental inputs, since it fulfils monotonicity and curvature restrictions.

Areal et al. (2012) analysed the TE of a balanced panel dataset comprising 215 dairy farms in England and Wales over the years 2000 to 2005 using the Farm Business Survey (FBS). They used the ratio of permanent and rough pasture land to total agricultural area as the proxy for environmental goods because information on environmental goods (e.g. manures and organic matter, decomposition of plant residues etc.) was unavailable in the FBS. Areal et al. (2012) conducted a DDF by assuming a translog function for the parametric distance function and using a Bayesian procedure to investigate TE in two models that included and excluded the provision of environmental outputs. They found that the rank of farm efficiency changed when the provision of environmental output was included in the efficiency analysis. With the incorporation of environmental output, 40% of the top ranked 25 farms using the model that excluded the provision of environmental output were not in the top ranked 25 using the model that included the provision of environmental output. In addition, 70% of these were not in the top ranked 50. Furthermore, 48% of the bottom ranked 25 farms using the model that excluded the provision of environmental output were not in the bottom ranked 25 using the model that included the provision of environmental output. In addition, 50% of these were not in the bottom ranked 50. Areal et al. (2012) concluded that these results would affect the implementation of policy targeting aimed at improving farm environmental efficiency. If the farms that have a low efficiency level using a ranking derived from a model excluding environmental output are chosen, the policy may be targeting the wrong farms because these farms have high NE levels (i.e. they are technically and environmentally efficient), and overlooking farms that have the potential to improve their efficiency.

Picazo-Tadeo et al. (2005) measured the NE scores of a cross-sectional sample of 35 Spanish ceramic tile producers in 1995 using DDF approach following Färe et al., (1989). The residues from ceramic tile producing were used as undesirable outputs (watery mud and used oil). In their investigation of the impact of environmental regulations on the performance of firms, they assumed that ceramic firms aimed to maximise their ceramic pavement production (desirable output) while simultaneously reducing inputs without a change in the undesirable outputs. This implies that inefficient firms would be able to improve their production process to become environmentally friendly producers and enable them to produce more ceramic pavements (desirable outputs) using less inputs while fixing the same amount of watery muds and used oil (bad outputs). The environmental measurement applied in Picazo-Tadeo et al. (2005) is different from that of Reinhard et al. (2000). Reinhard et al. (2000) measured the environmental performance of a producer in terms of its ability to reduce its environmentally detrimental inputs without changing any of its desirable outputs and conventional inputs. On the other hand, Picazo-Tadeo et al. (2005) measured the environmental performance of a producer in terms of its ability to simultaneously expand its desirable output and contract its conventional inputs without changing any of its undesirable outputs. Picazo-Tadeo et al. (2005) stated that a key issue in the DDF approach is the choice of directional vector, because it leads to specific directions of increase or decrease for all elements of the input, desirable output, and undesirable output vectors. For their directional vector, they chose the unity that decreases one unit of inputs and increases one unit of desirable outputs with no change in the undesirable outputs. They found that the aggregate goods output produced by their observations could be increased by 7% under the assumption of strong or free disposability (that allows any output to be disposed of without cost). Conversely, the potential expansion of goods output increased by 2.2% under the weak disposability of outputs assumption (the undesirable output may not be disposed of without cost because of regulatory restrictions). Picazo-Tadeo et al. (2005, p. 140) suggest that "environmental regulations have an opportunity cost that can be measured as a smaller feasible increase of good outputs". They conclude that the DDF provides a flexible and useful method to measure the cost of environmental regulations of undesirable outputs. Moreover, the methodological approach used in this research allows for maximising desirable outputs and minimising undesirable outputs, as well as inputs.

Coelli et al. (2007) demonstrated that efficiency models which incorporate environmental detrimental inputs as an undesirable output variable (e.g. Färe et al., 1989; Färe et al., 1996) or an input variable (e.g. Reinhard et al., 2000) into standard production technology models may be inconsistent with the "materials balance condition: MBC" when the MBC is applicable. The MBC implies that the nutrients balance equals the quantity of nutrients that farmers apply to their fields minus the quantity of nutrients absorbed by plants (Coelli et al, 2007; Reinhard and Thijssen, 2000). When environmental detrimental input is incorporated in the standard production efficiency model as an undesirable output variable, only efficient farms that produce on the production frontier are consistent with the MBC while inefficient farms that produce below the production frontier are inconsistent. Likewise, when environmentally detrimental input is incorporated in the standard production efficiency model as an input variable, only efficient farms that produce on the production frontier are consistent with the MBC, while inefficient farms that produce below production frontier are inconsistent. Coelli et al. (2007) proposed a new NE measurement based on the concept of the MBC by attempting to minimise the nutrient content in inputs. The minimum nutrient content in each farm's inputs is measured by employing the input-oriented DEA method which is similar to the cost-minimising DEA method. Then the NE scores of each farm are calculated by "the ratio of minimum nutrients over observed nutrients" (Coelli et al., 2007, p. 7). The NE score has a value between zero and one. An NE score of one indicates that a farm is fully NE. Moreover, the NE measure proposed by Coelli et al. (2007) can be decomposed into TE and environmental allocative efficiency in a similar manner to the cost-minimising DEA efficiency decomposition. This measure has been applied for other NE measurements (e.g. Hoang and Alauddin, 2012; Hoang and Coelli, 2011; Nguyen et al., 2012). Coelli et al. (2007) illustrated this measure using the case study of the phosphorus emission of a cross-section of 183 pig farms in Belgium in the accounting year 1996 to 1997. The TE and CE scores were computed by the standard DEA approaches. They concluded that the nutrient pollution of Belgian pig-finishing farms can be proportionally decreased in a cost-reducing manner.

3.5 Empirical studies of efficiency measurement using directional distance function

The DDF based on Luenberger's benefit function was introduced by Chambers et al. (1996; 1998). It has been used to measure the TE of farms for reducing inputs while simultaneously increasing outputs (Chambers et al., 1998; Ray, 2008; Färe and Grosskopt, 2005; Zofio, et al., 2013; Ang and Kerstens, 2016). This approach can help researchers to avoid making an arbitrary choice between input and output orientated DEA measures. However, the researcher has to specify directions for each farm when using the DDF approach (Coelli et al, 2005). The interpretation of inefficiency scores obtained by the DDF approach depends on the choice of directional vector, which is arbitrary, depending on the researchers' choice. The different choices of directional vectors that have been applied in previous studies are as follows.

Singbo and Lansink (2010, p. 369) proposed a theoretical model of inefficiency analysis called the "Two-stage semi-parametric and bootstrap model". They illustrated this measure using the case study of lowland farming systems in the Benin Republic (West Africa). This includes rice farming systems (28 farms), vegetable farming systems (35 farms), and rice-vegetable farming systems (30 farms). First, they employed the DDF method to measure the inefficiency of these systems. They chose the directional vector towards observed farms' own inputs and outputs following Chambers et al. (1998 cited in Singbo and Lansink, 2010, p. 373). Secondly, they examined factors affecting the inefficiency levels of these systems employing a single truncated bootstrap procedure proposed by Simar and Wilson (2007 cited in Singbo and Lansink, 2010, p. 372). They found that the main sources of inefficiency in the short run were scale, allocative and output inefficiency. They concluded that the inefficiency of lowland farming systems was different. They suggested promoting integrated rice-vegetable farming systems in West Africa using lowland development strategies in order to increase food security.

Färe et al. (2007) investigated the environmental performance of 92 coal-fired power plants using the DDF approach in 1995. The data set consists of one good output (net electrical generation), two bad outputs (sulphur dioxide and nitrogen oxides), and 5 inputs (capital stock, the number of employees, the heat content of coal, the heat content of oil, and the heat content of natural gas). They incorporated two bad outputs into the DDF model as input variables. This model is called the environmental directional distance function. Its concept is to simultaneously expand good output production and contract bad output production. This concept is different from that of Reinhard et al. (2000), who attempted to minimise multiple environmentally detrimental inputs by fixing the same level of desirable output and conventional inputs. Färe et al. (2007), on the other hand, attempted to simultaneously minimise multiple environmentally detrimental inputs and maximise desirable output by fixing the same level of conventional inputs. Moreover, the concept of Färe et al. (2007) is also different from that of Picazo-Tadeo et al. (2005), since the latter attempted to simultaneously minimise conventional inputs and maximise desirable output by fixing the same level of undesirable output. Färe et al. (2007) chose the directional vectors to be decreases one unit of input (i.e. two bad outputs) and increases one unit of output, fixing the same level of conventional inputs. This direction has also been chosen in other studies (e.g. Färe et al., 2005; Färe et al., 2012; Picazo-Tadeo et al., 2005; Machperson et al., 2010).

Ang and Kerstens (2016) employed the DDF approach to measure the inefficiency level of mixed farms in England and Wales over the period 2007 to 2013. The data set consists of two outputs (i.e. crop production and livestock production), 12 variable inputs, and six fixed factors. They used directional vector towards the observed farms' inputs used and output produced. This means that all inputs and outputs were adjusted in proportion for each individual farm. The reason for choosing this direction is to ensure that the DDF function is feasible and can be interpreted as simultaneously maximising proportional expansion of outputs and contraction of inputs. This directional vector has been applied in the DDF literature, including studies by Chung et al. (1997), Ray (2008), Singbo and Lansink (2010), and Riccardi et al. (2012).

Zofio et al. (2013) suggest choosing the directional vector that projects inefficient firms towards a profit maximising benchmark. The projecting point on the efficiency frontier is the point where the iso-profit line is tangent to the production possibility frontier. However, this directional vector is possible only when market prices of inputs and outputs are observed and firms have profit maximising behaviour. The DDF model that uses the directional vector towards the profit maximisation point is called the directional profit efficiency measure. This model is different from that used in other studies because the directional vector is not preassigned and its elements could take positive or negative values. Zofio et al. (2013) illustrate this model by measuring the inefficiency scores of eight firms that produce two outputs using two inputs. The inefficiency scores obtained from this model can be decomposed into technical inefficiency, which measures the distance to the frontier, and allocative inefficiency, which measures the deviation from the optimal mix of outputs and inputs (overall profit efficiency (OPE) = TE +AE). The firm is said to be profit efficient if the firm's profit is maximal. Then the technical and allocative inefficiency scores are equal to zero, or the firm is both technically and allocative efficient. When a firm is profit inefficient and its observed profit is not maximal, there are two possible reasons. First, the profit inefficiency is due to the technical inefficiency if the difference between observed profit and maximum profit is equal to the technical inefficiency score obtained from the standard DDF model. Second, the profit inefficiency is due to the allocative inefficiency if technical inefficiency score obtained from the standard DDF model is equal to zero (this firm is technically efficient, but allocatively inefficient).

3.6 Summary

This chapter has reviewed research investigating several areas relevant to the current study. Firstly, it discussed rice production efficiency measurement in Thailand and other countries, and then reviewed NE measurements in rice and other productions. Finally, it examined the application of DDF in previous literature. None of the empirical studies on efficiency measurement of rice production in Thailand has addressed efficiency analysis at farm level for the whole country, nor has it investigated the TE of Thai rice using output-oriented DEA and DDF approaches. Moreover, only one of the studies reviewed (Kiatpathomchai, 2008) has investigated the environmental efficiency of Thai rice farmers by incorporating N-leaching and N-emission in the input-oriented DEA model as input variables. None of empirical studies on the efficiency measurement of rice production in Thailand takes "the material balance condition" (Coelli et al., 2007) into NE consideration during its analysis.

Therefore, this study examines the technical and environmental efficiencies of Thai rice farmers for the whole country, using cross-sectional data from the crop year 2008/09 of 1,112 rice farms. These sample farms were categorised into 9 groups of observations, which will be explained in detail in Chapter 5.

Input-oriented DEA, output-oriented DEA, and DDF models will be used to measure the TE of a homogenous set of Thai rice farmers, since these farmers produced rice output using the same kind of inputs (i.e. seed, land cultivated, chemical fertiliser, organic fertiliser, pesticide, human labour, machinery labour, fuel, and other input costs). Since the choice of directional vector for the DDF approach is arbitrary, this study investigates the technical inefficiency of Thai rice farming using the directional vectors used by Ang and Kerstens (2016), and Zofio, et al. (2013).

Furthermore, this study integrates the concept of MBC, as proposed by Coelli et al. (2007), and the directional profit efficiency measure proposed by Zofio et al. (2013) to measure the NE of the Thai rice farming systems. The DDF model is measured using the directional vector that projects inefficient farms towards a nutrient surplus minimising frontier. The projecting point on the efficiency frontier is the point where the iso-nutrient line is tangent to the production possibility frontier. Nitrogen and phosphorus surplus from rice farming practice are key input variables for the NE measurement in this study. The environmental problems caused by rice cultivation have been reviewed in Chapter 2. Reducing the nitrogen and phosphorus surpluses arising from rice production can lead to the reduction of environmental problems, especially nitrate contamination of the surface and groundwater, and the eutrophication of surface water.

The major problems of Thai rice farmers are high production cost and low income. Improvement of TE by reducing input usage to produce the same quantity of rice output (input-oriented DEA model) can reduce the cost of production, as well as nutrient surplus from fertiliser application. Improvement of TE by using the same level of inputs to produce higher rice output (output-oriented DEA model) can increase farmers' income and reduce nutrient surplus from fertiliser application because farmers could use the same level of inputs but obtain a higher output level. In addition to the DDF approach, improvement of farm efficiency, by simultaneously increasing the amount of output together with reducing the amount of inputs, can increase farmers' income and reduce production costs as well as reducing nutrient surplus from fertiliser application.

Chapter 4

Methodology

4.1. Introduction

The main objective of this research is to measure the technical and environmental efficiency of Thai rice farming systems. Therefore, the purposes of this chapter are to introduce the methodology used in this research, and to introduce the directional nutrient surplus efficiency measure. The directional nutrient surplus efficiency measure incorporates nutrient surplus into the conventional Directional Distance Function (DDF) in a similar manner to that in which price information is normally incorporated in the directional profit efficiency measure (Zofio et al., 2013). This measure is used to assess the environmental performance of Thai rice production. The technical efficiency (TE) measurements using Data Envelopment Analysis (DEA) and the DDF are introduced. The basic concepts of directional profit efficiency measures (Zofio, et al., 2013), the material balance condition (MBC) (Coelli et al., 2007), the data cloud method (Wilson, 1993), and the non-parametric tests of returns to scale (Simar and Wilson, 2002) are also explained.

After the introduction in Section 1, the definition of production possibility set and its underlying basic assumptions are provided in Section 2 and Section 3. The concept of evaluation of farms' performance is illustrated in Section 4. Section 5 and Section 7 explain the concept of evaluation of farms' performance by using DEA and DDF approaches, respectively. The basic concepts of the MBC and the directional profit efficiency measure are explained in Section 6 and Section 8, respectively. Section 9 introduces the directional nutrient surplus efficiency measure. The data cloud method that is used to identify outliers in the non-parametric frontier model is presented in Section 10. The important of non-parametric tests of returns to scale is explained in Section 11.

4.2 Production technology

A decision making unit (DMU) in a farming system is a farm that decides its production plan by choosing a combination of inputs to produce outputs. Assume that a set of *n* farms is observed, with each farm $i = \{1, \dots, n\}$ using a set of *k* inputs to produce a set of *m* outputs. For the *i*th farm, $x^i = (x_1^i, x_2^i \dots, x_k^i) \in \mathbb{R}_+^k$ and $y^i = (y_1^i, y_2^i, \dots, y_m^i) \in \mathbb{R}_+^m$ are defined as the *k-vector* of inputs and *m-vector* of outputs, respectively[12]. The production plan for the i^{th} farm is defined as:

$$\left(x^i, y^i\right) \in \mathbb{R}_+^k \times \mathbb{R}_+^m \tag{4.1}$$

Note that $\mathbb{R}_+ = \{a \in \mathbb{R} | a \geq 0\}$. This implies that both inputs and outputs for the i^{th} farm are greater than or equal to zero (i.e. a non-negative number).

Therefore, the input data matrix X and the output data matrix Y for a set of n farms can be written as follows:

$$X = \begin{bmatrix} x_1^1 & x_2^1 & \dots & x_k^1 \\ x_1^2 & x_2^2 & \dots & x_k^2 \\ \vdots & \vdots & \vdots & \vdots \\ x_1^n & x_2^n & \dots & x_k^n \end{bmatrix}_{n \times k}$$

$$Y = \begin{bmatrix} y_1^1 & y_2^1 & \dots & y_m^1 \\ y_1^2 & y_2^2 & \dots & y_m^2 \\ \vdots & \vdots & \vdots & \vdots \\ y_1^n & y_2^n & \dots & y_m^n \end{bmatrix}_{n \times m}$$

The production possibility set (PPS) or the technology set, T, is defined as (Bogetoft and Otto, 2011; Thanassoulis et al., 2008):

$$T = \{(x, y) \in \mathbb{R}_+^k \times \mathbb{R}_+^m \mid x \; can \; produce \; y\} \tag{4.2}$$

This technology set or PPS is unknown in many applications, because the whole population of production systems is not observed. The estimate is based on the observed input and output data of sample farms, and then the observed inputs and outputs of a farm are evaluated relative to this estimated PPS (Bogetoft and Otto, 2011). In the DEA, the estimated technology set or PPS is constructed based on the minimal extrapolation principle. This implies that the estimated technology set is the smallest subset of $\mathbb{R}_+^k \times \mathbb{R}_+^m$ that contains the data $\left(x^i, y^i\right), i = 1, \dots, n$ and satisfies the assumptions of production technology (i.e. monotonicity, convexity, and various notions of returns to scale) without specifying any functional form (Banker et al., 1984; Bogetoft and Otto, 2011). The production technology assumptions of DEA are as follows (Thanassoulis et al., 2008; Bogetoft and Otto, 2011):

Assumption 1 (A1): Feasibility of input-output combinations. An input-output combination (x, y) is feasible when the output vector y can be produced by the input vector x. Assume

[12] Subscripts are used to indicate the different kinds of inputs and outputs, while superscripts are used to indicate the different farms. All the inputs or outputs are considered as a vector format when the subscripts are absent.

there exists a set of *n* farms using *k* inputs to produce *m* outputs. Let $x^i = \left(x_1^i,\ x_2^i\ \ldots, x_k^i\ \right)$ be the observed vector of inputs and $y^i = \left(y_1^i,\ y_2^i, \ldots, y_m^i\ \right)$ be the observed vector of outputs of the *i*th farm. Then for each farm $i\ =\ \{1, \ldots, n\}$, (x^i, y^i) is a feasible input-output combination (production plan). Thus, $\left(x^i, y^i\right) \in T$.

Assumption 2 (A2): Monotonicity or free disposability of inputs and output.

Free disposability of inputs: If $(x, y) \in T$ and $x' \geq x$ then $(x', y) \in T$. This implies that the same amount of outputs can be produced using a given amount of inputs, or using a greater amount of inputs, so long as the surplus inputs can be freely disposed of.

Free disposability of outputs: If $(x, y) \in T$ and $y' \leq y$ then $(x, y') \in T$. This means that a fixed amount of inputs can produce a fixed amount of outputs, or can produce fewer outputs, so long as surplus outputs can be freely disposed of.

Free disposability of inputs and outputs: If $(x, y) \in T$, $x' \geq x$ and $y' \leq y$, then $(x', y') \in T$. This means that the unnecessary inputs (i.e. excess inputs) and unwanted outputs can be freely disposed of.

Assumption 3 (A3): Convexity. The PPS or the technology set T is convex. This implies that any weight of feasible production plans (two input-output combinations) in the sample is also feasible: if $(x, y) \in T$, $(x', y') \in T$, and any weight $0 \leq \lambda \leq 1$, then the weighted sum $\left(x^\lambda, y^\lambda\right) = [(1 - \lambda)(x, y) + \lambda(x', y')] \in T$. i.e.

$$(x, y) \in T, (x', y') \in T, 0 \leq \lambda \leq 1\ \Rightarrow [(1 - \lambda)(x, y) + \lambda(x', y')] \in\ T$$

The weighted sum $\left(x^\lambda, y^\lambda\right)$ is called a convex combination of (x, y) and (x', y') with weight λ. This implies that any points (production plans) on the line between any two points (production plans) in the technology set *T* are also in *T*.

Assumption 4 (A4): Returns to scale (γ). The returns to scale (RTS) assumption suggests that rescaling of production plan is possible (Bogetoft and Otto, 2011). The production plan can be rescaled with any of a given set of factors:

$$(x, y) \in T, \beta \in \Gamma(\gamma)\ \Longrightarrow \beta(x, y) \in T, \beta \geq 0$$

where γ = constant returns to scale (CRS), decreasing returns to scale (DRS) or non-increasing returns to scale (NIRS), increasing returns to scale (IRS) or non-decreasing returns to scale (NDRS), and variable returns to scale (VRS)[13] . The possible rescaling factors sets for the different RTS assumptions are given by $\Gamma(CRS) = \mathbb{R}_0$ $(\beta \geq 0)$, $\Gamma(DRS) = [0,1]$ $(0 \leq \beta \leq 1)$, $\Gamma(IRS) = [1, \infty]$ $(\beta \geq 1)$, and $\Gamma(VRS) = \{1\}(\beta = 1)$ (Bogetoft and Otto, 2011).

In the DEA, the estimated production technologies are different depending on which assumption of RTS is chosen. Of these four RTS assumptions, the VRS assumption, which indicates that no rescaling is possible, is the weakest assumption, while the CRS assumption, that any combination of production plans can be arbitrarily scaled down or up, is the strongest assumption. Between the assumptions of CRS and VRS, the assumption of NIRS indicates that any degree of downscaling is possible but not any degree of upscaling. This implies that it cannot be disadvantageous to be small but that it may be disadvantageous to be large. Finally, the assumption of NDRS, which is less commonly used, states that it cannot be a disadvantage to be large but that it may be possibly be a disadvantage to be small (Bogetoft and Otto, 2011).

Assumption 5 (A5): No free lunch. This assumption states that no output can be produced without some input. If $y \geq 0$ and $y \neq 0$ then $(0, y) \notin T$.

4.3 The PPS under the assumption of constant returns to scale

Assumptions A1 – A4 are used to empirically construct a technology set or PPS from the observed inputs-outputs of farms in the sample without specifying any functional form of a production function. Consider the construction of a technology set or PPS of the observed input-output set $(\hat{x}, \hat{y}) \in T$ where $\hat{x} = \sum_{i=1}^{n} \mu^i x^i$ is a linear combination of inputs set, $\hat{y} = \sum_{i=1}^{n} \mu^i y^i$ is a linear combination of outputs set, $\sum_{i=1}^{n} \mu^i = 1$, and $\mu^i \geq 0$.

By (A1) $(\hat{x}, \hat{y})$ is feasible i.e. $(\hat{x}, \hat{y}) \in T$.

If $x \geq \hat{x}$ and $y \leq \hat{y}$, by assumption (A2) we conclude that the input output set (x, y) is also feasible i.e. $(x, y) \in T$.

For (A4), if we assume that the technology set or PPS exhibits CRS, then $(\beta\hat{x}, \beta\hat{y})$is also feasible set for any $\beta \geq 0$, $(\beta\hat{x}, \beta\hat{y}) \in T$

[13] CRS means that output will change by the same proportion as inputs are changed (e.g. a doubling of all inputs will double output). VRS reflects the fact that production technology may IRS (when we double all inputs, output is more than doubled), CRS, and DRS (when we double all inputs, output is less than doubled) (Coelli et al., 2002).

Since $x \geq \hat{x}$ and $y \leq \hat{y}$ then $x \geq \beta\hat{x}$ and $y \leq \beta\hat{y}$

Then, we get $x \geq \beta \sum_{i=1}^{n} \mu^i x^i$, $y \leq \beta \sum_{i=1}^{n} \mu^i y^i$, $\sum_{i=1}^{n} \mu^i = 1$, $\mu^i \geq 0$, $\beta \geq 0$.

$$x \geq \sum_{i=1}^{n} \beta\mu^i x^i , y \leq \sum_{i=1}^{n} \beta\mu^i y^i, \sum_{i=1}^{n} \mu^i = 1, \mu^i \geq 0, \beta \geq 0.$$

Next if $\lambda^i = \beta\mu^i$, then the above relationship translates into

$$x \geq \sum_{i=1}^{n} \lambda^i x^i , y \leq \sum_{i=1}^{n} \lambda^i y^i, \sum_{i=1}^{n} \lambda^i = \beta, \lambda^i \geq 0, \beta \geq 0$$

Note that $\sum_{i=1}^{n} \lambda^i = \sum_{i=1}^{n} \beta\mu^i = \beta \sum_{i=1}^{n} \mu^i$ since $\sum_{i=1}^{n} \mu^i = 1$

then $\sum_{i=1}^{n} \lambda^i = \beta, \lambda^i \geq 0, \beta \geq 0$

The only restriction on the construction of this technology set or PPS is that β is a non-negative value $(\beta \geq 0)$. As a result, λ^i has to be non-negative values, which is the only restriction on the λ^i. Since $\sum_{i=1}^{n} \lambda^i = \beta$. Therefore, the construction of the technology set or PPS is different depending on the β or the RTS assumption that assumes for the technology set or PPS

Based on the assumptions A1-A3, A4 under the assumption of CRS, and the observed input and output set, the technology set or PPS can be defined as follows:

$$\mathrm{T}^C = \left\{(x, y): y \leq \sum_{i=1}^{n} \lambda^i y^i , x \geq \sum_{i=1}^{n} \lambda^i x^i , \lambda^i \geq 0, i = 1, \ldots, n\right\} \qquad (4.3)$$

where the superscript C indicates that the technology set or PPS is characterised by the assumption of CRS.

4.4 Evaluation of farms' performances

The performance of a farm can be evaluated using a ratio of its inputs used to its outputs produced (i.e. the productivity ratio), and the relative performance evaluation or benchmarking (Bogetoft and Otto, 2011). Benchmarking is the systematic comparison of the performance of farms using the same type of inputs to produce the same type of output. It compares the performance of one farm against other farms in the sample (Bogetoft and Otto, 2011; Gadanakis, 2014). The performance of each farm is estimated by the distance from its position relative to a specific efficient production frontier (i.e. the production possibility frontier (PPF)) which represents the minimum of inputs used to produce a fixed amount of outputs or the maximum outputs produced by using a fixed amount of inputs.

The performance of farms can be compared by their TE scores, which are measured by either the input or the output approach. The input approach attempts to evaluate the ability to minimise the amount of inputs to produce a fixed amount of output, while the output approach attempts to evaluate the ability to maximise the amount of output by using a fixed amount of inputs. Therefore, a farm can be defined as technically efficient when it manages to minimise the amount of inputs to produce a fixed amount of output, or maximise the amount of output by using the same level of inputs (i.e. the farm operates on the production frontier) (Bogetoft and Otto, 2011).

The input-based Farrell efficiency (input efficiency or input distance function) and the output-based Farrell efficiency (output efficiency or output distance function) of a production plan (x, y) relative to PPS or technology T are defined as Eq. (4.4) and Eq. (4.5), respectively (Bogetoft and Otto, 2011).

$$E = E(x, y) = min\{E > 0 | (Ex, y) \in T\} \tag{4.4}$$

$$F = F(x, y) = max\{F > 0 | (x, Fy) \in T\} \tag{4.5}$$

where E and F represent the maximal proportional reduction of the amount of all inputs x that allows production of the same amount of outputs y, and the maximal proportional expansion of the quantity of all outputs y that can be produced with a fixed amount of inputs x, respectively. For example, if the input efficiency score of a farm equals 0.75 (E = 0.75), this implies that this farm could reduce all inputs by 25% and still obtain the same amount of all outputs. If the output efficiency score of a farm equals 1.2 (F = 1.2), it implies that this farm could expand all outputs by 20% by using the same amount of all inputs.

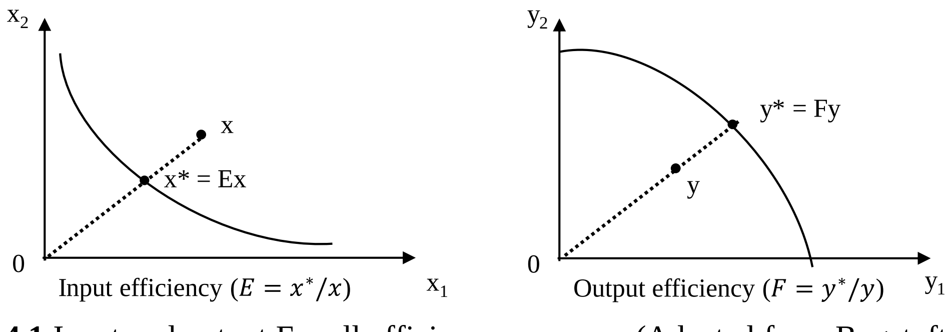

Figure 4.1 Input and output Farrell efficiency measures (Adapted from Bogetoft and Otto, 2011)

The concept of input and output based Farrell efficiency measures is illustrated in Figure 4.1 when there are two inputs and two outputs (Bogetoft and Otto, 2011). The left hand figure presents the input isoquant corresponding to the amount of outputs produced (y), while the right hand figure presents the output isoquant corresponding to the amount of inputs used (x). Inputs and outputs can be proportionally contracted and expanded along the dotted lines in the two graphs. The input-based Farrell efficiency of a farm is measured as the smallest number of E that is used to multiply the amount of x and then Ex remains above or on the input isoquant. Thus, the value of E is less than or equal to one ($E \leq 1$). Likewise, the output-based Farrell efficiency of a farm is measured as the largest number of F that is used to multiply the amount of y and then Fy remains below or on the isoquant. Thus, the value of F is greater than or equal to one ($F \geq 1$). The farm is less efficient when it has the smaller E or the larger F (Bogetoft and Otto, 2011).

The input distance function Eq. (4.4) and output distance function Eq. (4.5) give an alternative description of the PPS or technology T. Particularly, if $E(x, y)$ or $F(x, y)$ for all $(x, y) \in \mathbb{R}_+^k \times \mathbb{R}_+^m$ are known, the technology T is also known. Therefore, the input distance function and output distance function provide a complete characterisation of the technology T as

$$T = \{(x, y) \in \mathbb{R}_+^k \times \mathbb{R}_+^m | E(x, y) \leq 1\} \quad (4.6)$$

$$T = \{(x, y) \in \mathbb{R}_+^k \times \mathbb{R}_+^m | F(x, y) \geq 1\} \quad (4.7)$$

The inverse of the Farrell efficiency measures, which are commonly applied to measure TE in the literature, are called Shephard distance functions. Thus, the Shephard input distance function (D_i) and the Shephard output distance function (D_o) are defined as Eq. (4.8) and Eq. (4.9), respectively (Bogetoft and Otto, 2011; Chambers et al., 1998).

$$D_i = max\left\{D > 0 \left| \left(\frac{x}{D}, y\right) \in T\right.\right\} = 1/E(x, y) \quad (4.8)$$

$$D_o = min\left\{D > 0 \left| \left(x, \frac{y}{D}\right) \in T\right.\right\} = 1/F(x, y) \quad (4.9)$$

Similar to Farrell efficiency measures,

$$T = \{(x, y) \in \mathbb{R}_+^k \times \mathbb{R}_+^m | D_i(x, y) \geq 1\} \quad (4.10)$$

$$T = \{(x, y) \in \mathbb{R}_+^k \times \mathbb{R}_+^m | D_o(x, y) \leq 1\} \quad (4.11)$$

The concepts of the PPS or technology T, input-based and output-based Farrell efficiencies, and TE are illustrated in Figure 4.2 using one input (x) and one output (y) production plan of farms $\{A, B, C, D, E, F\}$. The PPF under the CRS assumption is represented by the dotted line OP, while the PPF under the VRS assumption is represented by the concave envelope EACD. The PPF is forced through the origin when CRS is assumed; this does not happen when VRS is assumed.

The technically efficient farms lie on the PPF, while the technically inefficient farms lie below the PPF (Coelli et al, 2002; Ahmed et al., 2011). Farm B in figure 4.2 is technically inefficient as it operates below the PPF under both CRS and VRS assumptions. The TE score of farm B using the input-oriented Farrell measure under the assumption of CRS (OP frontier) is the ratio *QR/QB*, while the TE score of farm B using the output-oriented Farrell measure under the assumption of CRS is the ratio *VB/VU*. Note that the TE scores obtained from input-oriented and output-oriented Farrell measures are equivalent only under the assumption of CRS i.e. *QR/QB* = *VB/VU* (Coelli et al, 2002; Bogetoft and Otto, 2011; Gadanakis, 2014).

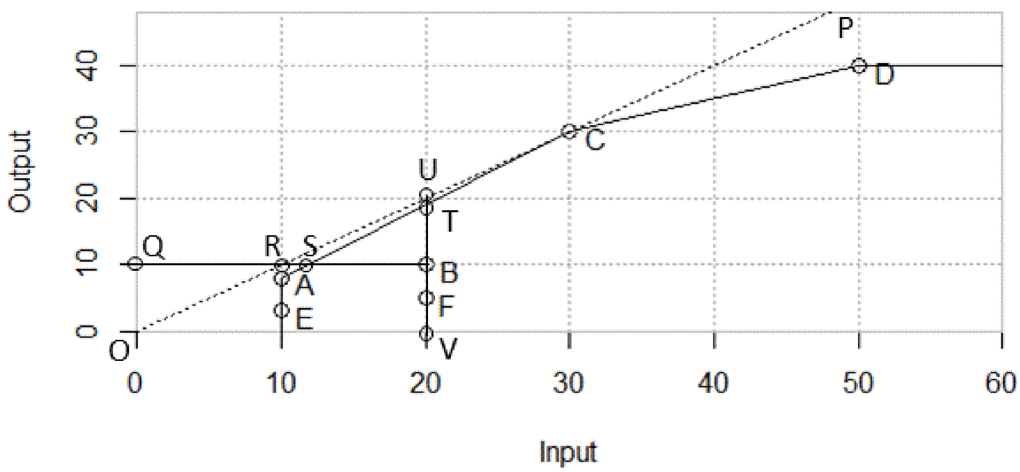

Figure 4.2 The production possibility set

The TE score of farm B, using the input-oriented Farrell measure under the assumption of VRS (EACD frontier), is the ratio *QS/QB*, while the TE score of farm B, using the output-oriented Farrell measure under the assumption of VRS, is the ratio *VB/VT*. Unlike the assumption of CRS, the assumption of VRS does not give equivalent measures of TE scores. Moreover, the TE scores obtained under the assumption of CRS are always less than or equal to the TE scores obtained under the assumption of VRS. This is because the PPF under VRS assumption envelops the data more tightly than the PPF under CRS assumption (Coelli et al., 2005).

The projecting point of farm B on the PPF under the VRS assumption (point S for input efficiency, or point T for output efficiency) lies between farms A and C. Thus, farms A and C are referred to as the “peers or reference set” of farm B. That is, points S and T are linear combinations of points A and C.

It is clear that there are two components that affect the measurement of TE scores. The first is the assumption about orientation (e.g. input-oriented, output-oriented). The second is that the assumption of RTS will affect the TE scores of the sample farms, because the TE score obtained from the CRS assumption is lower than the TE obtained from the VRS assumption. In this research, the underlying technology of the PPF will be determined by non-parametric tests of returns to scale, as proposed by Simar and Wilson (2002). In addition, the orientation will be determined by both input- and output-oriented models as well as a DDF (see the basic concept of this method in Section 4.7). This is because the major problems of Thai rice farming systems arise from situations where farmers are faced with high costs of rice production and low income (i.e. low profit), and from environmental problems caused by the overuse of chemical fertiliser and manure (i.e. water pollution). The input-oriented DEA model reveals to what extent inputs can be reduced without changing the amount of rice output produced. It can be used to identify which farmers are efficient or inefficient. The efficient farmers use less input than the inefficient farmers to produce the same level of rice output. It is interesting to know what strategies efficient farmers employ in their practice. Hence, the improvement of farm efficiency, according to this orientation, can automatically reduce production costs (i.e. farmers will make higher profits), as well as reducing nutrient surplus from fertiliser and manure application. The output-oriented DEA allows the research to determine the extent to which rice output can be expanded by using the same amount of inputs. This implies that the efficient farmers can get higher output than the inefficient farmers by using the same level of inputs. The improvement of farm efficiency by this orientation results in higher incomes for farmers, and lower nutrient surplus from fertiliser and manure application. The DDF model explores the extent to which production can be increased and inputs reduced simultaneously. The improvement of farm efficiency by this orientation can increase farmers' income and reduce production costs, as well as reducing nutrient surplus from fertiliser application. Thus, the results from this research can be used to combine with the previous literature to provide insights into how Thailand can sustainably intensify its rice production by minimising undesirable outputs (nutrient surplus).

4.5 Evaluating the performance of farms using data envelopment analysis

DEA is used to measure the relative efficiency of a homogenous set of DMUs, namely the rice farming households in this study, using linear programming problem solving in order to construct the piecewise frontier over the data (Coelli et al, 2005; Ahmed et al., 2011). It can be used to estimate the PPF for many outputs and inputs and evaluate where farmers perform in relation to this frontier. DEA determines which farmers are the "best" in the group. This implies that the best farmers can produce either the same amount of output with fewer inputs used or a greater amount of output with the same level of inputs used, compared to inefficient farmers in the group (Ahmed et al., 2011). On the other hand, the inefficient farmers can improve their performance to reach an efficient frontier by either increasing their current amount of outputs produced or decreasing their current amount of inputs used. The DEA approach has been applied to measure the TE of DMUs as it requires only data on physical amounts of inputs used and outputs produced (Coelli et al., 2005).

The linear programming of the input-oriented DEA approach under the assumption of VRS for a specific farm *o* is defined as follows.

$$\begin{aligned} & \min E^o \\ \text{Subject to} \quad & E^o x_k^o \geq \textstyle\sum_{i=1}^{n} \lambda^i x_k^i \quad , k = 1,\ldots,k \\ & y_m^o \leq \textstyle\sum_{i=1}^{n} \lambda^i y_m^i \quad , m = 1,\ldots,m \\ & \textstyle\sum_{i=1}^{n} \lambda^i = 1 \\ & \lambda^i \geq 0 \qquad , i = 1,\ldots,n \end{aligned} \tag{4.12}$$

where E^o is the TE score for the o^{th} farm being evaluated, $x_k^o = x_1^o,\ x_2^o\ \ldots, x_k^o$ are the inputs used for the o^{th} farm being evaluated, $y_m^o = y_1^o,\ y_2^o\ \ldots, y_m^o$ are the outputs produced for the o^{th} farm being evaluated, $\lambda^i = \lambda^1, \ldots, \lambda^n$ is a vector of weights and has dimension $n \times 1$. k and m are the *k-vector* of inputs and *m-vector* of outputs defined as $x^i = (x_1^i,\ x_2^i\ \ldots, x_k^i) \in \mathbb{R}_+^k$ and $y^i = (y_1^i,\ y_2^i, \ldots, y_m^i) \in \mathbb{R}_+^m$, respectively.

This Model is known as the BCC model, as proposed by Banker, Charnes, and Cooper in 1984. When the convexity constraint $\sum_{i=1}^{n} \lambda^i = 1$ is omitted, the CRS is assumed, and the Model (4.12) becomes the CCR model, as proposed by Charnes, Cooper, and Rhodes in 1978.

The value of E obtained from the Model (4.12) is the efficiency score of the o^{th} farm which ranges between 0 and 1. A value of 1 indicates that a farm is on the efficiency frontier (*T*) and hence that farm is technically efficient, while a value less than 1 indicates that a farm is below the efficiency frontier and hence that farm is technically inefficient (Coelli et al., 2005). The values of $\lambda^i = \lambda^1, \ldots, \lambda^n$ are applied as weights in the linear combination of other efficient farms (i.e. reference set or peer group) for an inefficient farm, which influences the projection of inefficient farms on the estimated efficiency frontier (Umanath and Rajasekar, 2013). The linear programming problem must be solved *n* times, once for each farm in the sample (Coelli et al., 2005). The input-oriented production frontier aims to find the largest proportional reduction in input quantities without changing the quantity of output produced, while remaining within the feasible input set (Coelli et al., 2002; Coelli et al., 2005).

The linear programming of the output-oriented DEA approach under the assumption of VRS for a specific farm *o* is very similar to their input-oriented counterparts which can be written as follows.

$$\max F^o$$

$$\text{Subject to} \quad x_k^o \geq \sum_{i=1}^{n} \lambda^i x_k^i \ , \quad k = 1,\dots,k$$

$$F y_m^o \leq \sum_{i=1}^{n} \lambda^i y_m^i \ , \quad m = 1,\dots,m \tag{4.13}$$

$$\sum_{i=1}^{n} \lambda^i = 1,$$

$$\lambda^i \geq 0 \qquad , \quad i = 1,\dots,n$$

where F^o is the efficiency score for the o^{th} farm being evaluated and its value is greater than or equal to one ($1 \leq F^o < \infty$). The TE score for the o^{th} farm is calculated by $1/F^o$. A value of 1 indicates that a farm is on the efficiency frontier and hence that farm is technically efficient, while a value less than 1 indicates that a farm is below the efficiency frontier and hence that farm is technically inefficient.

The output-oriented DEA model under the assumption of CRS can be measured by omitting the convexity constraint $\sum_{i=1}^{n} \lambda^i = 1$ in the Model (4.13).

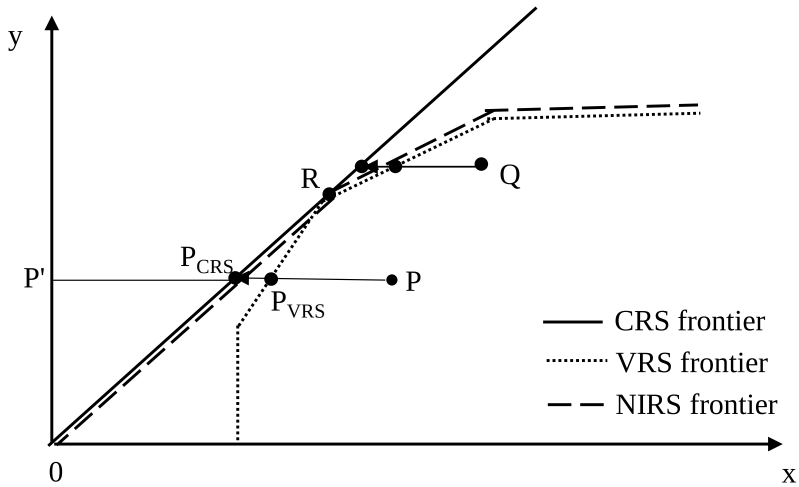

Figure 4.3 Returns to scale (CRS, IRS, and DRS) (Adapted from Coelli et al., 2005).

The results of TE scores obtained from the DEA model under the assumption of CRS (TE_{CRS}) are known as a measure of overall TE (OTE), and the results of TE scores obtained from the DEA model under the assumption of VRS (TE_{VRS}) are known as a measure of pure technical efficiency (PTE), allowing the calculation of the SE measure (Coelli et al., 2002; Bogetoft and Otto, 2011). The concept and calculation of SE is illustrated in Figure 4.3 using one input (*x*) and one output (*y*). The PPFs constructed by the DEA model under the assumptions of CRS, VRS, and NIRS are shown in the figure. The input-oriented technical inefficiency of point P under CRS assumption is the distance PP_{CRS}, while that of point P under VRS assumption is the distance PP_{VRS}. The difference between the input-oriented technical inefficiency measures under the CRS and VRS assumptions, which is the distance between points P_{CRS} and P_{VRS} ($P_{CRS}P_{VRS}$), is due to scale inefficiency. The ratio efficiency measures of these concepts can be written as:

$$TE_{CRS} = P'P_{CRS}/P'P \tag{4.14}$$

$$TE_{VRS} = P'P_{VRS}/P'P \tag{4.15}$$

$$SE = P'P_{CRS}/P'P_{VRS} \tag{4.16}$$

The value of SE in Eq. (4.16) is equal to the ratio of Eq. (4.14) over Eq. (4.15). Thus, the SE scores can be calculated as

$$SE = TE_{CRS}/TE_{VRS} \tag{4.17}$$

The value of the SE score, which is bounded by zero and one because $TE_{CRS} \leq TE_{VRS}$, reveals whether a farm operates close to the optimal scale size (CRS). The *SE = 1* indicates that a farm operates at the optimal scale size. A larger SE indicates that a farm operates closer to the optimal scale size (Bogetoft and Otto, 2011). The SE score can be applied to indicate potential benefits from farm size adjustment (Gadanakis, 2014). In addition, from Eq. (4.17) TE_{CRS} is decomposed to PTE and SE.

$$TE_{CRS} = TE_{VRS} \times SE \tag{4.18}$$

The SE score can be used to indicate whether a farm operates under CRS or VRS. A farm operates under CRS when its SE score is equal to one (i.e. $TE_{CRS}=TE_{VRS}$), while a farm operates under VRS (i.e. IRS or DRS) when its SE score is less than one (i.e. $TE_{CRS} \leq TE_{VRS}$). In the case of VRS, the SE score cannot be used to indicate whether the farm operates under IRS or DRS (Coelli et al., 1998 cited in Umanath and Rajasekar, 2013). The IRS or DRS can be investigated by running an additional DEA problem with NIRS (Coelli et al., 2005; Coelli et al., 2002). This can be done by substituting the convexity constraint $\sum_{i=1}^{n} \lambda^i = 1$ in the DEA model (4.12) with the convexity constraint $\sum_{i=1}^{n} \lambda^i \leq 1$ and then computing the relevant TE (TE_{NIRS}) for each farm in the sample (Coelli et al., 2002). If the $TE_{CRS} = TE_{NIRS} < TE_{VRS}$, then that farm operates below the optimal scale size or under the IRS (farm P). If the $TE_{NIRS} = TE_{VRS} > TE_{CRS}$, then that farm operates above the optimal scale size or under the DRS (farm Q). If the $TE_{NIRS} = TE_{VRS} = TE_{CRS}$, then that farm operates at optimal scale size or under the CRS (farm R) (Figure 4.3).

4.6 Material balance condition (Coelli et al., 2007)

Production activity not only produces good outputs but also produces undesirable outputs (emissions) that cause environmental problems. Some of the nutrients applied are absorbed by plants, however the rest are discharged into the environment. Coelli et al. (2007, p. 4) state that "the nutrient balance of a farm is calculated as the amount of nutrient that enters the farm in inputs minus the amount that leaves the farm bound up in useful output".

Coelli et al (2007) define a surplus measure as $z \in \mathbb{R}_+$ which is evaluated based on the material balance equation. That is, the nutrient surplus equals the total amount of nutrient in inputs minus the total amount of nutrient in outputs which can be written in mathematical form as

$$z = a'X - b'Y \tag{4.19}$$

where a is $(k \times 1)$ vector of nutrient content of inputs, b is $(m \times 1)$ vector of nutrient content of outputs[14], X is an input matrix with $(k \times n)$ dimension, and Y is an output matrix with $(m \times n)$ dimension.

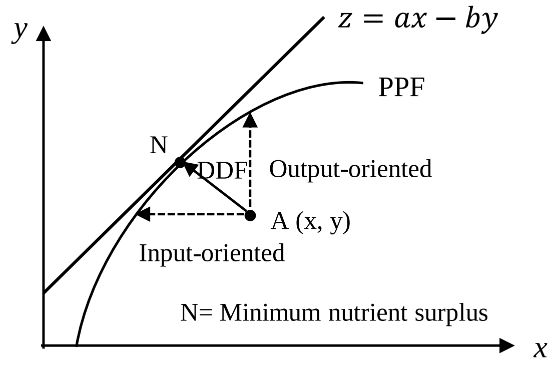

Figure 4.4 Nutrient surplus minimisation

The basic concept of MBC is illustrated in Figure 4.4. Assume that a farm uses one input to produce one output. The curve represents the PPF and the line represents the iso-nutrient surplus line $z = ax - by$. Assume that N is the minimum nutrient surplus point where the iso-nutrient surplus line is tangent to the PPF. Farm A is technically inefficient because it

[14] Note that it is possible that some inputs or outputs to have zero quantities of the interested nutrient content. For example, labour and machinery inputs do not have nitrogen content.

operates under the PPF. There are three possible ways for farm A to move from its position to the PPF. Firstly, farm A could proportionally increase the output quantities produced without changing the input quantities used, which is output-oriented DEA. With this direction of improvement, the nutrient surplus of farm A is also reduced, but it is not at the minimum surplus point. Secondly, farm A could proportionally reduce the input quantities used without altering the output quantities produced, which is input-oriented DEA. With this direction of improvement, the nutrient surplus is also reduced, but it is not at the minimum surplus point. Coelli et al. (2007) measure environmental performance of farming systems along this direction. They minimise nutrients for each farm using the input-oriented DEA, which is similar to the cost-minimising DEA model. Then the environmental efficiency for each farm is calculated by "the ratio of minimum nutrients over observed nutrients" (Coelli et al., 2007, p. 7). Finally, farm A could simultaneously increase the amount of output produced and reduce the amount of input used which is the DDF approach. With this direction of improvement, the nutrient surplus can be reduced to the minimum point. Consequently, only the improvement of farm efficiency using the DDF measure can achieve nutrient surplus minimisation efficiency.

4.7 Evaluating the performance of farms using the directional distance function

The DDF, based on Luenberger's benefit function, was introduced by Chambers et al. (1998). It is used to evaluate the TE of farms for reducing inputs used while increasing outputs simultaneously (Chambers et al., 1998; Färe and Grosskopt, 2005; Zofio, et al., 2013; Ang and Kerstens, 2016). The DDF is defined as (Chambers et al., 1998; Färe and Grosskopt, 2005; Zofio, et al., 2013):

$$D_T\left(x, y; g_x, g_y\right) = \max_{\beta}\left\{\beta : \left(x - \beta g_x, y + \beta g_y\right) \in T\right\}, x \in \mathbb{R}_+^k, y \in \mathbb{R}_+^m \qquad (4.20)$$

where (g_x, g_y) is a preassigned non-zero vector and $(g_x, g_y) \in \mathbb{R}_+^k \times \mathbb{R}_+^m$

The DDF reveals that the amount of outputs produced could be expanded in the direction g_y by adding the amount of β times the elements of g_y , and the amount of inputs used could be contracted in the direction g_x by subtracting the amount of β times the elements of g_x (Färe and Grosskopt, 2005; Zofio, et al., 2013). If value of βg_x (βg_y) is a small number, the percentage of input reduction (output expansion) needed for a technically inefficient farm to improve its efficiency level is small. On the other hand, if the value of βg_x (βg_y) is a large number, the percentage of the improvement of inputs (outputs) needed to reach the efficiency benchmark is large. The DDF can be interpreted as a technical inefficiency measurement for any production plan $(x, y) \in T$ by measuring the distance from its current position to the efficiency frontier, which is constructed by the technically best practice farms in the direction (g_x, g_y) or the actual direction $(-g_x, g_y)$ since βg_x is subtracted from *x* (Zofio, et al., 2013). A farm is technically efficient in the (g_x, g_y) direction if the distance from its current position to the efficiency frontier is equal to zero: $D_T(x, y; g_x, g_y) = 0$. Thus, this farm produces on the efficiency frontier. A farm is technically inefficient in the (g_x, g_y) direction if the distance from its current position to the PPF is greater than zero: $D_T(x, y; g_x, g_y) > 0$. Hence, this farm produces below the efficiency frontier.

Figure 4.5 illustrates the concept of the DDF approach. The area between the ray emanating from the origin and x-axis (including the x-axis) represents the technology set, *T*. The directional vector (g_x, g_y) is located in the 4th quadrant which indicates that input is contracted and output is expanded (Färe and Grosskopt, 2005). The DDF translates the vector (*x*, *y*) along the directional vector (g_x, g_y) onto the boundary of *T*, (i.e. point (x^*, y^*) on the efficiency frontier), where $(x^*, y^*) = (x - D_T(x, y; g_x, g_y)g_x, y + D_T(x, y; g_x, g_y)g_y))$. Since the vector (x, y) is below the efficiency frontier (i.e. interior to *T*), the value of the distance function is greater than zero and equal to $0a/0g$. That is $D_T(x, y; g_x, g_y) = 0a/0g$, where *0a* is equal to the distance from (x, y) to (x^*, y^*), and *0g* is the ray from the origin to(g_x, g_y) (Färe and Grosskopt, 2005). Note that if the (x, y) vector is translated onto the boundary of *T* in the direction $(g_x, 0)$, then it is the input-oriented DEA. If the (x, y) vector is translated onto the boundary of *T* in the direction $(0, g_y)$, then it is the output-oriented DEA.

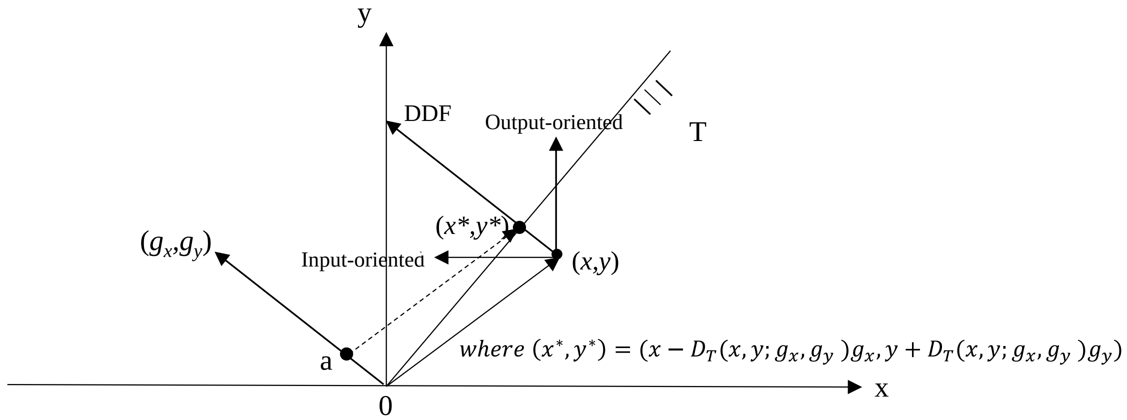

Figure 4.5 Directional technology distance function (adapted from Färe and Grosskopf, 2005)

The corresponding optimisation problem of the DDF measure used to evaluate the performance of the o^{th} farm in the potential improvement direction (g_x, g_y) with the VRS technology can be written as

$$D_T(x^o, y^o; g_x, g_y) = \max_{\beta^o, \lambda^i} \beta^o$$

$$\begin{aligned} \text{Subject to} \quad & x_k^o - \beta^o g_x \geq \textstyle\sum_{i=1}^{n} \lambda^i x_k^i \ , k = 1,\dots,k \\ & y_m^o + \beta^o g_y \leq \textstyle\sum_{i=1}^{n} \lambda^i y_m^i \ , m = 1,\dots,m \\ & \textstyle\sum_{i=1}^{n} \lambda^i = 1 \\ & \lambda \geq 0 \end{aligned} \tag{4.21}$$

where β^o is the technical inefficiency score of farm o.

4.8 Directional Profit Efficiency Measure (Zofio et al., 2013)

The concept of directional profit efficiency measure, proposed by Zofio et al., (2013), is illustrated in Figure 4.6. The directional profit maximising point (x^*, y^*) is the point where iso-profit line (i.e. profit maximising benchmark) is tangent to the PPF. The farm (x, y) is profit inefficient as its produces below the profit efficiency frontier. It can improve its profit efficiency by moving from its current position to the maximum profit point (x^*, y^*) in the direction (g_x^*, g_y^*) that projects this farm onto the profit maximising frontier at point (x^*, y^*). As a result, the farm (x, y) could expand the output quantities produced in the direction g_y^* by $D_T^*(x, y; g_x^*, g_y^*) \times g_y^*$ unit and reduce the input quantities used in the direction g_x by $D_T^*(x, y; g_x^*, g_y^*) \times g_x^*$ unit.

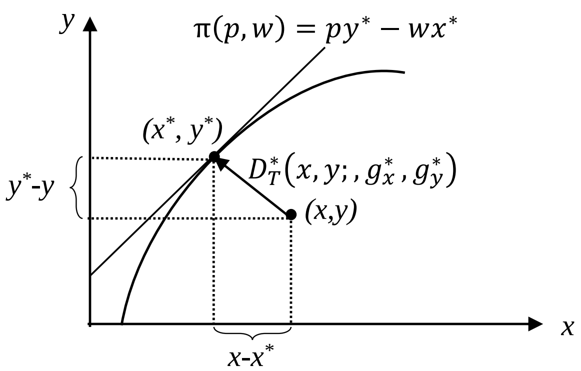

Figure 4.6 Profit maximising benchmark

Zofio et al., (2013) define the directional profit efficiency measure $D_T^*(x, y; p, w)$ as

$$D_T^*(x, y; p, w) := D_T^*\left(x, y; g_x^*, g_y^*\right)$$
$$= \max_{\beta}\left\{\beta: \left(x - \beta g_x^*, y + \beta g_y^*\right) \in T\right\}, x \in \mathbb{R}_+^k, y \in \mathbb{R}_+^m \quad (4.22)$$

where (p, w) is the vector of output and input prices, and the directional vector $\left(g_x^*, g_y^*\right) = [\pi(p, w) - (py - wx)]^{-1}\,(x - x^*, y^* - y)$. The elements of the directional vector $\left(g_x^*, g_y^*\right)$ may have negative values. This implies that it is possible to increase the quantities of inputs used and decrease the quantities of outputs to reach the profit efficiency frontier. When $D_T^*(x, y; p, w) = 0$ a farm is profit efficient, otherwise a farm is profit inefficient.

The corresponding optimisation problem of the directional profit efficiency measure used to evaluate the profit efficiency of the o^{th} farm in the potential improvement direction $\left(g_x^*, g_y^*\right)$ (i.e. towards the profit maximising benchmark) under the VRS assumption can be written as follows (Zofio et al., 2013).

$$D_T^*(x^o, y^o; p, w) = \max_{\beta^o, \lambda^i, g_x^*, g_y^*} \beta^o$$

$$\begin{aligned} \text{Subject to} \quad & x_k^o - \beta^o g_{x_k}^* \geq \textstyle\sum_{i=1}^n \lambda^i x_k^i \ , k = 1,\dots,k \\ & y_m^o + \beta^o g_{y_m}^* \leq \textstyle\sum_{i=1}^n \lambda^i y_m^i \ , m = 1,\dots,m \qquad (4.23) \\ & \textstyle\sum_{m=1}^m p_m g_{y_m}^* + \sum_{k=1}^k w_k g_{x_k}^* = 1 \\ & \textstyle\sum_{i=1}^n \lambda^i = 1, \quad \lambda \in \mathbb{R}_+^i \end{aligned}$$

where β^o is the profit inefficiency score of farm *o*.

The directional vector $\left(g_x^*, g_y^*\right)$ in the Model (4.23) is not preassigned, it needs to be calculated and satisfy the price normalization constraint, $pg_y^* + wg_x^* = 1$. The elements of $\left(g_x^*, g_y^*\right)$ could be positive and negative values as long as $\left(g_x^*, g_y^*\right) \neq (0_k, 0_m)$and hence the constraint $\sum_{m=1}^m p_m g_y^* + \sum_{k=1}^k w_k g_x^* = 1$ prevents that from happening.

From the Model (4.23), the farm is profit inefficient when $D_T^*(x^o, y^o; p, w) > 0$ and the farm is profit efficient when $D_T^*(x^o, y^o; p, w) = 0$ Finally, the Model (4.23) is clearly nonlinear because of variables $\beta^o g_{x_k}^*$ and $\beta^o g_{y_m}^*$. However, it can be transformed into linear model by changing these variables to $\gamma_{x_k}^o = \beta^o g_{x_k}^*, k = 1, \dots, k$, and $\gamma_{y_m}^o = \beta^o g_{y_m}^*, m = 1, \dots, m$.

By substituting $g^*_{y_m} = \gamma^o_{y_m}/\beta^o$ and $g^*_{x_k} = \gamma^o_{x_k}/\beta^o$ in the constraint $\sum_{m=1}^{m} p_m g^*_y + \sum_{k=1}^{k} w_k g^*_x = 1$,

we get $$\sum_{m=1}^{m} p_m \left(\frac{\gamma^o_{y_m}}{\beta^o}\right) + \sum_{k=1}^{k} w_k \left(\frac{\gamma^o_{x_k}}{\beta^o}\right) = 1$$

by rearranging, this constraint is translated as

$$\sum_{m=1}^{m} p_m \gamma^o_{y_m} + \sum_{k=1}^{k} w_k \gamma^o_{x_k} = \beta^o \quad , \beta^o > 0$$

Consequently, the Model (4.23) is translated as

$$D^*_T(x^o, y^o; p, w) = \max_{\beta^o, \lambda^i, g^*_x, g^*_y} \beta^o$$

$$\begin{aligned} \text{Subject to} \quad & x^o_k - \gamma^o_{x_k} \geq \sum_{i=1}^{n} \lambda^i x^i_k \;, k = 1, \ldots, k \\ & y^o_m + \gamma^o_{y_m} \leq \sum_{i=1}^{n} \lambda^i y^i_m \;, m = 1, \ldots, m \qquad (4.24) \\ & \sum_{m=1}^{m} p_m \gamma^o_{y_m} + \sum_{k=1}^{k} w_k \gamma^o_{x_k} = \beta^o \quad , \beta^o > 0 \\ & \sum_{i=1}^{n} \lambda^i = 1, \quad \lambda \in \mathbb{R}^i_+ \end{aligned}$$

where β^o is the profit inefficiency score of farm o. Note that the objective function is not modified the Models (4.23) and (4.24) are equivalent if and only if $\beta^o > 0$ (Zofio et al., 2013).

4.9 The Directional Nutrient Surplus Efficiency Measure

By integrating the concept of MBC (Coelli et al., 2007) and directional profit efficiency measures (Zofio et al., 2013), this research will propose the measurement for nutrient surplus minimisation within the theoretical context of the DDF with the nutrient surplus minimum point direction to evaluate the environmental efficiency of Thai rice farmers. This measurement is called "*the directional nutrient surplus efficiency measure*".

The concept of the directional nutrient surplus efficiency measure within the theoretical context of DDF can be explained using Figure 4.7. Assume the minimum nutrient surplus farm is $B(x^*, y^*)$, where the iso-nutrient surplus line $N(a_N, b_N) = a_N x - b_N y$ tangent to the production possibility frontier (PPF), T. (a_N, b_N) denotes the vectors of input $(a_N \in \mathbb{R}^k_+)$ and output $(b_N \in \mathbb{R}^m_+)$ nutrients, respectively. The concept of nutrient surplus (i.e. material balance condition) is demonstrated in Section 4.6. The PPF is constructed by farms A, B, C, and D using the conventional DDF model, where (g^T_x, g^T_y), which is represented by a dashed line vector, is a nonzero vector in $\mathbb{R}_+^k \times \mathbb{R}_+^m$ (preassigned directional vector). Recall from Section 4.7 that the DDF towards (g_x^T, g_y^T) direction is defined as

$$D_T(x, y; g_x^T, g_y^T) = \max_{\beta}\{\beta : (x - \beta g_x^T, y + \beta g_y^T) \in T\}, x \in \mathbb{R}_+^k, y \in \mathbb{R}_+^m \tag{4.25}$$

where $D_T(x, y; g_x^T, g_y^T)$ represents the technical inefficiency of each farm which is measured by the distance from its position to the PPF. Farms A, B, C, and D are technically efficient farms as they produce on the PPF and their distances along the directional vector (g_x^T, g_y^T) from their positions to the PPF are equal to zero, $D_T(x^1, y^1; g_x^T, g_y^T) = D_T(x^*, y^*; g_x^T, g_y^T) = D_T(x^3, y^3; g_x^T, g_y^T) = D_T(x^4, y^4; g_x^T, g_y^T) = 0$. Farms E and F are technically inefficient as they produce below the PPF and their distances along the directional vector (g_x^T, g_y^T) from their positions to the PPF are greater than zero, $D_T(x, y; g_x^T, g_y^T) > 0$, $D_T(x^6, y^6; g_x^T, g_y^T) > 0$.

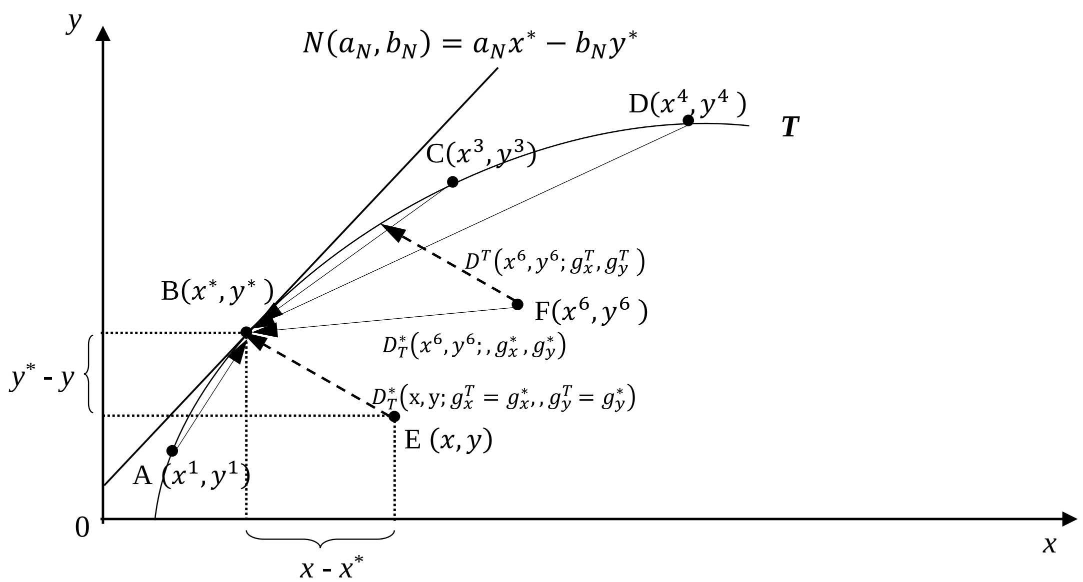

Figure 4.7 Nutrient surplus efficiency measure

The nutrient surplus efficiency, or environmental efficiency, of each farm is measured by the distance from its position to the minimum nutrient surplus benchmark $B(x^*, y^*)$ (i.e. the nutrient surplus minimising frontier). The DDF with the direction towards the nutrient surplus minimising frontier can be written as

$$D_T^*(x, y; g_x^*, g_y^*) = \max_{\beta}\{\beta : (x - \beta g_x^*, y + \beta g_y^*) \in T\}, x \in \mathbb{R}_+^k, y \in \mathbb{R}_+^m \tag{4.26}$$

where (g_x^*, g_y^*) is a directional vector that projects sample farms onto the nutrient surplus minimising point (x^*, y^*). The directional vector (g_x^*, g_y^*) is a nonzero vector in

$\mathbb{R}_+^k \times \mathbb{R}_+^m$ and is not preassigned. The estimation of the directional vector $\left(g_x^*, g_y^*\right)$ will be explained below in this section. Thus, only farm B is nutrient surplus efficient as it produces on the nutrient surplus minimising frontier, $D_T\left(x^*, y^*; g_x^*, g_y^*\right) = 0$. Farms A, C, D, E, and F are nutrient surplus inefficient farms as they are not located on the nutrient surplus minimising frontier, $D_T\left(x^1, y^1; g_x^*, g_y^*\right) > 0$, $D_T\left(x^3, y^3; g_x^*, g_y^*\right) > 0$, $D_T\left(x^4, y^4; g_x^*, g_y^*\right) > 0$, $D_T\left(x, y; g_x^*, g_y^*\right) > 0$, $D_T\left(x^6, y^6; g_x^*, g_y^*\right) > 0$.

Farms A, C, and D are technically efficient farms when measuring their efficiency using DDF with $\left(g_x^T, g_y^T\right)$ orientation, but they are nutrient surplus inefficient when measuring their efficiency using the DDF with the direction targeting on the nutrient surplus minimising point, $\left(g_x^*, g_y^*\right)$ orientation. These nutrient surplus inefficiencies of farms A, C, and D are due to the allocative inefficiency of mixed nutrients. This implies that these farms failed to choose the correct mix of nutrient minimising input-output quantities at the percentage of nutrient content when they were on the PPF in the (g_x^T, g_y^T) orientation. The allocative inefficiency levels of farms A, C, and D are the distance between nutrient surplus at their technically efficient projections (points A, C, and D) and the minimum nutrient surplus point B along the direction $\left(g_x^*, g_y^*\right)$ that are $D_T\left(x^1, y^1; g_x^*, g_y^*\right)$, $D_T\left(x^3, y^3; g_x^*, g_y^*\right)$, $D_T\left(x^4, y^4; g_x^*, g_y^*\right)$, respectively. Thus, farms A, C, and D need to gain allocative efficiency in order to reach the nutrient surplus minimising benchmark.

On the other hand, farms E and F are technically inefficient farms when measuring their efficiency using DDF with $\left(g_x^T, g_y^T\right)$ orientation, and they are also nutrient surplus inefficient when measuring their efficiency using the DDF with the direction targeting on the nutrient surplus minimising point $\left(g_x^*, g_y^*\right)$ orientation. The nutrient surplus inefficiency of farm E is due to technical inefficiency, while the nutrient surplus inefficiency of farm F is due to both technical and allocative inefficiencies. If the directional vector $\left(g_x^T, g_y^T\right)$ were chosen, the reduction of the technical inefficiency level of farm E would result in both technical and nutrient surplus efficiencies, since the direction $\left(g_x^T, g_y^T\right)$ would be the same as the direction of $\left(g_x^*, g_y^*\right)$. In the case of farm F, however, if the directional vector $\left(g_x^T, g_y^T\right)$ were chosen, the reduction of the technical inefficiency level of farm F would result in technical efficiency, but it would still be in the position of nutrient surplus inefficiency. Then farm F would have to take a further step to reduce its nutrient surplus inefficiency, which would be costly. However, if the directional vector $\left(g_x^*, g_y^*\right)$ were chosen, the reduction of the technical inefficiency level of farm F would result in both technical and nutrient surplus efficiencies that would be less costly than choosing the $\left(g_x^T, g_y^T\right)$ orientation. Consequently, the improvement of nutrient surplus inefficiency in the direction towards the nutrient surplus minimum point $\left(g_x^*, g_y^*\right)$ would result in both technical and nutrient surplus efficiency and would be less costly than the other direction.

Moreover, the improvement of a farm's nutrient surplus efficiency does not consist only of contracting input and expanding output. According to Figure 4.7, farm A has to increase both input and output, farms C, D, and F have to reduce both input and output, and farm E has to reduce input and expand output to reach the nutrient surplus minimising frontier. Thus, the directional vector $\left(g_x^*, g_y^*\right)$ for each farm is different and its elements could be positive or negative. The estimation of nutrient surplus efficiency and the directional vector targeting the nutrient surplus minimising benchmark are as follows.

Consider farms $B\ (x^*, y^*)$ and $E\ (x, y)$ in Figure 4.7, and assume the directional vector of farm E targeting the nutrient surplus minimising benchmark (farm B) is $\left(g_x^*, g_y^*\right)$ which is a nonzero vector in $\mathbb{R}_+^k \times \mathbb{R}_+^m$. Farm E could reduce its input $(x - x^*)$ unit and expand its output $(y^* - y)$ unit when it produces on the nutrient surplus minimising benchmark. Thus, the directional vector can be written as

$$\left(g_x^*, g_y^*\right) = \tau(x - x^*, y^* - y) \tag{4.27}$$

where τ is scalar. If the scalar τ in Eq. (4.27) is known, then the directional vector $\left(g_x^*, g_y^*\right)$ can be calculated. After the directional vector $\left(g_x^*, g_y^*\right)$ is calculated, then the nutrient surplus inefficiency or environmental inefficiency of farm E (i.e. the distance from farm E to the minimum nutrient surplus benchmark, farm B) can be estimated using Eq. (4.26).

Assume β^* is the solution of Eq. (4.26), i.e. $\beta^* = D_T^*\left(x, y; g_x^*, g_y^*\right)$. When farm $E\ (x, y)$ moves from its position along the $\left(g_x^*, g_y^*\right)$ direction to the projected minimum nutrient surplus point $B(x^*, y^*)$ (i.e. to produce on the nutrient surplus minimising benchmark or to become a nutrient surplus efficient farm), we get

$$(x^*, y^*) = \left(x - \beta^* g_x^*, y + \beta^* g_y^*\right) \tag{4.28}$$

Thus, the nutrient surplus at the projected point on the nutrient surplus minimisation frontier is

$$a_N x^* - b_N y^* = a_N(x - \beta^* g_x^*) - b_N\left(y + \beta^* g_y^*\right) \tag{4.29}$$

Substituting $\left(g_x^*, g_y^*\right) = \tau(x - x^*, y^* - y)$ from Eq. (4.27) into Eq. (4.29), we obtain

$$\beta^* = 1/\tau \tag{4.30}$$

Therefore,

$$D_T^*(x, y; g_x^*, g_y^*) = 1/\tau \tag{4.31}$$

In other words, the distance between farm E (x, y) and its projected vector at the minimum nutrient surplus frontier at point $B(x^*, y^*)$ (i.e. the nutrient surplus inefficiency score of farm E) is equal to $1/\tau$. The estimation of scalar τ can be demonstrated as follows.

From the concept of the MBC as presented in Section 4.6, the nutrient surplus of any farm in the sample can be calculated by $a_N x - b_N y$ where (a_N, b_N) denotes the vectors of input $(a_N \in \mathbb{R}_+^k)$ and output $(b_N \in \mathbb{R}_+^m)$ nutrients, respectively. At the minimum nutrient surplus point $B(x^*, y^*)$, the nutrient surplus is minimal, so the nutrient surplus minimisation equation can be defined as

$$N(a_N, b_N) = \min_{x,y}\{a_N x - b_N y: (x, y) \in T\} \tag{4.32}$$

From Eq. (4.32), $N(a_N, b_N)$ is less than or equal to the observed nutrient surplus of any farms in the sample (i.e. any input–output vector belonging to the technology), thus

$$N(a_N, b_N) \leq a_N x - b_N y; \qquad \forall (x, y) \in T \tag{4.33}$$

From Eq. (4.26), for any farms in the sample, the projected vector at the minimum nutrient surplus point $B(x^*, y^*)$ can be written as

$$\left(x - D_T^*(x, y; g_x^*, g_y^*)g_x^*,\ y + D_T^*(x, y; g_x^*, g_y^*)g_y^*\right) \in T \tag{4.34}$$

Substituting the projected vector Eq. (4.34) into minimum nutrient surplus inequality Eq. (4.33), we observe that

$$N(a_N, b_N) \leq a_N\left[x - D_T^*(x, y; g_x^*, g_y^*)g_x^*\right] - b_N\left[\ y + D_T^*(x, y; g_x^*, g_y^*)g_y^*\right] \tag{4.35}$$

Rearranging inequality Eq. (4.35), we get

$$D_T^*(x, y; g_x^*, g_y^*) \leq -[N(a_N, b_N) - (a_N x - b_N y)]/\left(a_N g_x^* + b_N g_y^*\right) \tag{4.36}$$

Inequality Eq. (4.36) implies that the distance from any farm in the sample towards the minimum nutrient surplus point $B(x^*, y^*)$ along the direction $\left(g_x^*, g_y^*\right)$ is equal to a negative of the difference between the minimum nutrient surplus and the observed nutrient surplus of any farms in the sample divided by $\left(a_N g_x^* + b_N g_y^*\right)$. This distance is always greater than or equal to zero (i.e. $D_T^*(x, y; g_x^*, g_y^*) \geq 0$) because $N(a_N, b_N) - (a_N x - b_N y) \leq 0$ as

$N(a_N, b_N)$ is the minimum nutrient surplus in the sample. This indicates that the distance $D_T^*(x, y; g_x^*, g_y^*)$ depends on the choice of (g_x^*, g_y^*). If we choose an orientation that satisfies

$$a_N g_x^* + b_N g_y^* = 1 \tag{4.37}$$

then

$$D_T^*(x, y; g_x^*, g_y^*) \leq -[N(a_N, b_N) - (a_N x - b_N y)] \tag{4.38}$$

Thus, the minimal distance from any observed data point $(x, y) \in T$ to the minimal nutrient surplus frontier at point $B(x^*, y^*)$ by given output and input nutrient contents can be written as

$$D_T^*(x, y; g_x^*, g_y^*) \leq \min_{a_N, b_N} \{-[N(a_N, b_N) - (a_N x - b_N y)]: a_N g_x^* + b_N g_y^* = 1\} \tag{4.39}$$

The value of τ can be calculated by substituting $(g_x^*, g_y^*) = \tau(x - x^*, y^* - y)$ from Eq. (4.27) into Eq. (4.37). We obtain

$$a_N \tau(x - x^*) + b_N \tau(y^* - y) = 1 \tag{4.40}$$

Rearranging Eq. (4.40), we get

$$\tau = -1/[(a_N x^* - b_N y^*) - (a_N x - b_N y)] \tag{4.41}$$

Since $B(x^*, y^*)$ is the minimum nutrient surplus point, then $a_N x^* - b_N y^* = N(a_N, b_N)$. Hence, Eq. (4.41) can be rewritten as

$$\tau = -1/[N(a_N, b_N) - (a_N x - b_N y)] \tag{4.42}$$

Thus the minimum distance from farm $E\,(x, y)$ to the minimum nutrient surplus point $B(x^*, y^*)$ (i.e. nutrient surplus minimising frontier) along the (g_x^*, g_y^*) direction can be estimated by substituting Eq. (4.42) into Eq. (4.31). Thus we obtain

$$D_T^*(x, y; g_x^*, g_y^*) = -[N(a_N, b_N) - (a_N x - b_N y)] \tag{4.43}$$

Therefore from Eq. (4.43) and inequality Eq. (4.39), the directional nutrient surplus efficiency measure for any input–output vector belonging to the technology towards the minimum nutrient surplus point can be defined as

$$D_T^*(x, y; a_N, b_N) \coloneqq D_T^*(x, y; g_x^*, g_y^*) = \min_{\beta} \{-\beta: (x - \beta g_x^*, y + \beta g_y^*) \in T\} \tag{4.44}$$

where $(g_x^*, g_y^*) = \tau(x - x^*, y^* - y)$ and $\tau = -1/[N(a_N, b_N) - (a_N x - b_N y)]$ with satisfy $a_N g_x^* + b_N g_y^* = 1$ constraint. Note that $-\beta$ ensures that $D_T^*(x, y; g_x^*, g_y^*) \geq 0$.

This directional nutrient surplus efficiency measure in Eq. (4.44) is duality to the directional profit efficiency measure proposed by Zofio et al. (2013). Therefore, the corresponding optimisation problem used to calculate the directional nutrient surplus efficiency measure under the assumption of variable returns to scale for the *o*th farm to the nutrient surplus minimising benchmark is

$$D_T^*(x^o, y^o; a_N, b_N) = \min_{\beta^o, \lambda^i, g_x^*, g_y^*} -\beta^o$$

Subject to $\quad x_k^o - \gamma_{x_k}^o \geq \sum_{i=1}^{n} \lambda^i x_k^i \ , k = 1, \ldots, k$

$$y_m^o + \gamma_{y_m}^o \leq \sum_{i=1}^{n} \lambda^i y_m^i \ , m = 1, \ldots, m \tag{4.45}$$

$$\sum_{m=1}^{m} a_{N_k} \gamma_{x_k}^o + \sum_{k=1}^{k} b_{N_m} \gamma_{y_m}^o = \beta^o \qquad , \beta^o > 0$$

$$\sum_{i=1}^{n} \lambda^i = 1, \qquad \lambda \in \mathbb{R}_+^i$$

where β^o is the nutrient surplus (or environmental) efficiency score of farm *o*, $\gamma_{x_k}^o = \beta^o g_{x_k}^*, k = 1, \ldots, k$, $\gamma_{y_m}^o = \beta^o g_{y_m}^*, m = 1, \ldots, m$, $x_k^o = x_1^o,\ x_2^o\ \ldots, x_k^o$ are the input usage for the o^{th} farm being evaluated, $y_m^o = y_1^o,\ y_2^o\ \ldots, y_m^o$ are the output for the o^{th} farm being evaluated, $\lambda^i = \lambda^1, \ldots, \lambda^n$is a vector of weights and has dimension $n \times 1$. k and m are the *k-vector* of inputs and *m-vector* of outputs defined as $x^i = \left(x_1^i,\ x_2^i\ \ldots, x_k^i\ \right) \in \mathbb{R}_+^k$ and $y^i = \left(y_1^i,\ y_2^i, \ldots, y_m^i\ \right) \in \mathbb{R}_+^m$, a_{N_k} and b_{N_m} are the nutrient content in inputs and outputs, respectively.

The directional nutrient surplus efficiency measure Model (4.45) is different from the conventional DDF model as the directional vector $\left(g_x^*, g_y^*\right)$ for each farm is not preassigned. In addition, it involves the incorporation of the MBC into the model in a similar manner to that in which price information is normally incorporated in the directional profit efficiency measure, proposed by Zofio et al., (2013).

Likewise, in the directional profit efficiency measure proposed by Zofio et al. (2013), the nutrient surplus efficiency which is measured by the Model (4.45) can be decomposed into TE and AE. That is nutrient surplus efficiency = TE + AE. When $D_T^*(x^o, y^o; a_N, b_N) = 0$, a farm is nutrient surplus, technically and allocatively efficient. When $D_T^*(x^o, y^o; a_N, b_N) > 0$, a farm is nutrient surplus inefficient. For the nutrient surplus inefficient farm, the source of inefficiency can be determined in conjunction with the conventional DDF model. That is the source of nutrient surplus inefficiency is technical if $D_T\left(x, y; g_x^T, g_y^T\right) > 0$ or allocative if $D_T\left(x, y; g_x^T, g_y^T\right) = 0$.

4.10 Identifying outliers in a nonparametric frontier model: The data cloud method

Data quality is an important issue in efficiency and productivity measurement, especially in the context of DEA. The estimation of the PPF in the DEA model may be sensitive to measurement errors in sample data because it is determined by these extreme observations. Therefore, outliers could seriously influence the construction of the efficiency frontier by extending it out. This would then affect the efficiency scores of other observations in the sample and their interpretation (Wilson, 1993; Bogetoft and Otto, 2011; Banker and Chang, 2006). Theoretically, efficient observations provide guidelines to management on how to improve the performance of the inefficient observations. If one or more of the efficient observations is an outlier, these guidelines would be meaningless and even misleading (Banker and Chang, 2006). The DEA approach is used to measure efficiency scores of Thai rice farming and the dataset contains a large number of observations which cannot be visually checked for the presence of errors and outliers. Hence, it is desirable to consider suitable approaches that can be applied to identify and exclude outliers before doing an efficiency analysis using the DEA approach (Baker and Chang, 2006).

Several methods have been used for detecting influential observations (i.e. outliers) in the deterministic non-parametric frontier models (Jahanshahloo et al., 2004). The most widely cited are the data cloud method proposed by Wilson (1993) (e.g. Gadanakis, 2014; Blancard and Martin, 2014; LaPlante, 2015), and the super-efficiency DEA or leave-one-out method proposed by Winson (1995) (e.g. Banker and Chang, 2006; Johnson and McGinnis, 2008: Chen and Johnson, 2010; Serra et al. 2014). These methods are very useful when data checking is costly and resources are limited (Wilson, 1995). However, the super-efficiency method can identify only a single farm outlier. If the data set contains multiple outliers this method may fail because the omission of only one outlier may have little impact if one or more other outliers are masking it (Bogetoft and Otto, 2011). Therefore, the presence of outliers in the dataset used in this research is identified by using the data cloud method. The concept of the data cloud method can be explained as follows.

The combined matrix $[XY]$ which contains the input data matrix X and the output data matrix Y for a set of n farms (as presented in Section 4.2) can be written as follows (Bogetoft and Otto, 2011).

$$[XY] = \begin{bmatrix} x_1^1 & x_2^1 & \dots & x_k^1 & y_1^1 & y_2^1 & \dots & y_m^1 \\ x_1^2 & x_2^2 & \dots & x_k^2 & y_1^2 & y_2^2 & \dots & y_m^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_1^n & x_2^n & \dots & x_k^n & y_1^n & y_2^n & \dots & y_m^n \end{bmatrix}_{n\times(k+m)} \tag{4.46}$$

The different rows in the combined matrix $[XY]$ represent a farm which can be seen as a data cloud in the $\mathbb{R}_+^k \times \mathbb{R}_+^m$ space. The volume of the data cloud ($|Z|$) can be calculated from the determinant of the inner product $Z = [XY]'[XY]$. That is

$$|Z| = |\,[XY]'[XY]| \tag{4.47}$$

The concept of the data cloud method for identifying outliers in the dataset is that the volume of the data cloud in Eq. (4.47) will be changed when one or more outliers have been removed from the dataset. If a farm is removed from the combined matrix $[XY]$ (i.e. any one row of the combined matrix is deleted), then the volume of the data cloud of the remaining farms may decrease. If this farm is removed from the middle of the cloud, the volume of the data cloud of the remaining farms will be unchanged. This indicates that this farm is not an outlier. On the other hand, if this farm is removed from outside the remaining cloud, the volume of the data cloud of the remaining farms will be much smaller. This indicates that this farm is an outlier. Hence, in order to investigate whether the dataset has one or more outliers, we can investigate how the volume of the cloud changes when one or more farms are removed from the dataset for the indication of outliers (Bogetoft and Otto, 2011).

If we would like to remove only one farm which is an outlier from the dataset, it is calculated as follows. Let us assume $|Z^{(i)}|$ is the new volume of the data cloud which is equal to the determinant of inner product after eliminating farm *i*, and $R^{(i)}$ is the ratio of the new volume of the data cloud, $|Z^{(i)}|$, to the old volume of the data cloud, $|Z|$, i.e.

$$R^{(i)} = |Z^{(i)}|/|Z| \tag{4.48}$$

Note that $R^{(i)}$ is dimensionless (i.e. it does not depend on the units in either the input matrix *X* or the output matrix *Y*). If $R^{(i)}$ is close to 1, farm *i* is not an outlier because $|Z^{(i)}|$ does not change much. On the other hand, if $R^{(i)}$ is much smaller than 1, farm *i* is a potential outlier. The farm that has the smallest value of $R^{(i)}$ is the outlier. Therefore, outliers are identified by the smallest value of $R^{(i)}$ which are denoted as $R_{min}^{(i)}$.

The procedure for calculating $R^{(i)}$ when we would like to remove only one farm which is an outlier from the data set is as follows:

1) Calculate the determinant of the inner product : $|Z| = |[XY]'[XY]|$
2) Calculate the determinant of the inner product after removing farm *i* $\left|Z^{(i)}\right|$. This step consists of two stages. First, the *i^th^* row of combined matrix $[XY]$ is eliminated. Then the determinant of the remaining inner product $Z^{(i)}$ is calculated. For example, if farm number 1 is removed,

$$\left|Z^{(1)}\right| = \left|\left[XY^{(1)}\right]'\left[XY^{(1)}\right]\right|$$

where $$XY^{(1)} = \begin{bmatrix} x_1^2 & x_2^2 & \dots & x_k^2 & y_1^2 & y_2^2 & \dots & y_m^2 \\ x_1^3 & x_2^3 & \dots & x_k^3 & y_1^3 & y_2^3 & \dots & y_m^3 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_1^n & x_2^n & \dots & x_k^n & y_1^n & y_2^n & \dots & y_m^n \end{bmatrix}_{(n-1)\times(k+m)}$$

In this step, $\left|Z^{(1)}\right|, \left|Z^{(2)}\right|, \dots, \left|Z^{(n)}\right|$ which are the determinants of the remaining inner product after removing farm number *1, 2,…, n*, respectively, are calculated.
3) Calculate $R^{(i)} = \left|Z^{(i)}\right|/|Z|$. In this step $R^{(1)}, R^{(2)}, \dots, R^{(n)}$ which are the ratios of the new volume of the data cloud after removing farm *1, 2,…, n*, respectively, to the old volume of the data cloud, are calculated.
4) Looking for the minimum value of $R^{(i)}$ or $R_{min}^{(i)}$ from the 3^rd^ step. The farm that has the smallest value of $R^{(i)}$ will be identified as an outlier.

Moreover, this method can be used to identify groups of outliers by removing two or more farms from the data cloud. If we would like to remove a group of *r* farms which are outliers from the data set, it is calculated as follows. Let $\left|Z^{(r)}\right|$ be the determinant of inner product after removing a group of *r* farms, and $R^{(r)}$ is the ratio of the new volume of the data cloud, $\left|Z^{(r)}\right|$, to the old volume of the data cloud, $|Z|$, which can be written as

$$R^{(r)} = \left|Z^{(r)}\right|/|Z| \tag{4.49}$$

A group of outliers can be identified by looking for the smallest values of $R^{(r)}$ which are denoted as $R_{min}^{(r)}$. A group of farms that has the smallest values of $R^{(r)}$ will be identified as outliers.

The interesting question is how many farms will be outliers in the dataset. If the potential outliers in the dataset are equal to *s* farms, they are identified by eliminating groups of *1, 2, …, r* farms. If $s > r$, the remaining dataset still has more potential outliers, and we should not expect to find a very small value of $R^{(r)}$. If $s < r$, all potential outliers are eliminated and the value of $R^{(r)}$ is assumed to be very small. Consequently, the maximum number of removed observations should be large enough. In order to choose which group of *1, 2, …, r* farms are outliers in the dataset, a graphical method can be used to plot the ordered pairs between $\left(r, log\left(R^{(r)}/R_{min}^{(r)}\right)\right)$, where *r* is the number of eliminated farms.

The outliers in the graph can be investigated by looking for the first single isolated small value when examining the values of $R^{(r)}$. An isolated small value is an isolated minimum value $log\left(R^{(r)}/R_{min}^{(r)}\right) = log(1) = 0,$ or, in words, the point at *0* should be isolated from other values of $log\left(R^{(r)}/R_{min}^{(r)}\right)$ or the points above *0*. Hence, in the graph, we look for isolated low points where there is a gap between the point at *0* and the points above *0*; the *r* with isolated low points gives an indication of *r* outliers.

The data cloud method can be applied in the case of many inputs and outputs and allows for outlier identification in the dataset by using a graphical analysis (Gadanakis, 2014). It can be used to identify one or more outliers that influence the efficiency frontier by focusing on the changes of the volume of the data cloud when one or more farms are eliminated from the sample (Bogetoft and Otto, 2011). However, the choice of the maximum number of removed observations is arbitrary. Therefore, we must choose a large enough number of observations for outliers to be removed in order to allow for masking produced by one or more outliers in the dataset (Gadanakis, 2014; Wilson 1995; Bogetoft and Otto, 2011). Another limitation of the data cloud method is that the computational process takes a considerable amount of time and may become unfeasible when the dimensions of input and output space and number of observations increase (Wilson, 1995; 2010).

4.11 Non-parametric tests of returns to scale

Simar and Wilson (2002) state that before estimating the efficiency scores of the observations we need to know whether the underlying technology of the sample farms exhibits CRS, IRS, or DRS. They suggest that the question of whether a technology exhibits CRS throughout the frontier has important economic implications because some farms may be found to be either too small (i.e. farms operate under IRS) or too large (i.e. farms operate under DRS) when the technology does not exhibit CRS. If researchers estimate efficiency using DEA methods and assume the technology exhibits CRS, but it really exhibits VRS, this may seriously distort the efficiency scores of the sample (i.e. the efficiency scores of the sample will be lower than they should be). On the other hand, if researchers assume the technology is VRS but it is really CRS, then the efficiency scores of the sample will be higher than they should be. Therefore, it necessary to test the underlying technology of the PPF in order to assume the appropriate returns to scale before estimating TE using the DEA and DDF methods. This can be done by using a bootstrap procedure for testing hypotheses regarding returns to scale in the context of non-parametric approaches of TE, as proposed by Simar and Wilson (2002). Simar and Wilson (2002) suggest that researchers can first test whether returns to scale are constant by using the bootstrap procedures proposed by them, and then choosing appropriate methods to measure efficiency.

In this study, the underlying technology of the 9 observation groups of Thai rice farmers are investigated to ascertain whether they exhibit CRS or VRS by using the non-parametric test of returns to scale procedure proposed by Simar and Wilson (2002). The computational code in R programme of this procedure was written by Simm and Besstremyannaya (2016). This code is called “rst.test” in the package Robust Data Envelopment Analysis (rDEA) in the R programme. Thus, the p-values used to indicate whether the null hypothesis of CRS can be rejected are estimated using the function “rst.test” in the package rDEA. If the p-value obtained from the function “rst.test” is less than 0.05 with B = 2000 bootstrap replications, the null hypothesis can be rejected at the confidence level alpha = 0.05. This indicates that the technology exhibits VRS. If the p-value obtained from the function “rst.test” is greater than 0.05 with B = 2000 bootstrap replications, the null hypothesis cannot be rejected at the confidence level alpha = 0.05. This indicates that the technology exhibits CRS.

4.12 Summary

In this chapter, the concept of the directional nutrient surplus efficiency measure within the theoretical context of the directional distance function, something that has not been undertaken before, was introduced. This measure provides a greater choice of directional vectors, and assumes a nutrient surplus minimising behaviour in order to determine the difference between observed and minimal nutrient surplus along an optimal direction that projects any farm towards the nutrient surplus minimising benchmark. This measure is able to classify the nutrient surplus inefficiency of a farm as either technical (if the farm is located below the technical efficiency frontier, a technically inefficient farm) or allocative (if the farm is located on the technical efficiency frontier, a technically efficient farm). Even through the Thai rice dataset has not really been designed to enable this research to answer the environmental efficiency question with sufficient accuracy, this research has developed this new approach and highlights the kind of data that needs to be collected in order to perform the environmental efficiency measurement with greater accuracy.

In addition, the methodology used in this research was presented. To summarise, DEA is a non-parametric benchmarking approach that can readily be applied to evaluate the performance of farming systems in agricultural studies since it requires only data on the amount of inputs used and outputs produced. The performance of farms can be compared by the efficiency scores. Inefficient farms produce below the PPF, while efficient farms produce on the PPF. Inefficient farms could improve their performance sufficiently to achieve the PPF (i.e. become efficient farms) either by increasing their current quantity of output produced without changing the quantities of inputs used, or decreasing their current input quantities without changing the quantity of output produced. The DDF approach can be used to measure the TE of farms in reducing the amount of inputs used while increasing the amount of outputs produced simultaneously, depending on the directional vector. This implies that inefficient farms could improve their performance to achieve the PPF (i.e. become efficient farms) by simultaneously increasing the current quantity of output produced and reducing the quantities of inputs used.

DEA models differ according to the assumptions made about the underlying technologies and orientation of improvement. In this research, the technology is determined by the non-parametric tests of returns to scale. The orientation includes both input-oriented DEA and output-oriented DEA models, as well as the DDF. This is because of the major problems faced by farmers in Thai rice farming systems, namely high costs of rice production and low income (i.e. low profit), and environmental problems caused by the overuse of chemical fertiliser and manure (i.e. water pollution). The improvement of the performance of farmers using input-oriented DEA, output-oriented DEA, and DDF approaches results in higher profits for farmers and lower nitrogen and phosphorus surplus from rice cultivation. However, only the improvement of the performance of farmers using the DDF approach can lead to the reduction of nitrogen and phosphorus surplus from rice cultivation at the minimum surplus points. The dataset used in this research is explained in detail in Chapter 5. The empirical results of technical and environmental efficiency analysis of Thai rice farming are presented and discussed in Chapter 6.

Chapter 5

Data

5.1 Introduction

The main objective of this research is to measure the technical efficiency (TE) and environmental efficiency (NE) of Thai rice farming systems using the directional distance function (DDF) and directional nutrient surplus efficiency measure, respectively. Thus, the main purpose of this chapter is to describe sources of data, how to build the data analysed in this analysis, data cleaning, and the descriptive statistics used for this research. The dataset used in this research is derived from the national Thai input survey of rice farming systems cultivated during the wet season for the crop year 2008/09 at farm level for the whole country. Thailand is divided into four geographical regions (North, Northeast, Central, and South). Consequently, climate and soil fertility may differ across the sample, which may bias the results of the efficiency analysis. However, data on climate and soil fertility for the sample are unavailable. The exogenous variable that this research uses to capture the differences in soil fertility across the sample is the provincial average calculated yield of rice in the wet season for the crop year 2007/08. This variable is used to adjust the input data of this research, helping to remove some of the expected input heterogeneity and subsequent bias in efficiency measurement. After adjustment of input data, the rice farmers are put into 4 different categories, according to their regions, in order to capture the differences in climate and soil across the sample, and further split by rice type (jasmine rice, non-jasmine rice, and glutinous rice), helping to remove some of the expected input and output heterogeneity and the subsequent bias in efficiency measurement.

This chapter is organised as follows. Section 2 describes the sources of data used in this research, and the initial data cleaning. Section 3 explains how to adjust input data by using the provincial average calculated yield of rice in the wet season for the crop year 2007/08. Section 4 explains how to reduce input and output heterogeneity for efficiency analysis. Section 5 illustrates the results and discusses the use of the data cloud method to identify outliers in the sample. Section 6 discusses the results of the non-parametric test of returns to scale for TE analysis. The descriptive statistics of the samples for TE analysis are provided in Section 7. Section 8 explores conceptually the inflows and outflows of nitrogen and phosphorus in rice systems. Section 9 presents a descriptive statistical summary of inputs and outputs, nitrogen surplus (NS) and phosphorus surplus (PS) for the observed sample data for NE analysis.

5.2 Data

Data is derived from the national Thai input survey of rice farming systems cultivated during the wet season (major rice) for the crop year 2008/09 at farm level. In this survey, rice farmers who had rice-planted areas greater than 0.16 hectare were interviewed (a total 1,287 households were observed)[15]. All paddy fields in this survey are irrigated. The dataset was obtained from the Office of Agricultural Economics of Thailand (OAE)[16]. This dataset consists of farmers' names, farmers' addresses, types of rice (glutinous rice, jasmine rice, and non-jasmine rice), rice varieties' names (e.g. RD Kao-Kho, Khao Dawk Mali 105, and Suphanburi), farm-gate prices of paddy rice, per farm data of rice output produced and the combination of inputs used. The inputs, obtained in terms of both quantity and their corresponding prices, are planted area, seed, manure, bio-fertiliser, pesticide, fuel, and chemical fertilisers with their specific proportions of N, P, and K. The inputs obtained in terms of monetary value are the cost of machinery for land preparation, human labour cost including both hired and family labour, and other input costs (e.g. plastic rope, plastic bags). In addition, other secondary data related to efficiency analysis, for example the percentage of N and P contents in rice output and inputs used to calculate nitrogen and phosphorus surplus, agricultural policy, and rice production's relationship with the environment, are gathered from various sources (e.g. journals, books, statistic reports, and research reports). All prices are in Thai Baht and planted areas of rice have been converted from rai (Thai measurement unit of land area) into hectares (6.25 rai = 1 hectare).

The amount of chemical fertilisers and manure that farmers applied to their farms is known precisely, and specific formulae for chemical fertilisers (such as 46-0-0, 16-20-0, 15-15-15) and types of manure (i.e. beef, swine, and poultry) are also known. The percentages of N, P, and K in each type of manure are shown in Table 4.1. Therefore, N-fertiliser, P-fertiliser,

[15] Four provinces, Samut Songkhram, Ranong, Phangnga, and Phuket were excluded from this survey because the total planted area of rice in these provinces was less than 1,600 hectares. Furthermore, two southern border provinces, Yala and Narathiwat, were not surveyed because there was insurgency in these provinces.
[16] The OAE is the major organisation responsible for the proposal of agricultural policies; it prepares strategic plans for agricultural development and measurement, as well as managing public relations and organising discussions of agricultural trade and economic cooperation in international agriculture. This organisation also collects and disseminates agricultural information for other government organisations, private sectors, and farmers.

and K-fertiliser are calculated from the summation of each nutrient in manure and chemical fertilisers.

Table 5.1 Nutrient contents in manure

Nutrients	N (%)	P_2O_5 (%)	K_2O (%)
Manure1/			
• Beef	1.91	0.56	1.40
• Swine	3.11	12.20	1.84
• Poultry	3.77	1.89	1.76

Note: 1/ Ratneetoo (2012).

The average price of pesticide is used as a representative for the price of pesticide for the farms that did not use pesticide. With regard to the price of bio-fertiliser and fuel, the prices paid for these inputs by neighbouring farms are used as representatives for those farms that did not use them. In this analysis, the price of chemical fertiliser formula 46-0-0, 0-46-0, and 0-0-60 are used to represent the price of N-fertiliser, P-fertiliser, and K-fertiliser, respectively. Prices of chemical fertiliser formula 46-0-0 are available for each farm that applied this fertiliser in rice fields. The prices paid by neighbouring farms are used as representatives for farms that did not apply N-fertiliser. The price of chemical fertiliser formula 0-46-0 is not available for each farm, since this is not specifically a fertiliser that farmers apply in rice fields. However, the average price of chemical fertiliser formula 0-46-0 is available at country level. Therefore, the average price for the whole country is used as representative for the price of P-fertiliser for every farm in the sample. The price of chemical fertiliser formula 0-0-60 is not available for each farm since this is not specifically a fertiliser that farmers apply in rice fields. However, the average price of chemical fertiliser formula 0-0-60 is available at provincial level, so the average price in each province is used as representative for the price of K-fertiliser for every farm in that province. All chemical fertiliser prices were obtained from the OAE.

The initial dataset of the total number of observations of 1,287 households obtained from the OAE was checked for the presence of outliers using the sample means, standard deviations, minimum and maximum values, zero values in important inputs (i.e. land, seed, human labour, and machinery), and rice output per hectare (i.e. yield)[17]. According to the previous statistics from the OAE, the possible yield of Thai rice ranges between 625 to 9,375 kg/ha. A farm with a yield out of this range is an unusual observation, which may be caused

[17] Yield is calculated from the ratio of total amount of rice output per farm to the total planted area per farm.

by typographical errors when keying in the data. As a result, 1 farm that had a yield over 9,375 kg/ha and 6 farms that had a yield below 625 kg/ha were eliminated from the dataset. Furthermore, 66 farms that had some damaged areas resulting in a comparatively low yield were eliminated from the dataset because we cannot compare the TE results with the other farms without damaged areas. There is no information about the kind of damage (flood, pest, or drought). Therefore, 1,214 farms remained in the dataset after the initial data cleaning.

5.3 The adjustment of input data

Input data for the remaining 1,214 farms was adjusted by the relative index number of the provincial average calculated yield of rice in the wet season for the crop year 2007/08 and the yield of the sample farms in order to capture the differences in soil fertility across the sample; that would help to remove some of the expected input heterogeneity and subsequent bias in efficiency measurement. The relative index number of farm *i* is calculated as follows.

Relative index number of farm *i* (I^i) = (yield of farm *i* in 2008/09) / (the average yield of the same rice type of farm *i* in the province where farm *i* is located in 2007/08)

This relative index number of farm *i* is used to multiply input data of farm *i*. Thus, the input data matrix *X* (as presented in Section 4.2) after adjustment with the relative index number of each farm can be written as follows.

$$X_{adjustment} = \begin{bmatrix} I^1x_1^1 & I^1x_2^1 & \cdots & I^1x_{11}^1 \\ I^2x_1^2 & I^2x_2^2 & \cdots & I^2x_{11}^2 \\ \vdots & \vdots & \vdots & \vdots \\ I^nx_1^n & I^nx_2^n & \cdots & I^nx_{11}^n \end{bmatrix}_{n\times k}$$

5.4 Reduction of input and output heterogeneity for efficiency analysis

After adjustment of input data, the national sample of 1,214 farms were put into 4 different categories, according to their regions (North, Northeast, Central, and South), in order to capture the differences in climate and soil across the sample, helping to remove some of the expected input heterogeneity and subsequent bias in efficiency measurement. Further, in order to remove the effect of heterogeneity in the output variable, the farms are then split by rice type (jasmine rice, non-jasmine rice, and glutinous rice). The total number of observations of each rice type in each region is presented in Table 5.2. This table shows that jasmine rice is mainly cultivated in the Northern, North-eastern, and Central regions; non-jasmine rice is cultivated in all regions; glutinous rice is cultivated only in the Northern and

North-eastern regions. Thus, there are 9 groups of observations of Thai rice farmers in this research. These 9 groups of observations of Thai rice farmers are named jasmine rice North, jasmine rice Northeast, jasmine rice Central, non-jasmine rice North, non-jasmine rice Northeast, non-jasmine rice Central, non-jasmine rice South, glutinous rice North, and glutinous rice Northeast: they represent jasmine rice farms in the Northern region, jasmine rice farms in the North-eastern region, jasmine rice farms in the Central region, non-jasmine rice farms in the Northern region, non-jasmine rice farms in the North-eastern region, non-jasmine rice farms in the Central region, non-jasmine rice farms in the Southern region, glutinous rice farms in the Northern region, and glutinous rice farms in the North-eastern region, respectively. The total number of observations for these 9 groups is presented in the following Table.

Table 5.2 Number of observations categorised by region and type of rice

Region	**Type of rice**		
	Jasmine rice	**Non-jasmine rice**	**Glutinous rice**
North	76	162	100
Northeast	199	76	194
Central	67	226	0
South	0	114	0
Total observations	**342**	**578**	**294**

Source: Author’s analysis of sample data (a total of 1,214 farms were observed).

5.5 Identifying outliers using the data cloud method

The presence of outliers in the dataset may bias efficiency estimates: this could make the resulting guidelines, intended to improve the performance of those perceived as inefficient, meaningless and misleading. The data cloud method is useful in identifying and removing outliers in the data, thus leading to more accurate efficiency estimates. Therefore, the data sets for 9 groups of Thai rice farmers were tested for outliers, employing the data cloud method proposed by Wilson (1993). The benefit of this method is that it enables identification of observations as outliers even if they lie below the PPF, i.e. inefficient farms (Wilson, 1993). For each group observed, a combined matrix $[XY]$ was created and the number of eliminated farms (r) was determined to be 15 (i.e. $r = 15$). The graph plotting ordered pairs for the number of eliminated farms and the log ratio $\left(r, log\left(R^{(r)}/R_{min}^{(r)}\right)\right)$, and the table of the values of $R_{min}^{(r)}$ and the farm number to be deleted in each group of outliers for each group of observations are presented in Appendix A[18]. The example of how to identify outliers in each group of observations is demonstrated by the outliers' identification of jasmine rice farms in the Northern region.

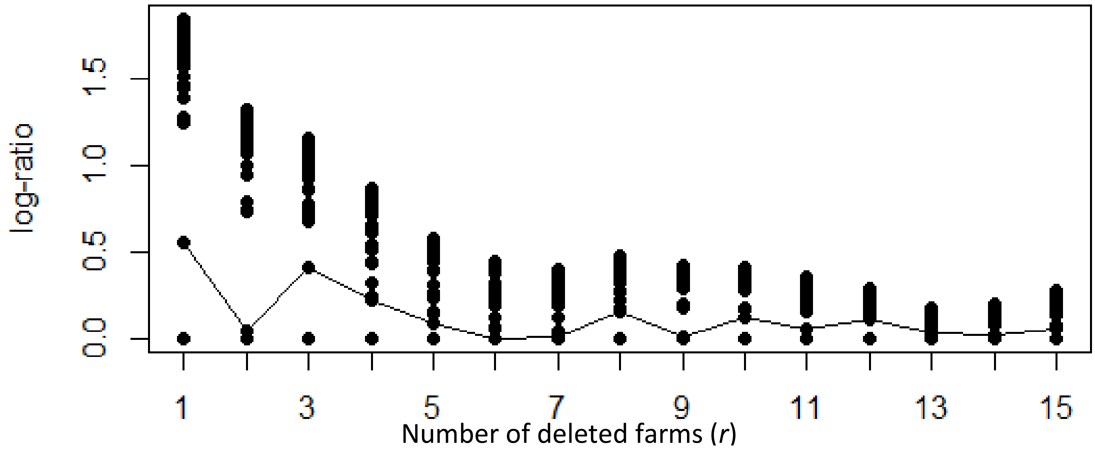

Figure 5.1 Log-ratio plot for outlier identification of jasmine rice farms in the Northern region

Table 5.3 The values of $R_{min}^{(r)}$ and the farm number to be deleted in each group of outliers for jasmine rice farms in the Northern region dataset

r	**Deleted observations**															$\boldsymbol{R_{min}^{(r)}}$
1	34															0.1304
2	35	34														0.0283
3	**35**	**70**	**34**													**0.0063**
4	16	35	70	34												0.0021
5	16	69	35	70	34											0.0008
6	16	75	60	35	70	34										0.0003
7	16	75	60	69	35	70	34									0.0001
8	**33**	**16**	**75**	**60**	**69**	**35**	**70**	**34**								**0.0001**
9	33	7	16	75	60	69	35	70	34							0.0000
10	**33**	**15**	**7**	**16**	**75**	**60**	**69**	**35**	**70**	**34**						**0.0000**
11	55	33	15	7	16	75	60	69	35	70	34					0.0000
12	**55**	**33**	**15**	**12**	**7**	**16**	**75**	**60**	**69**	**35**	**70**	**34**				**0.0000**
13	55	33	53	15	12	7	16	75	60	69	35	70	34			0.0000
14	38	57	33	15	41	12	7	16	75	60	69	35	70	34		0.0000
15	46	38	57	33	15	41	12	7	16	75	60	69	35	70	34	0.0000

Figure 5.1 illustrates the ordered pairs plot of the number of eliminated farms and the log ratio $\left(r, log\left(R^{(r)}/R_{min}^{(r)}\right)\right)$. The lines peak at r = 3, r = 8, r = 10, and r = 12 indicating that the potential outliers in the dataset are 3, 8, 10 or 12 farms. The values of $R_{min}^{(r)}$ for $r =$

[18] Function "*ap*" from the package FEAR: A Software Package for Frontier Efficiency Analysis with R was used to calculate log-ratio and $R_{min}^{(r)}$ for the data cloud method (Wilson, 2008).

$1, \ldots, 15$ and the farm number to be deleted in each group of outliers are shown in Table 5.3. Table, *r* = 12 gives the smallest values of $R_{min}^{(r)}$ compared to *r* = 3, *r* = 8, *r* = 10, thus, the farms in group *r = 12* are identified as outliers by use of the data cloud method.

Farms that were identified as outliers in each group of observations were deleted from the sample. As a result, there remained 64 farms for jasmine rice North, 189 farms for jasmine rice Northeast, 58 farms for jasmine rice Central, 152 farms for non-jasmine rice North, 63 farms for non-jasmine rice Northeast, 214 farms for non-jasmine rice Central, 100 farms for non-jasmine rice South, 92 farms for glutinous rice North, and 180 farms for glutinous rice Northeast which were used to estimate the TE of Thai rice farming systems.

5.6 Testing for Returns to scale

The underlying technologies of 9 groups of Thai rice farmers were tested to ascertain whether they exhibited CRS or VRS by using the non-parametric test of returns to scale as explained in Section 4.11. The results show that the p-values of these 9 groups of observations are greater than 0.05 indicating that the null hypothesis of CRS cannot be rejected at the confidence level alpha = 0.05, except that the p-values of non-jasmine rice Northeast and glutinous rice North are less than 0.03, indicating that the null hypothesis of CRS is rejected at the confidence level alpha = 0.05. Thus, the CRS is assumed to the technology when estimating the technical efficiency of jasmine rice North, jasmine rice Northeast, jasmine rice Central, non-jasmine rice North, non-jasmine rice Central, non-jasmine rice South, and glutinous rice Northeast using the DEA and DDF models. However, the VRS is assumed to the technology when estimating the technical efficiency of non-jasmine rice Northeast and glutinous rice North using the DEA and DDF models.

5.7 Descriptive statistics of sample farms for technical efficiency analysis

The efficiency analysis of this research is based on per farm data of rice production of 9 groups of Thai rice farmers. In each group of observations, there is 1 output variable and 11 input variables for TE analysis. The output variable is rice production (*y*) and the corresponding price of rice (*p*). The 11 input variables, after adjustment with the relative index number, consist of the planted area (x_1), seed (x_2), bio-fertiliser (x_3), N-fertiliser (x_4), P-fertiliser (x_5), K-fertiliser (x_6), pesticide (x_7), human labour cost (x_8), machinery cost (x_9), fuel (x_{10}), other costs (x_{11}) and the corresponding prices of these inputs, which are the price of the planted area (w_1), seed (w_2), bio-fertiliser (w_3), N-fertiliser (w_4), P-fertiliser (w_5), K-fertiliser (w_6), pesticide (w_7), human labour (w_8), machinery (w_9), fuel (w_{10}), and other inputs (w_{11}).

The descriptive statistics of jasmine rice produced and the combination of inputs used per hectare of the sample jasmine rice North farms, jasmine rice Northeast farms, and jasmine rice Central farms for TE analysis are presented in the third to sixth columns of Table 5.5, the seventh to tenth columns of Table 5.5, and the eleventh to fourteenth columns of Table 5.5, respectively. The average yield of jasmine rice produced and the combination of inputs used per hectare and their corresponding prices for the sample jasmine rice farms in the Northern, North-eastern, and Central regions are presented in the third, seventh, and eleventh columns of the Table, respectively. The average yield of jasmine rice produced in the Northern region is higher than that in the North-eastern and Central regions by 34% and 23%, respectively. The average farm-gate price of jasmine rice in the North-eastern region is higher than that in the other two regions. The average planted area of jasmine rice farms in all regions is less than 3.2 hectares, indicating that the majority of jasmine rice farmers in Thailand are small-scale farmers[19]. The average planted area of jasmine rice farms in the Central region is 3.08 hectares, which is higher than that of jasmine rice farms in the Northern and North-eastern regions, indicating that the majority of jasmine rice farms in the Central region are commercial farms. The average seed used per hectare by jasmine rice farmers in the Northern region is less than that of jasmine rice farmers in the other two regions by 21%. However, the average N-fertiliser used per hectare by jasmine rice farmers in the Northern region is higher than that of jasmine rice farmers in the North-eastern and Central regions by 1% and 17%, respectively. The average amount of P-fertiliser used per hectare by jasmine rice farmers in the Northern region is higher than that of jasmine rice farmers in the Central region by 6%, but lower than that of jasmine rice farmers in the North-eastern region by 16%.

Table 5.5 presents the descriptive statistics of non-jasmine rice produced and the combination of inputs used per hectare of the sample non-jasmine rice North farms, non-jasmine rice Northeast farms, non-jasmine rice Central farms and non-jasmine rice South farms for TE analysis. The average yield of non-jasmine rice produced and the combination of inputs used per hectare and their corresponding prices on the sample non-jasmine rice North farms, non-jasmine rice Northeast farms, non-jasmine rice Central farms and non-jasmine rice South farms are presented in the third, seventh, eleventh and fifteenth columns of the Table, respectively. The average yield of non-jasmine rice produced in the Central region is higher than that in the Northern, Central, and Southern regions by 6%, 42% and 28%, respectively. However, the average farm-gate price of non-jasmine rice in the Southern region is the highest

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[19] Small-scale farmers have planted areas greater than or equal to 0.16 and less than or equal to 3.2 hectares ($0.16 \leq$ area ≤ 3.2). Medium-scale farmers have planted areas greater than 3.2 and less than or equal to 6.4 hectares ($3.2 <$ area ≤ 6.4). Large-scale farmers have planted areas more than 6.4 hectares (area > 6.4).

of the four regions. The average amounts of N-fertiliser and P-fertiliser used per hectare by non-jasmine rice farmers in the Central region are the highest of the four regions. Moreover, the average planted areas of non-jasmine rice farms in the Northern and Central regions are greater than 3.2 hectares, indicating that the majority of non-jasmine rice farmers in these two regions are medium-scale farmers (running commercial farms). However, the majority of non-jasmine rice farmers in the North-eastern and Southern regions are small-scale farmers.

The descriptive statistics of glutinous rice produced and the combination of inputs used per hectare of the sample f glutinous rice North farms and glutinous rice Northeast farms for TE analysis are presented in the third to sixth columns of Table 5.6, and the seventh to tenth columns of Table 5.6, respectively. The average yield of glutinous rice produced and the combination of inputs used per hectare and their corresponding prices on the sample glutinous rice North farms and glutinous rice Northeast farms are presented in the third and the seventh columns of the Table, respectively. The average yield of glutinous rice produced in Northern region is higher than that in North-eastern region by 37%. However, the average use of seed, N-fertiliser, and P-fertiliser per hectare on glutinous rice farms in the Northern region was lower than that on farms in the North-eastern region by 58%, 42%, and 39%, respectively. The average farm-gate prices of glutinous rice in both regions are similar, but they are comparatively low compared to the average farm-gate prices of jasmine and non-jasmine rice. Furthermore, the average planted areas on glutinous rice farms in the Northern and North-eastern regions are 0.91 and 1.26 hectares per farm, respectively, indicating that the majority of glutinous rice farmers in these two regions are small-scale farmers.

Considered within each region, the average yield of jasmine rice is lowest compared to non-jasmine and glutinous rice, while the average yield of non-jasmine rice is highest (Table 5.4 – Table 5.6). In the Northern region, the average amount of N-fertiliser and planted area of non-jasmine rice farmers are higher than those of jasmine rice and glutinous rice farmers. In the North-eastern region, the average amount of N-fertiliser applied to glutinous rice is higher than that applied to jasmine and non-jasmine rice. However, the average planted area of jasmine rice is higher than that of non-jasmine rice and glutinous rice. In the Central region, the average planted area, use of N-fertiliser and use of P-fertiliser on non-jasmine rice farms are higher than those on jasmine rice farms.

Table 5.4 Descriptive statistics of jasmine rice produced and inputs used with sample data categorised by region for efficiency analysis

Regions		North				Northeast				Central			
Description	**Unit**	**Mean**	**Std. dev.**	**Min.**	**Max.**	**Mean**	**Std. dev.**	**Min.**	**Max.**	**Mean**	**Std. dev.**	**Min.**	**Max.**
Quantity													
Yield	Kg/Ha	3,107	447	2,446	4,091	2,062	215	1,647	2,523	2,389	341	1,905	3,051
Planted area	Ha/Farm	1.65	1.11	0.18	4.78	1.60	1.38	0.16	8.94	3.08	2.52	0.53	12.62
Seed	Kg/Ha	121	72	13	315	147	51	25	312	147	78	16	685
Bio-fertiliser	Kg/Ha	2,316	4,600	0	15,730	3,428	5,757	0	31,153	463	2,196	0	15,611
N-fertiliser	Kg/Ha	45	35	0	144	44	37	0	205	37	25	0	108
P-fertiliser	Kg/Ha	18	19	0	99	21	24	0	198	17	15	0	52
K-fertiliser	Kg/Ha	6	16	0	101	16	20	0	105	4	8	0	35
Pesticide	Kg/Ha	16	41	0	313	3	9	0	62	2	3	0	18
Human labour	Baht/Ha	7,647	2,824	3,681	15,854	8,036	2,801	2,762	15,864	4,361	1,045	2,801	7,268
Machinery	Baht/Ha	3,747	1,018	1,250	5,931	3,575	1,078	1,248	6,878	3,637	1,076	1,688	5,622
Fuel	Litre/Ha	4	12	0	78	5	14	0	120	1	4	0	21
Other costs	Baht/Ha	797	907	0	3,712	820	1,207	0	9,756	150	241	0	938
Price													
Rice output	Baht/Kg	11.44	1.47	6.85	15.00	12.55	1.59	8.22	18.09	10.65	1.11	7.65	14.00
Planted area	Baht/Ha	5,873	2,869	1,563	15,275	4,277	2,003	938	12,363	3,853	2,109	1,250	8,750
Seed	Baht/Kg	18	6	9	35	18	4	8	28	16	5	8	30
Bio-fertiliser	Baht/Kg	7	34	0	230	2	28	0	380	12	31	0	130
N-fertiliser	Baht/Kg	24	4	14	32	26	2	15	30	26	2	17	29
P-fertiliser	Baht/Kg	26	0	26	26	26	0	26	26	26	0	26	26
K-fertiliser	Baht/Kg	30	1	29	32	32	0	32	32	29	0	29	32
Pesticide	Baht/Kg	160	134	3	500	215	101	12	600	223	119	40	728
Human labour	Baht/Unit	1	0	1	1	1	0	1	1	1	0	1	1
Machinery	Baht/Unit	1	0	1	1	1	0	1	1	1	0	1	1
Fuel	Baht/Litre	39	3	33	46	39	4	20	50	41	5	20	60
Other costs	Baht/Unit	1	0	1	1	1	0	1	1	1	0	1	1

Table 5.5 Descriptive statistics of non-jasmine rice produced and inputs used with sample data categorised by region for efficiency analysis

Regions		North				Northeast				Central				South			
Description	**Unit**	**Mean**	**Std. dev.**	**Min.**	**Max.**	**Mean**	**Std. dev.**	**Min.**	**Max.**	**Mean**	**Std. dev.**	**Min.**	**Max.**	**Mean**	**Std. dev.**	**Min.**	**Max.**
Quantity																	
Yield	Kg/Ha	3,644	258	3,182	4,153	2,230	300	1,829	2,759	3,863	757	1,948	4,800	2,787	493	2,188	3,667
Planted area	Ha/Farm	3.28	2.57	0.19	12.92	1.01	0.71	0.15	3.44	4.28	3.10	0.44	20.66	1.81	2.09	0.18	13.66
Seed	Kg/Ha	173	74	21	327	149	47	31	250	174	39	17	313	178	187	30	1,143
Bio-fertiliser	Kg/Ha	1,728	4,093	0	25,011	5,759	11,865	0	73,217	1,879	5,437	0	37,457	952	2,895	0	13,385
N-fertiliser	Kg/Ha	73	47	0	215	48	44	0	236	82	45	0	288	48	37	0	144
P-fertiliser	Kg/Ha	18	18	0	75	20	25	0	118	31	23	0	102	27	21	0	75
K-fertiliser	Kg/Ha	3	8	0	43	15	21	0	110	2	6	0	37	1	5	0	33
Pesticide	Kg/Ha	14	25	0	234	3	8	0	38	9	18	0	219	7	10	0	50
Human labour	Baht/Ha	7,030	3,195	3,660	22,536	7,438	2,646	3,026	14,633	6,010	1,682	1,355	14,093	8,940	4,462	3,454	17,905
Machinery	Baht/Ha	3,369	1,019	1,562	6,264	3,669	1,333	1,391	7,192	3,274	892	1,562	9,371	4,405	848	2,812	6,310
Fuel	Litre/Ha	10	22	0	159	4	10	0	47	26	39	0	306	6	10	0	48
Other costs	Baht/Ha	494	736	0	5,129	545	765	0	3,459	175	258	0	1,791	346	436	0	2,145
Price																	
Rice output	Baht/Kg	9.89	1.68	6.57	15.00	10.29	1.82	6.80	15.43	9.85	1.29	5.90	14.00	11.77	2.15	8.18	16.00
Planted area	Baht/Ha	4,535	2,103	1,250	11,250	4,016	1,884	1,563	9,375	5,158	2,590	1,250	13,750	2,405	747	938	3,750
Seed	Baht/Kg	17	6	8	28	14	5	4	25	17	5	8	26	13	5	5	22
Bio-fertiliser	Baht/Kg	8	32	0	250	3	16	0	123	19	62	0	422	3	20	0	200
N-fertiliser	Baht/Kg	25	3	13	29	26	2	15	29	26	3	16	38	25	4	13	31
P-fertiliser	Baht/Kg	26	0	26	26	26	0	26	26	26	0	26	26	26	0	26	26
K-fertiliser	Baht/Kg	30	0	29	32	32	0	32	32	29	1	29	32	27	1	26	28
Pesticide	Baht/Kg	213	149	1	800	176	78	4	500	325	175	16	1,100	145	131	10	850
Human labour	Baht/Unit	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	1
Machinery	Baht/Unit	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	1
Fuel	Baht/Litre	39	4	25	50	39	4	25	47	41	4	20	50	37	6	20	49
Other costs	Baht/Unit	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	1

Table 5.6 Descriptive statistics of glutinous rice produced and inputs used with sample data categorised by region for efficiency analysis

Regions		North				Northeast			
Description	**Unit**	**Mean**	**Std. dev.**	**Min.**	**Max.**	**Mean**	**Std. dev.**	**Min.**	**Max.**
Quantity									
Yield	Kg/Ha	3,355	341	2,692	3,853	2,109	160	1,905	2,500
Planted area	Ha/Farm	0.91	0.55	0.17	2.40	1.26	0.82	0.10	4.10
Seed	Kg/Ha	100	62	32	314	158	56	21	338
Bio-fertiliser	Kg/Ha	1,185	3,791	0	23,429	4,004	6,831	0	39,345
N-fertiliser	Kg/Ha	37	38	0	179	52	54	0	310
P-fertiliser	Kg/Ha	14	17	0	75	19	21	0	97
K-fertiliser	Kg/Ha	3	6	0	24	20	30	0	217
Pesticide	Kg/Ha	12	15	0	56	3	9	0	64
Human labour	Baht/Ha	10,055	3,989	4,222	22,912	8,442	3,069	2,726	17,756
Machinery	Baht/Ha	4,628	1,215	636	7,505	3,552	1,092	1,235	5,975
Fuel	Litre/Ha	10	18	0	83	3	9	0	47
Other costs	Baht/Ha	893	951	0	4,703	873	1,060	0	8,727
Price									
Rice output	Baht/Kg	7.46	0.84	6.20	10.00	7.04	0.68	6.25	11.18
Planted area	Baht/Ha	4,682	2,384	813	12,000	3,395	1,397	938	9,375
Seed	Baht/Kg	17	5	10	35	16	5	4	27
Bio-fertiliser	Baht/Kg	6	32	0	225	1	7	0	90
N-fertiliser	Baht/Kg	24	4	15	30	26	2	15	32
P-fertiliser	Baht/Kg	26	0	26	26	26	0	26	26
K-fertiliser	Baht/Kg	30	0	29	30	32	0	32	32
Pesticide	Baht/Kg	156	142	0	650	213	147	18	1,667
Human labour	Baht/Unit	1	0	1	1	1	0	1	1
Machinery	Baht/Unit	1	0	1	1	1	0	1	1
Fuel	Baht/Litre	39	4	28	50	40	3	33	49
Other costs	Baht/Unit	1	0	1	1	1	0	1	1

5.8 Nitrogen Surplus and Phosphorus Surplus in Sample data

The application of the material balance condition (MBC) to a farm requires the inflows and outflows of N and P (Nguyen et al., 2012). Figure 5.2 presents inflows and outflows of N and P in rice farming systems. The inflows consist of N and P contained in manure (i.e. manure from beef, poultry, and swine), chemical fertiliser, bio-fertiliser, seed and land area (soil), as well as N and P from other natural processes, for example biological fixation, atmospheric deposition, precipitation, and in irrigation water (Nguyen et al., 2012). In Thailand, farmers typically produce their own bio-fertiliser by using different combinations of raw materials, including residues from plants or fruits or animal (for example fish and snails), molasses or other sugars, water, and effective microorganisms (Maneewon, 2015). The outflows of N and P in paddy rice are found also in rice straw, soil, the atmosphere, underground water, and surface water. However, the data on N and P inflows and outflows related to soil (land area), bio-fertiliser, biological fixation, atmospheric deposition, precipitation, in irrigation water and straw for each farm in the sample are unavailable. Therefore, only the inputs and outputs that have N and P contents are considered for this study. These are seed (x_2), N-fertiliser (x_4, summation of N content in manure and chemical fertiliser), P-fertiliser (x_5, summation of P content in manure and chemical fertiliser), and the rice itself (y). The other input variables, namely planted areas, bio-fertiliser (no information on specific combination of bio-fertiliser and the percentage of N and P contents in bio-fertiliser), K-fertiliser, pesticide, human labour, machinery, fuel, and other inputs, are assumed to have zero N and P contents.

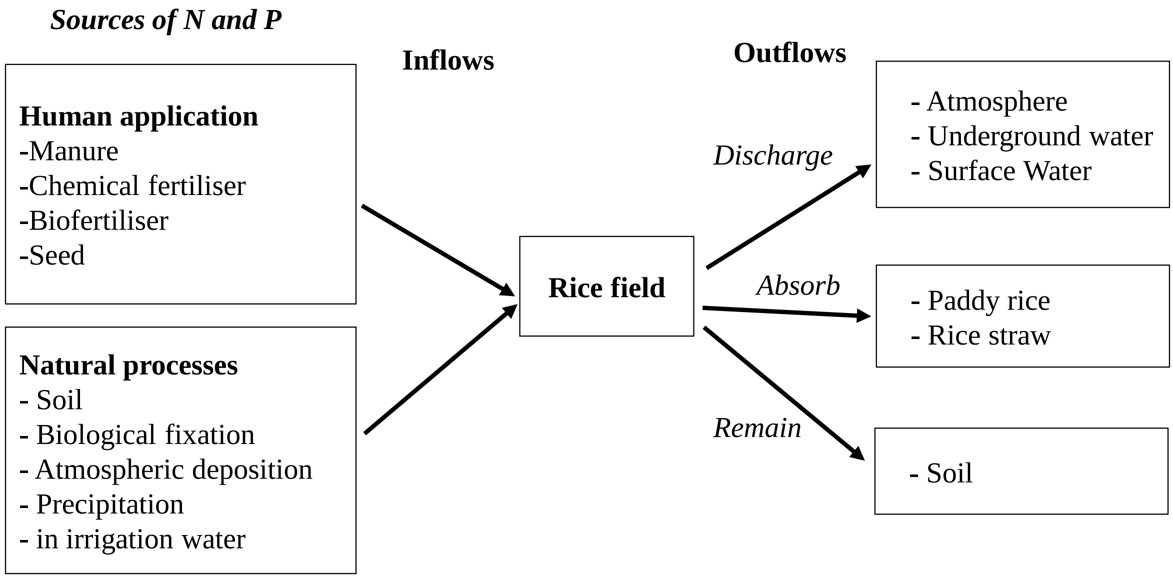

Figure 5.2 Inflows and outflows of N and P in rice fields

From the review of previous studies related to the inflows of N and P nutrients from natural processes and outflows of N and P nutrients in rice straw, this study found that there is no good proxy that can be used as representative of these variables for the NE analysis of Thai rice farming. Promnart (2001) reported that the N and P contents in rice straw are 0.65%, and 0.10%, respectively. However, the amount of rice straw produced by each farm in this study's sample is unavailable. Promnart (2001) also reported that N inflows from natural processes in Thai rice fields are approximately 40 – 80 kg/ha, while Dobermann et al. (2002) reported that the initial N and P nutrients in soil in rice fields in Suphanburi province, in the Central region of Thailand, are 73 and 16 kg/ha, respectively. Limtong (2012) indicated that the soil in the Central and Northern regions has high fertility and is suitable for rice cultivation, while soil in the North-eastern region of Thailand has low fertility compared to other three regions. Nevertheless, he does not report the quantity of N and P nutrients in the soil in each region. Since N and P inflows from natural processes are different across regions, it is not logical to use only one value as a proxy for N and P nutrients from natural processes for all farms in the sample. Thus, the omission of N and P inflow variables from bio-fertiliser and natural processes (i.e. soil, biological fixation, atmospheric deposition, precipitation, and in irrigation water) and outflow variables (rice straw, and soil) from this study will lead to underestimation of the NS and PS of each farm, because the N and P inflow variables are greater than the N and P outflow variables. However, the rank of NS and PS efficiency in the sample will not change if a proxy of inflows and outflows variables is the same across all farms in the sample.

Nitrogen and phosphorus contents in paddy seed (both y and x_2) are 1.1% and 0.2%, respectively (Promnart, 2001). The observed NS for the i^{th} farm is calculated by the total amount of N content in inputs minus the total amount of N content in outputs, that is $NS^i = \left(0.011x_2^i + x_4^i\right) - 0.011y^i$ where x_2^i is the quantity of paddy seed used on farm *i*, x_4^i is the summation of N contents in manure and chemical fertiliser that farm *i* applied to its field, and y^i is the quantity of paddy output of farm *i*. The observed PS for the i^{th} farm is calculated by the total amount of P content in inputs minus the total amount of P content in outputs, that is $PS^i = \left(0.002x_2^i + x_5^i\right) - 0.002y^i$ where x_2^i is the quantity of paddy seed used on farm *i*, x_5^i is the summation of P contents in manure and chemical fertiliser that farm *i* applied to its field, and y^i is the quantity of paddy output of farm *i*.

5.9 The data set for environmental efficiency analysis

The surplus of two nutrients, N and P, is an important indicator for the environmental efficiency of rice cultivation. Thus, two models, namely the nitrogen surplus minimisation model (NSMM) and the phosphorus surplus minimisation model (PSMM), are applied to measure the environmental efficiency of 9 groups of Thai rice farmers. The NSMM is used to measure NS efficiency of the farmers in each group, using the directional nutrient surplus efficiency measure with the directional vector towards the nitrogen surplus minimising frontier. The PSMM is used to measure PS efficiency of farmers in each group, using the directional nutrient surplus efficiency measure with the directional vector towards the phosphorus surplus minimising frontier. The data set used for the NSMM and PSMM for each group of observations is discussed in the following sections.

5.9.1 The data set for NSMM

The NS of each farm in the 9 observed groups of Thai rice farms that were used to estimate TE scores is calculated. Note that the total numbers of observations for TE analysis of 9 groups of Thai rice farms are presented in the third column of Table 5.7. The distributions of NS for these 9 groups of Thai rice farms are shown in Figure 5.3. Farms with negative or zero NS were removed from each group of observations. The remaining positive NS farms in each group of observations (as showed in the fourth column of Table 5.7) were tested for outliers employing the data cloud method (Appendix B). The total numbers of observations, after removing outliers from the 9 observed groups of Thai rice farms used to estimate NS efficiency of Thai rice farming systems using NSMM, are shown in the sixth column of Table 5.7.

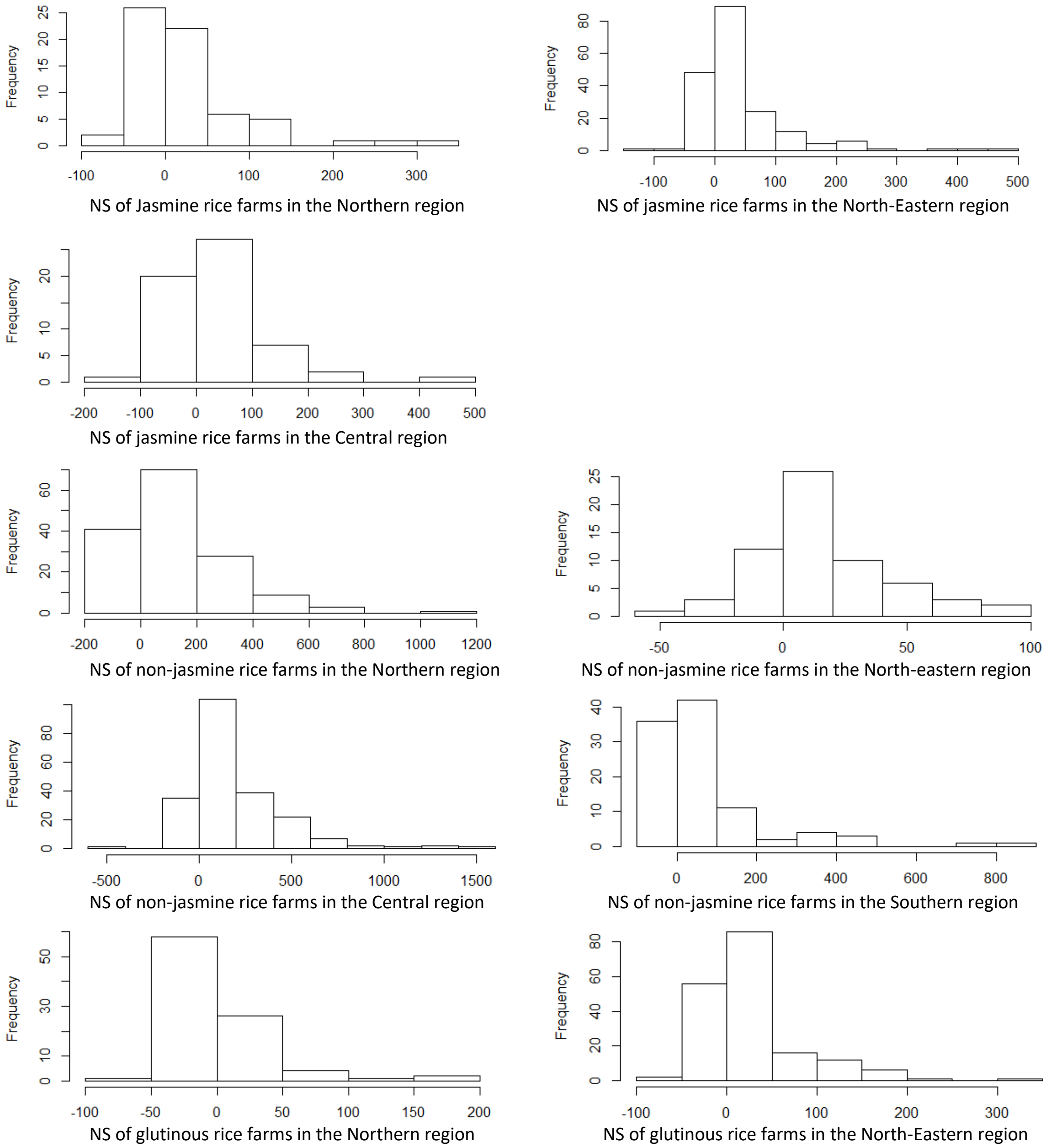

Figure 5.3 Histogram of nitrogen surplus for each group of observations

Table 5.7 The total number of observations for TE analysis, positive NS, positive PS, and NE analysis for each type of rice in each region

Type of rice	Region	No. of observations for TE analysis	No. of observations		No. of observations for NE analysis	
			Positive NS	Positive PS	NSMM	PSMM
Jasmine rice	North	64	36	40	21	26
	Northeast	189	139	140	126	126
	Central	58	37	41	23	27
Non-jasmine rice	North	152	111	87	100	73
	Northeast	63	47	42	34	30
	Central	214	178	167	164	154
	South	100	64	76	50	61
Glutinous rice	North	92	33	49	19	34
	Northeast	180	122	133	109	118
Total no. of observations		**1,112**	**767**	**775**	**646**	**649**

5.9.2 Descriptive statistics of sample farms for NSMM

The descriptive statistics of rice produced and the combination of inputs used per hectare on 9 groups of Thai rice farms for NSMM is presented in Table 5.8. The average N-fertiliser used and the average yield obtained by jasmine rice farmers in the Northern region are the highest of the three regions. The average yield of non-jasmine rice farmers in the Central region is highest compared to the other three regions. The average amounts of N-fertiliser used by non-jasmine rice farmers in the Central and Northern regions are higher than those used by non-jasmine rice farmers in the North-eastern and Southern regions. The average amount of N-fertiliser used and the average yield obtained by glutinous rice farmers in the Northern region are higher than the results for glutinous rice farmers in the North-eastern region. Considered within each region, the average yield of jasmine rice is lowest compared to non-jasmine and glutinous rice, while the average yield of non-jasmine rice is highest. In the Northern region, the average amount of N-fertiliser applied to non-jasmine rice is higher than that applied to jasmine and glutinous rice. In the North-eastern region, the average amount of N-fertiliser applied to glutinous rice is higher than that applied to jasmine and non-jasmine rice. In the Central region, the average amount of N-fertiliser applied to non-jasmine rice is higher than that applied to jasmine rice.

Table 5.8 Descriptive statistics of rice output produced and inputs used based on sample data for NSMM

Unit: Kg/Ha

Type of rice	Region	Description	Mean	Std. dev.	Min	Max
Jasmine rice	North	Output	3,237.47	582.46	2,551.02	4,090.91
		Seed	134.89	74.00	62.22	314.68
		N-fertiliser	61.30	25.89	29.77	144.43
	Northeast	Output	2,065.45	206.47	1,647.06	2,522.52
		Seed	146.10	51.23	31.28	311.52
		N-fertiliser	56.15	31.08	20.74	187.89
	Central	Output	2,286.93	328.86	1,904.76	3,050.85
		Seed	139.86	21.65	100.19	188.08
		N-fertiliser	49.10	22.49	20.84	107.72
Non-jasmine rice	North	Output	3,649.74	261.26	3,181.82	4,151.84
		Seed	195.98	61.18	31.33	327.35
		N-fertiliser	92.09	34.36	35.65	215.45
	Northeast	Output	2,180.76	286.03	1,829.27	2,758.62
		Seed	153.78	49.91	31.31	249.59
		N-fertiliser	66.76	45.40	24.15	235.76
	Central	Output	3,898.79	762.33	1,948.45	4,800.00
		Seed	175.81	37.43	16.64	312.91
		N-fertiliser	91.85	36.64	23.48	269.23
	South	Output	2,843.97	488.60	2,196.08	3,666.67
		Seed	143.96	74.36	30.18	522.37
		N-fertiliser	61.54	26.14	24.88	120.06
Glutinous rice	North	Output	3,361.47	312.24	2,906.98	3,853.21
		Seed	102.07	45.24	50.20	187.63
		N-fertiliser	74.43	38.44	38.91	178.96
	Northeast	Output	2,111.82	160.56	1,904.76	2,500.00
		Seed	148.24	55.45	20.80	338.49
		N-fertiliser	68.26	48.77	21.51	310.15

5.9.3 The data set for PSMM

The PS of each farm in 9 groups of Thai rice farms that were used to estimate TE scores is calculated. The distributions of PS for these 9 groups of Thai rice farms are shown in Figure 5.4. Farms with negative or zero PS were removed from each group of observations. The remaining positive PS farms in each group of observations (as showed in the fifth column of Table 5.7) were tested for outliers employing the data cloud method (Appendix C). The total number of observations, after removing outliers from 9 groups of Thai rice farms, that were used to estimate the PS efficiency of Thai rice farming systems using PSMM are shown in the seventh column of Table 5.7.

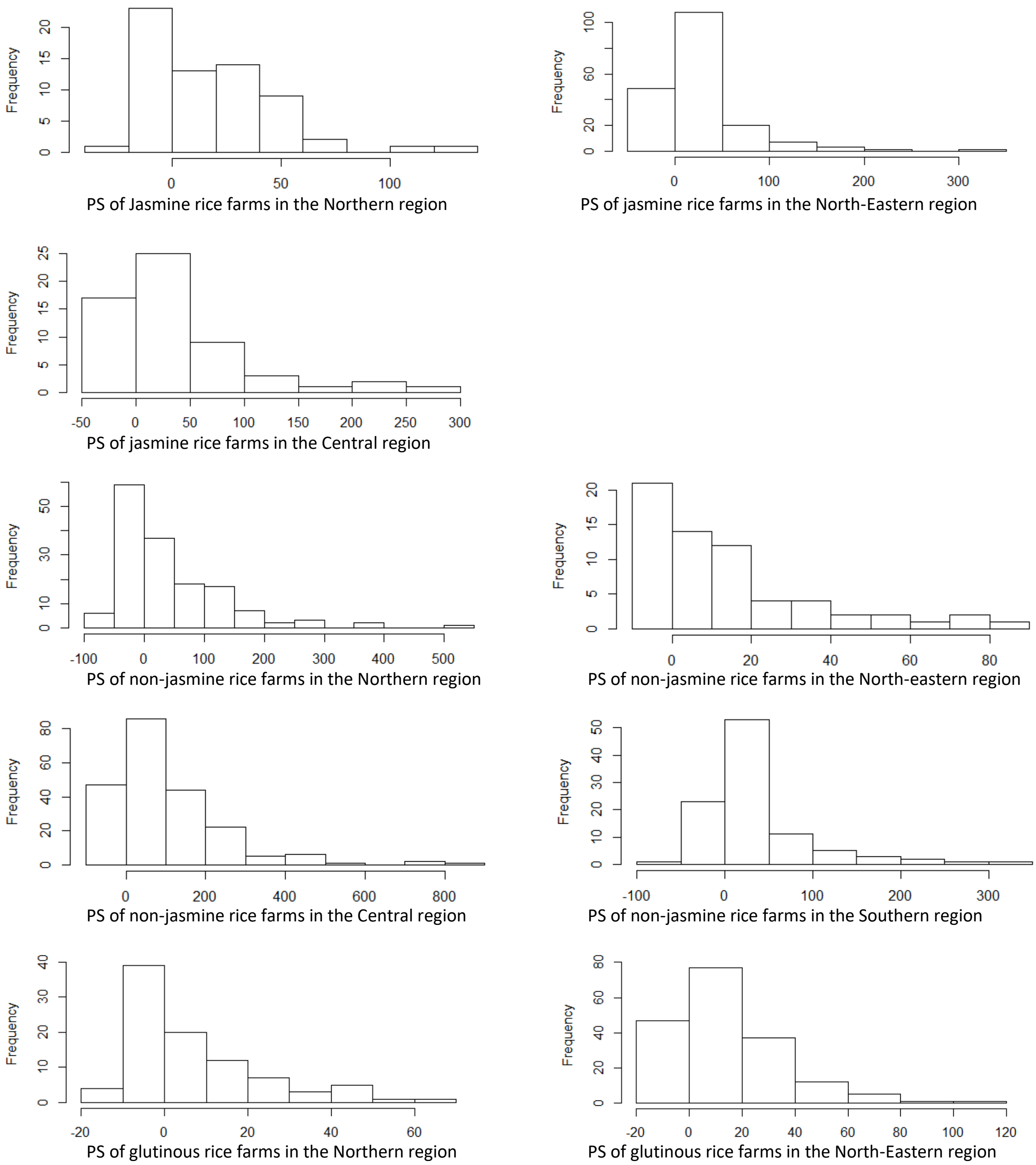

Figure 5.4 Histogram of phosphorus surplus for each group of observations

5.9.4 Descriptive statistics of sample farms for PSMM

The descriptive statistics of rice produced and the combination of inputs used per hectare of 9 groups of Thai rice farms for PSMM is presented in Table 5.9. The average P-fertiliser used and the average yield obtained by jasmine rice farmers in the Northern region are higher than in the other two regions. The average amount of P-fertiliser used and the average yield obtained by non-jasmine rice farmers in the Central region are higher than in the other three regions. The average amounts of P-fertiliser used by glutinous rice farmers in the Northern and North-eastern regions are nearly the same, but farmers in the Northern region obtained a 38% better yield than farmers in the North-eastern region. Considered within each region, the average yield of jasmine rice is lowest compared to non-jasmine and glutinous rice, while the average yield of non-jasmine rice is highest. In the Northern region, the average amount of P-fertiliser applied to jasmine rice is higher than that applied to non-jasmine and glutinous rice. In the North-eastern region, the average amount of P-fertiliser applied to non-jasmine rice is higher than applied to jasmine rice and glutinous rice. In the Central region, the average amount of P-fertiliser applied to non-jasmine rice is higher than that applied to jasmine rice.

Table 5.9 Descriptive statistics of rice output produced and inputs used based on sample data for PSMM

Unit: Kg/Ha

Type of rice	Region	Description	Mean	Std. dev.	Min	Max
Jasmine rice	North	Output	3,123.29	332.35	2,551.02	3,640.00
		Seed	93.10	38.11	43.32	166.33
		P-fertiliser	31.24	17.13	14.20	98.61
	Northeast	Output	2,060.52	209.77	1,647.06	2,514.97
		Seed	146.27	52.20	31.28	311.52
		P-fertiliser	26.73	23.60	4.17	197.67
	Central	Output	2,341.44	365.21	1,904.76	3,050.85
		Seed	132.30	34.78	15.98	188.08
		P-fertiliser	22.43	12.46	5.01	51.88
Non-jasmine rice	North	Output	3,618.45	278.94	3,181.82	4,148.47
		Seed	186.68	69.88	46.91	327.35
		P-fertiliser	27.48	11.54	8.72	62.43
	Northeast	Output	2,127.00	225.23	1,902.78	2,727.27
		Seed	149.85	49.31	62.02	249.59
		P-fertiliser	31.31	25.61	6.97	118.20
	Central	Output	3,888.56	755.64	1,948.87	4,797.98
		Seed	172.22	38.97	16.64	312.91
		P-fertiliser	37.62	18.21	7.49	101.69
	South	Output	2,792.95	485.46	2,187.50	3,666.67
		Seed	135.47	94.55	30.18	632.23
		P-fertiliser	34.43	15.51	11.35	74.80
Glutinous rice	North	Output	3,405.14	316.54	2,790.70	3,853.21
		Seed	77.63	30.62	32.06	189.24
		P-fertiliser	25.05	16.18	6.21	75.14
	Northeast	Output	2,107.35	164.92	1,904.76	2,500.00
		Seed	159.54	52.30	49.98	338.49
		P-fertiliser	25.98	19.51	4.20	95.29

5.9.5 The descriptive statistics of observed NS and PS

The descriptive statistics of observed NS and PS in 9 groups of Thai rice farms are presented in Table 5.10. The average NS of the sample farms in each group is higher than the average

PS. The average NS of non-jasmine rice farms is higher than the average NS of jasmine and glutinous rice farms across the regions. In the Northern region, jasmine rice farmers discharged more PS into the environment than non-jasmine and glutinous rice farmers. In the North-eastern region, non-jasmine rice farmers discharged more PS into the environment than jasmine and glutinous rice farmers. In the Central region, non-jasmine rice farmers discharged more PS into the environment than jasmine rice farmers.

Table 5.10 Descriptive statistics of nitrogen and phosphorus content in rice output and its inputs: nitrogen surplus and phosphorus surplus of sample data

Unit: Kg/Ha

Type of rice	Region	Description	Mean	Std. dev.	Min.	Max.
Jasmine rice	North	observed NS	27.17	22.37	1.58	101.60
		observed PS	25.18	16.88	7.08	91.65
	Northeast	observed NS	35.04	30.53	0.15	164.46
		observed PS	22.90	23.49	0.71	193.41
	Central	observed NS	25.48	22.28	0.57	84.23
		observed PS	18.01	12.80	0.04	48.32
Non-jasmine rice	North	observed NS	54.10	34.50	0.38	174.29
		observed PS	20.62	11.64	1.42	55.48
	Northeast	observed NS	44.46	45.58	2.98	216.36
		observed PS	27.36	25.63	3.12	114.67
	Central	observed NS	50.90	34.23	0.06	218.55
		observed PS	30.19	17.91	0.24	95.33
	South	observed NS	31.84	23.89	0.42	84.64
		observed PS	29.11	15.70	5.92	70.37
Glutinous rice	North	observed NS	38.58	38.81	0.48	143.73
		observed PS	18.39	15.88	0.75	67.84
	Northeast	observed NS	46.66	48.18	0.46	287.96
		observed PS	22.09	19.41	0.34	91.65

5.10 Summary

The main purpose of this chapter was to provide detail on sources of data, how to build the data analysed in this analysis, data cleansing, and relevant descriptive statistics used for this research. The dataset used in this research is derived from the national Thai input survey of rice farming systems cultivated during the wet season (major rice) for the crop year 2008/09 at farm level for the whole country, based on observations of a total of 1,287 farms. The initial data cleansing was performed by checking the sample means, standard deviations, minimum and maximum values, zero values for important inputs and rice output per hectare. As a result, 73 farms were removed from the dataset. After that the input data of the remaining 1,214 farms was adjusted by the relative index number of the provincial average calculated yield of rice in the wet season for the crop year 2007/08 and the yield of the sample farms, in order to capture the differences in soil fertility across the sample: that would help to remove some of the expected input heterogeneity and subsequent bias in efficiency measurement. Then this sample of 1,214 Thai rice farmers was put into 4 categories, according to their regions (North, Northeast, Central, and South) in order to capture the differences in climate and soil across the sample, and then split by rice type (jasmine rice, non-jasmine rice, and glutinous rice): that would help to remove some of the expected input and output heterogeneity and subsequent bias in efficiency measurement. Consequently, 9 groups of Thai rice farmers are observed in this research (as discussed in Section 5.4).

The data sets of the 9 observed groups of Thai rice farmers were tested for outliers, employing the data cloud method proposed by Wilson (1993). The total number of observations, after the removal of the outliers, of these 9 groups of Thai rice farmers that were used to estimate TE of Thai rice farming systems using the DEA and DDF models are presented in the third column of Table 5.7. Moreover, the results of non-parametric test of returns to scale indicate that the underlying technologies of jasmine rice North, jasmine rice Northeast, jasmine rice Central, non-jasmine rice North, non-jasmine rice Central, non-jasmine rice South, and glutinous rice Northeast exhibit CRS, while the underlying technologies of non-jasmine rice Northeast and glutinous rice North exhibit VRS.

For the dataset of NS and PS efficiency analysis using the NSMM and PSMM, farms that have negative or zero NS and PS were removed from each group of Thai rice farmers. The remaining positive NS and PS farms in each group of observations were tested for outliers employing the data cloud method. The total number of observations, after the removal of the outliers, of the 9 groups of Thai rice farms that were used to estimate the NS and PS efficiency of Thai rice farming systems are shown in the sixth and seventh columns of Table 5.7, respectively.

Chapter 6

The Technical and Environmental Efficiency of Thai Rice Farming

6.1 Introduction

The purposes of this chapter are to evaluate and compare the empirical results obtained by evaluating the technical efficiency (TE) and environmental efficiency (NE) of the Thai rice farmers who were divided into 9 categories for observation for the crop year 2008/09. The objective of undertaking a TE analysis of Thai rice farming is to demonstrate variously the extent to which the farmers in each category can reduce their inputs whilst producing the same level of rice output; maximise rice output whilst using the same level of inputs; or reduce all inputs and increase rice output simultaneously. The data envelopment analysis (DEA) and directional distance function (DDF) models were applied to estimate the production frontiers based on the observed data. The DEA efficiency analysis was carried out on both input-oriented and output-oriented frontiers. The input-oriented DEA model can be used to demonstrate how Thai rice efficiency can be improved by reducing inputs to produce the same level of rice output, thus resulting in a reduction of the total cost of rice production. The output-oriented DEA model demonstrates how Thai rice efficiency can be improved through increasing rice output whilst using the same level of input, thus resulting in the increase of farmers' incomes. Using the DDF model shows how Thai rice efficiency can be improved by simultaneously increasing the amount of output together with reducing the amount of inputs, resulting in a simultaneous increase in farmers' incomes and reduction of production costs. The scale efficiency (SE) based on the DEA models is also applied to examine Thai rice farmers' returns to scale. The TE results were estimated using the R programme. Both DEA and DDF models were estimated using the package "Benchmarking" (Bogetoft and Otto, 2014), a software package for frontier efficiency analysis in the R programme.

Analysis of the environmental efficiency of Thai rice farming investigates two important nutrient contents in rice output and inputs that can harm the environment: nitrogen and phosphorus. Some of the nitrogen and phosphorus applied is absorbed by rice plants, but the excess is discharged into groundwater, rivers, and finally coastal areas, leading to the problem of water pollution. The evidence of negative effects of nitrogen and phosphorus surplus on the environment has been reviewed in Chapter 2. Reducing the nitrogen and phosphorus surplus resulting from rice cultivation increases the efficiency of their use and helps to reduce the environmental problem. The calculation of nitrogen and phosphorus surpluses in this analysis is based on the material balance condition followed Coelli et al. (2007) as presented in Section 5.8. These surpluses are incorporated into the conventional directional distance function (DDF): that has not been undertaken before. This is similar to the manner in which price information is normally incorporated in the directional profit efficiency measure (Zofio et al., 2013). This measure is called the directional nutrient surplus efficiency measure (as demonstrated in Section 4.9) which is used to evaluate the efficiency of nitrogen and phosphorus use by Thai rice farmers. The NE results were estimated using the programme R.

This chapter is organised as follows. Section 2 presents the empirical results and discussion of the efficiency analysis of Thai rice farming using the DEA and DDF models. The environmental efficiency, or the nutrient surplus efficiency, results are presented in Section 3. Section 4 compares the improvement of rice output produced and the combination of inputs used per hectare of the average farm by different directional vectors. Section 5 presents the rice output produced and the combination of inputs used by the environmental best practice farms compared to the technical and profit best practice farms. The discussion of technical and environmental efficiency results is presented in Section 6. Finally, Section 7 concludes the chapter.

6.2 Technical efficiency results

The TE scores using the DDF model will differ, according to which direction of improvement is chosen. In order to examine which direction is appropriate for the improvement of Thai rice farming, four different strategies are proposed for the 9 observed groups (with 11 inputs and one rice output in each group of observations), with four different directional vectors for efficiency measurement using the DDF. These four measures are named DDF1 to DDF4, as shown in Table 6.1. The DDF provides the maximum unit contraction in the inputs and the unit expansion of output and serves as a measure of inefficiency (Färe et al, 2005). A farm is technically efficient in the (g_x, g_y) direction if $D_T(x, y; g_x, g_y) = 0$. However, a farm is technically inefficient in the (g_x, g_y) direction if $D_T(x, y; g_x, g_y) > 0$. Note that the directional vectors of the DDF1 – DDF3 measures are preassigned, while the directional vector for the DDF4 measure is not preassigned. The DDF4 measure provides insight into which technically efficient farm achieves profit efficiency.

Table 6.1 The proposed directional vectors for this study

Name	Proposed Directional Vector (g_x, g_y)	Price data	Remark
DDF1	$D_T(x^o, y^o; x^o, 0)$	No	Direction towards observed farm's individual inputs used holding output fixed (Input-oriented DEA)
DDF2	$D_T(x^o, y^o; 0, y^o)$	No	Direction towards observed farm's individual output produced holding all inputs fixed (Output-oriented DEA)
DDF3	$D_T(x^o, y^o; x^o, y^o)$	No	Direction towards observed farm's individual inputs used and output produced (Ang and Kerstens, 2016)
DDF4	$D_T^*\left(x, y; \dfrac{(x - x^*, y^* - y)}{(py^* - wx^*) - (py - wx)}\right)$	Yes	Direction towards profit maximisation benchmark (Zofio et al., 2013)

Note that (x^*, y^*) is the directional profit maximising point (the point where the iso-profit line is tangential to the production possibility frontier).

DDF1 is used to measure the technical inefficiency (TIE) of the 9 observed groups of Thai rice farmers in reducing inputs to produce the same level of output in the direction of the observed farms' individual inputs usage. Thus, the TIE scores obtained from DDF1 measures are as same as the TIE scores obtained from the input-oriented DEA or the traditional input-based Farrell efficiency measure. That is $D_T(x^o, y^o; x^o, 0) = 1 - E(x, y)$ (Bogetoft and Otto, 2011). Note that the TE score of each farm obtained from the DDF1 model and input-oriented DEA model is identical. Thus, the improvement of the farm's TE with DDF1 or input-oriented DEA would both result in lower production costs, and reduce the amount of nitrogen and phosphorus surplus discharged into the environment because the farmer would need to apply less N and P fertiliser.

DDF2 is used to measure the TIE of the 9 observed groups of Thai rice farmers in increasing output using the same level of inputs in the direction of the observed farms' individual rice output produced. Hence, the TIE scores obtained from DDF2 measures are the same as the TIE scores obtained from the output-oriented DEA or the traditional output-based Farrell efficiency measure. That is $D_T(x^o, y^o; 0, y^o) = F(x, y) - 1$. Thus, the improvement of the farm's TE with DDF2 or output-oriented DEA would result in higher profits. The amount of nitrogen and phosphorus surplus discharged into the environment would be reduced in respect of the material balance condition concept because rice plants would absorb more N and P nutrients (i.e. higher production).

DDF3 is used to measure the TIE of the 9 observed groups of Thai rice farmers in reducing inputs while increasing outputs simultaneously in the direction of the observed farms' individual use of inputs and production of outputs. This direction has been used in previous studies' efficiency analyses (e.g. Ang and Kerstens, 2016; Singbo and Lansink, 2010; Riccadi et al. 2012). Thus, the improvement of a farm's TE with DDF3 would result in lower costs of production, higher profit, and lower nitrogen and phosphorus surplus discharged into the environment.

DDF4 is used to measure the profit inefficiency of the 9 observed groups of Thai rice farmers in the direction of the profit maximisation benchmark. The measurement of DDF4, known as the directional profit efficiency measure (Zofio et al., 2013), is presented in Section 4.8. This measure needs data relating to both the quantity of inputs and outputs and their corresponding prices. The DDF4 model measures the distance between the highest profit farm (i.e. the farm that produces on the profit maximising frontier) and the other farms in the sample (i.e. farms producing below the profit maximising frontier). Thus, the inefficiency level of each farm represents the minimal distance from its observed data point to the profit maximising frontier in terms of given output and input prices.

From the results of non-parametric tests of returns to scale, as discussed in Chapter 5 Section 5.5, the DDF1 – DDF3 models of jasmine rice North, jasmine rice Northeast, jasmine rice Central, non-jasmine rice North, non-jasmine rice Central, non-jasmine rice South, and glutinous rice Northeast were estimated under the assumption of CRS, while the DDF1 – DDF3 models of non-jasmine rice Northeast and glutinous rice North were estimated under the assumption of VRS. However, the estimation of the profit efficiency of all 9 groups of Thai rice farmers using the DDF4 model was performed under the assumption of VRS. This is because the results obtained from the DDF4 model may be either unbounded profit or zero maximum profit if the CRS hypothesis is assumed (Färe et al., 2007 cited in Zofio et al., 2013, p. 263).

The estimates of the TIE results of jasmine rice farms, non-jasmine rice farms, and glutinous rice farms in each region using the DDF1 – DDF4 efficiency measures are summarised in

Table 6.2, Table 6.3, and Table 6.4, respectively[20]. The percentage of farms that define the efficiency frontier of each directional vector for each group is given in the third column of these three Tables. The average level of inefficiency scores for each directional vector for each group is presented in the fourth column of these three Tables. The results from the DDF1 – DDF3 measures for each group indicate that the technically efficient farms in each observed group remain the same, implying that different TE measurements (i.e. different directional vectors) do not change the status of the technically efficient farms in the observation. The DDF4 measure is different from the DDF1 – DDF3 measures, as it is not only a target to improve the TE of farmers, but also a target to improve their profit efficiency. The farm that earns the highest profit in the sample will construct the profit efficiency frontier. This profit efficiency frontier (i.e. iso-profit line) is tangential to the production possibility frontier at the profit maximising point. Hence, only the farm that earns the highest profit in each group in the sample will determine the profit efficiency frontier, using the DDF4 measure (Table 6.2 – Table 6.4).

The average TIE scores obtained from the DDF1 measure (or input-oriented DEA) of 9 groups of Thai rice farmers range from 1.7% to 12.5% (the fourth column of Table 6.2 – Table 6.4). This indicates that the average farms of these 9 groups would be able to reduce their current amount of inputs on average from 1.7% to 12.5% to obtain their current levels of rice output if they were to operate efficiently. The average TIE scores obtained from the DDF2 measure (or output-oriented DEA) of 9 groups of Thai rice farmers range from 2.1% to 15.9% (the fourth column of Table 6.2 – Table 6.4). This indicates that the average farms of these 9 groups could expand rice output on average from 2.1% to 15.9% by using the same level of inputs if they were to operate efficiently. The average TIE scores obtained from the DDF3 measure of 9 groups of Thai rice farmers range from 1% to 7% (the fourth column of Table 6.2 – Table 6.4). This indicates that, on average, the farms in these 9 groups could expand rice output on average from 1% to 7%, and simultaneously contract their current amount of inputs on average from 1% to 7% if they were to operate efficiently.

The research now turns to considering the efficiency level of Thai farmers for each rice type. For jasmine rice production, the results indicate that more than half of the jasmine rice farmers observed in the Northern and Central regions are technically efficient, while only 26% of the jasmine rice farmers observed in the North-eastern region are technically efficient (the third column of Table 6.2). Moreover, the results show that the average TIE scores

[20] All efficiency measurements are computed for each farm in the sample; the results of the measurements, taking account of all observations, are presented in Appendix D.

obtained from the DDF1 – DDF3 measures of jasmine rice farms in the Northern are lowest, while the average inefficiency scores obtained from the DDF1 – DDF3 measures of jasmine rice farms in the North-eastern are highest (the fourth column of Table 6.2). This implies that jasmine rice farmers in the Northern region are more efficient than jasmine rice farmers in the Central and North-eastern regions.

Table 6.2 Estimates of inefficiency results of jasmine rice farms using DDF

Region	Directional vector	% of frontier farms	Mean	Std. dev.	Min.	Max.
North	DDF1	70.3	0.0274	0.07	0.00	0.3498
	DDF2	70.3	0.0343	0.09	0.00	0.5380
	DDF3	70.3	0.0152	0.04	0.00	0.2120
	DDF4	1.6	93,086.62	21,108.26	0.00	119,769.57
Northeast	DDF1	25.9	0.1247	0.10	0.00	0.3409
	DDF2	25.9	0.1594	0.14	0.00	0.5173
	DDF3	25.9	0.0698	0.06	0.00	0.2055
	DDF4	0.53	94,446.54	14,667.39	0.00	130,244.62
Central	DDF1	55.2	0.0773	0.11	0.00	0.3181
	DDF2	55.2	0.0997	0.14	0.00	0.4665
	DDF3	55.2	0.0435	0.06	0.00	0.1891
	DDF4	1.7	69,151.08	21,528.71	0.00	97,675.26

Source: Author's analysis of sample data (the total numbers of observations in the Northern, North-eastern, and Central regions are 64, 189, and 58 farms, respectively).

The average level of profit inefficiency of jasmine rice farms in the Northern region is 93,086.62 Baht/farm, while the profit efficient farm earned a profit of 113,082.42 Baht/farm. This indicates that jasmine rice farmers in the Northern region earned an average profit of 19,995.38 Baht/farm or 12,118.4 Baht/ha. The average level of profit inefficiency of jasmine rice farms in the North-eastern region is 94,446.54 Baht/farm, while the profit efficient farm earned a profit of 100,178.83 Baht/farm. This indicates that jasmine rice farmers in the North-eastern region earned an average profit of 5,732.29 Baht/farm or 3,582.68 Baht/ha. The average level of profit inefficiency of jasmine rice farms in the Central region is 69,151.08 Baht/farm, while the profit efficient farm earned a profit of 94,072.06 Baht/farm. This indicates that jasmine rice farmers in the Central region earned an average profit of 24,920.98 Baht/farm or 8,091.23 Baht/ha. Thus, on average, jasmine rice farmers in the Northern region earn more profit than jasmine rice farmers in the Central and North-eastern regions.

With regard to non-jasmine rice production, the results show that more than half of the total of non-jasmine rice farmers observed in the Northern and North-eastern regions are technically efficient (the third column of Table 6.3). Furthermore, the results also indicate that the average inefficiency scores obtained from the DDF1 – DDF3 measures of non-jasmine rice farms in the Northern and North-eastern regions are nearly the same as and lower than the average inefficiency scores obtained from the DDF1 – DDF3 measures of non-jasmine rice farms in the Central and Southern regions (the fourth column of Table 6.3). This implies that farmers in the Northern and North-eastern regions are more efficient in growing non-jasmine rice than farmers in the Central and Southern regions.

Table 6.3 Estimates of inefficiency results of non-jasmine rice farms using DDF

Region	Directional vector	% of frontier farms	Mean	Std. dev.	Min.	Max.
North	DDF1	54.6	0.0423	0.06	0.00	0.2008
	DDF2	54.6	0.0489	0.07	0.00	0.2513
	DDF3	54.6	0.0227	0.03	0.00	0.1116
	DDF4	0.66	194,757.76	46,695.13	0.00	251,777.01
Northeast	DDF1	63.5	0.0459	0.08	0.00	0.2645
	DDF2	63.5	0.0569	0.10	0.00	0.4461
	DDF3	63.5	0.0247	0.04	0.00	0.1661
	DDF4	1.6	42,360.06	8,311.88	0.00	60,671.81
Central	DDF1	39.7	0.1008	0.14	0.00	0.5218
	DDF2	39.7	0.1488	0.24	0.00	1.0911
	DDF3	39.7	0.0594	0.09	0.00	0.3530
	DDF4	0.47	309,427.99	61,590.31	0.00	438,730.03
South	DDF1	46.0	0.1060	0.13	0.00	0.3967
	DDF2	46.0	0.1483	0.20	0.00	0.6574
	DDF3	46.0	0.0616	0.08	0.00	0.2474
	DDF4	1.0	136,482.90	30,259.86	0.00	182,985.98

Source: Author's analysis of sample data (the total numbers of observations in the Northern, North-eastern, Central, and Southern regions are 152, 63, 214, and 100 farms, respectively).

The average level of profit inefficiency of non-jasmine rice farms in the Northern region is 194,757.76 Baht/farm, while the profit efficient farm earned a profit of 238,475.43 Baht/farm. This indicates that non-jasmine rice farmers in the Northern region earned an average profit of 43,717.67 Baht/farm or 13,328.56 Baht/ha. The average level of profit inefficiency of non-jasmine rice farms in the North-eastern region is 42,360.06 Baht/farm, while the profit efficient farm earned a profit of 43,912.34 Baht/farm. This indicates that non-jasmine rice farmers in the North-eastern region earned an average profit of 1,552.28 Baht/farm or 1,536.91 Baht/ha. The average level of profit inefficiency of non-jasmine rice farms in the Central region is 309,427.99 Baht/farm, while the profit efficient farm earned a profit of 368,406.28 Baht/farm. This indicates that non-jasmine rice farmers in the Central region earned an average profit of 58,978.29 Baht/farm or 13,779.97 Baht/ha. The average level of profit inefficiency of non-jasmine rice farms in the Southern region is 136,482.90 Baht/farm, while the profit efficient farm earned a profit of 157,663.52 Baht/farm. This indicates that non-jasmine rice farmers in the Southern region earned an average profit of 21,180.62 Baht/farm or 11,702 Baht/ha. Hence, on average, non-jasmine rice farmers in the Central region earn more profit than non-jasmine rice farmers in the other three regions. Furthermore, non-jasmine rice farmers in the North-eastern region earn comparatively low profits compared to non-jasmine rice farmers in the other three regions.

Table 6.4 Estimates of inefficiency results of glutinous rice farms using DDF

Region	Directional vector	% of frontier farms	Mean	Std. dev.	Min.	Max.
North	DDF1	78.3	0.0173	0.05	0.00	0.2939
	DDF2	78.3	0.0207	0.07	0.00	0.4261
	DDF3	78.3	0.0094	0.03	0.00	0.1756
	DDF4	1.1	20,813.56	6,398.78	0.00	50,389.13
Northeast	DDF1	33.9	0.0749	0.07	0.00	0.2093
	DDF2	33.9	0.0872	0.08	0.00	0.2647
	DDF3	33.9	0.0403	0.04	0.00	0.1169
	DDF4	0.6	19,853.60	8,184.01	0.00	55,238.49

Source: Author's analysis of sample data (the total numbers of observations in the Northern and North-eastern regions are 92 and 180 farms, respectively).

With regard to glutinous rice production, approximately 78% of the glutinous rice farmers observed in the Northern region are technically efficient, while approximately 34% of the glutinous rice farmers observed in the North-eastern region are technically efficient (the third column of Table 6.4). Moreover, the results show that the average inefficiency scores obtained from the DDF1 – DDF3 measurements of glutinous rice farms in the Northern region are lower than those of glutinous rice farms in the North-eastern regions (the fourth column of Table 6.4). This implies that glutinous rice farmers in the Northern region are more efficient than glutinous rice farmers in the North-eastern region.

The average level of profit inefficiency of glutinous rice farms in the Northern region is 20,813.56 Baht/farm, while the profit efficient farm earned a profit of 21,433.84 Baht/farm. This indicates that glutinous rice farmers in the Northern region earned an average profit of 620.28 Baht/farm or 681.63 Baht/ha. The average level of profit inefficiency of glutinous rice farms in the North-eastern region is 19,853.60 Baht/farm, while the profit efficient farm earned a profit of 11,121.36 Baht/farm. This indicates that glutinous rice farmers in the North-eastern region suffered a loss of 8,732.24 Baht/farm or 6,930.35 Baht/ha. Thus, glutinous rice farmers in the Northern region are more profit efficient than glutinous rice farmers in the North-eastern region.

Comparing the efficiency level of Thai rice farmers within each region, in the Northern region, glutinous rice farmers are more technically efficient than jasmine rice and non-jasmine rice farmers. However, they earned comparatively low profits compared to jasmine rice and non-jasmine rice farmers. In the North-eastern region, non-jasmine rice farmers are more efficient than glutinous rice and jasmine rice farmers. However, jasmine rice farmers are more profit efficient than non-jasmine rice and glutinous rice farmers. In addition, jasmine rice farmers in the Central region are more efficient than non-jasmine rice farmers, but they earned lower profits than non-jasmine rice farmers.

Considering the efficiency level of Thai rice farmers for the whole country, glutinous rice farmers in the Northern region are more TE than those in other observed groups, but they earned very low profit of 681.63 Baht/ha. Jasmine rice farmers in the North-eastern region are less TE than the other observed groups and earned a low profit of 1,536.91 Baht/ha. Non-jasmine rice farmers in the Central and Northern regions earned the highest profit of 13,779.97 and 13,328.56 Baht/ha, respectively. At the same time, glutinous rice farmers in the North-eastern region had the lowest profit efficiency and suffered a loss of 6,930.35 Baht/ha. In addition, glutinous rice farmers are less profit efficient compared with jasmine rice and non-jasmine rice farmers.

Table 6.5 Comparison of average SE and percentage of returns to scale for each type of rice in each region

Type of rice	Region	Observations	Average SE	CRS	DRS	IRS
Jasmine rice	North	64	0.9890	71.9%	15.6%	12.5%
	Northeast	189	0.9599	29.6%	36.0%	34.4%
	Central	58	0.9606	55.2%	36.2%	8.6%
Non-Jasmine rice	North	152	0.9875	57.2%	26.3%	16.4%
	Northeast	63	0.9657	52.4%	28.6%	19.0%
	Central	214	0.9810	42.5%	36.0%	21.5%
	South	100	0.9523	46.0%	35.0%	19.0%
Glutinous rice	North	92	0.9797	53.3%	28.3%	18.5%
	Northeast	180	0.9787	36.1%	47.8%	16.1%

Table 6.5 is shown that the average SEs for each type of rice in each region are greater than 0.95. This indicates that the average scale inefficiencies are less than 5%, which is quite small. The majority of rice farmers across all types of rice and all regions operated close to the optimal scale size (CRS), except jasmine rice and glutinous rice farmers in the North-

eastern region. The main reasons for the scale inefficiencies of jasmine rice farmers in the North-eastern region are DRS or farmers operating above the optimal scale and IRS or farmers operating below the optimal scale. However, the main reason for the scale inefficiencies of glutinous rice farmers in the North-eastern region is DRS or farmers operating above the optimal scale.

6.3 Environmental efficiency using the directional nutrient surplus efficiency measure

Two models, namely the nitrogen surplus minimisation model (NSMM) and the phosphorus surplus minimisation model (PSMM), are applied to measure the environmental efficiency of the 9 observed groups of Thai rice farmers. The NSMM is used to measure NS efficiency of the farmers in each group, using the directional nutrient surplus efficiency measure with the directional vector towards the nitrogen surplus minimising frontier. The PSMM is used to measure PS efficiency of farmers in each group, using the directional nutrient surplus efficiency measure with the directional vector towards the phosphorus surplus minimising frontier. The estimations of NS and PS efficiency of 9 groups of Thai rice farmers using the NSMM and PSMM were performed under the assumption of VRS. This is because the results obtained from the NSMM (PSMM) may be either unbounded NS (PS) or zero minimum NS (PS) if the CRS hypothesis is assumed (Färe et al., 2007 cited in Zofio et al., 2013, p. 263). The results of the application of the NSMM and PSMM to the Thai rice farmers are presented in the following sections.

6.3.1 Nitrogen surplus efficiency results

The descriptive statistics of variables used for the NSMM measures of the 9 observed groups of Thai rice farmers are presented in Section 5.9. The descriptive statistics of the inefficiency levels of the NSMM for each group are presented in Table 6.6[21]. The inefficiency level of each farm in each group of observations represents the minimal distance from its observed data point to the minimum NS frontier of that group by given output and input nitrogen contents. The average NS inefficiency, TIE, and allocative inefficiency (AIE) of each group of observations are given in the fifth column of Table 6.6. The number of efficient farms that lie on the NS efficiency, TE, and allocative efficiency (AE) frontiers for each group of observations is shown in the fourth column of Table 6.6. The results show that only one farm in each observed group is nitrogen surplus, technically, and allocatively efficient since $D_T^*(x^o, y^o; a_N, b_N) = 0$. The NSMM results of jasmine rice farms in the Northern region are

[21] The NS efficiency measure is computed for each farm in the sample; the results of this measurement are presented in Appendix D.

used as an example, demonstrating how to interpret the results of TIE and AIE for each group of observations using the NSMM. The number of TE jasmine rice farms in the Northern region is 7, indicating that 1 farm is NS efficient and 6 farms are technically efficient but NS inefficient. The NS inefficiency of these 6 farms is due to allocative inefficiency of mixed nitrogen contents (these 6 farms are technically efficient farms when their TE scores are estimated using the conventional DDF model). Moreover, the number of AE jasmine rice farms in the Northern region is 15, indicating that 1 farm is NS efficient and 14 farms are allocatively efficient but NS inefficient. The NS inefficiency of these 14 farms is due to technical reasons, i.e. wrong management practices (these 14 farms are technically inefficient when their TE scores are estimated using the conventional DDF model).

The average level of NS inefficiency of jasmine rice farms in the Northern region is 25.13 kg/farm, while the NS efficient farm discharged NS 2.18 kg/farm. This indicates that jasmine rice farmers in the Northern region discharged an average NS of 27.31 kg/farm or 20.08 kg/ha. The average level of NS inefficiency of jasmine rice farms in the North-eastern region is 48.88 kg/farm, while the NS efficient farm discharged NS 0.07 kg/farm. This indicates that jasmine rice farmers in the North-eastern region discharged an average NS of 48.95 kg/farm or 35.47 kg/ha. The average level of NS inefficiency of jasmine rice farms in the Central region is 42.92 kg/farm, while the NS efficient farm discharged NS 0.95 kg/farm. This indicates that jasmine rice farmers in the Central region discharged an average NS of 43.87 kg/farm or 26.59 kg/ha. Thus, on average, jasmine rice farmers in the North-eastern region discharged a higher amount of NS into the environment than jasmine rice farmers in the Northern and Central regions.

The average level of NS inefficiency of non-jasmine rice farms in the Northern region is 165.1 kg/farm, while the NS efficient farm discharged NS 0.56 kg/farm. This indicates that non-jasmine rice farmers in the Northern region discharged an average NS of 165.66 kg/farm or 50.66 kg/ha. The average level of NS inefficiency of non-jasmine rice farms in the North-eastern region is 23.99 kg/farm, while the NS efficient farm discharged NS 1.28 kg/farm. This indicates that non-jasmine rice farmers in the North-eastern region discharged an average NS of 25.27 kg/farm or 34.62 kg/ha. The average level of NS inefficiency of non-jasmine rice farms in the Central region is 193.78 kg/farm, while the NS efficient farm discharged NS 0.06 kg/farm. This indicates that non-jasmine rice farmers in the Central region discharged an average NS of 193.84 kg/farm or 49.83 kg/ha. The average level of NS inefficiency of non-jasmine rice farms in the Southern region is 47.39 kg/farm, while the NS efficient farm discharged NS 0.39 kg/farm. This indicates that non-jasmine rice farmers in the Southern region discharged an average NS of 47.78 kg/farm or 33.18 kg/ha. Therefore, on average, non-jasmine rice farmers in the Northern and Central regions discharged more NS into the environment than non-jasmine rice farmers in the North-eastern and Southern regions.

Table 6.6 Summary statistics of nitrogen surplus inefficiency of each type of rice farms in each region

Type of rice	Regions	Inefficiency	Number of frontier farms	Mean	Std. dev.	Min.	Max.
Jasmine	North	NS inefficiency	1	25.13	18.26	0	68.57
		TIE	7	21.33	20.09	0	68.57
		AIE	15	3.80	9.99	0	42.32
	Northeast	NS inefficiency	1	48.88	55.68	0	240.29
		TIE	12	46.40	55.33	0	240.29
		AIE	115	2.48	16.47	0	173.66
	Central	NS inefficiency	1	42.92	45.34	0	160.07
		TIE	8	32.93	44.44	0	160.07
		AIE	16	9.99	27.73	0	104.98
Non-jasmine	North	NS inefficiency	1	165.10	130.40	0	558.57
		TIE	13	155.05	131.62	0	558.57
		AIE	88	10.04	53.17	0	454.65
	Northeast	NS inefficiency	1	23.99	18.30	0	64.49
		TIE	8	19.23	18.71	0	64.49
		AIE	27	4.76	13.16	0	60.47
	Central	NS inefficiency	1	193.78	163.55	0	684.41
		TIE	12	184.34	166.67	0	684.41
		AIE	153	9.44	49.71	0	416.67
	South	NS inefficiency	1	47.39	49.73	0	214.47
		TIE	9	42.94	49.83	0	214.47
		AIE	42	4.45	19.49	0	105.19
Glutinous	North	NS inefficiency	1	20.23	16.26	0	43.40
		TIE	7	17.57	17.93	0	43.40
		AIE	13	2.67	6.46	0	27.01
	Northeast	NS inefficiency	1	37.64	37.38	0	168.34
		TIE	11	35.18	37.38	0	168.34
		AIE	99	2.46	13.21	0	104.91

Source: Author's analysis of sample data (the total number of observations of jasmine rice North, jasmine rice Northeast, jasmine rice Central, non-jasmine rice North, non-jasmine rice Northeast, non-jasmine rice Central, non-jasmine rice South, glutinous rice North, and glutinous rice Northeast is 21, 126, 23, 100, 34, 164, 50, 19, and 109, respectively).

The average level of NS inefficiency of glutinous rice farms in the Northern region is 20.23 kg/farm, while the NS efficient farm discharged NS 0.58 kg/farm. This indicates that glutinous rice farmers in the Northern region discharged an average NS of 20.81 kg/farm or 28.12 kg/ha. The average level of NS inefficiency of glutinous rice farms in the North-eastern region is 37.64 kg/farm, while the NS efficient farm discharged NS 0.6 kg/farm. This indicates that glutinous rice farmers in the North-eastern region discharged an average NS of 38.24 kg/farm or 36.08 kg/ha. Thus, glutinous rice farmers in the Northern region are more NS efficient than glutinous rice farmers in the North-eastern region.

Considering the NS efficiency of Thai rice within each region, in the Northern region, jasmine rice farmers are more NS efficient than non-jasmine rice and glutinous rice farmers. The average amount of NS per hectare that non-jasmine rice farmers discharged into the environment is more than double that discharged by jasmine rice farms. In the North-eastern region, the average amount of NS discharged by jasmine rice, non-jasmine rice, and glutinous rice are nearly the same. Non-jasmine rice farmers are more NS efficient than glutinous rice and jasmine rice farmers. Jasmine rice farmers in the Central region are more NS efficient than non-jasmine rice farmers in the Central region. Furthermore, jasmine rice farmers in the Northern region are the most NS efficient in the Thai rice farming system as they discharged the lowest amount of NS into the environment compared to the other 8 groups observed. On the other hand, non-jasmine rice farmers in the Northern and Central regions discharged the largest amount of NS into the environment compared to the other 7 observed groups. .

6.3.2 Phosphorus surplus efficiency results

The descriptive statistic of variables used for PSMM measures of the 9 groups of observations of Thai rice farmers are presented in Section 5.9. The descriptive statistics of the inefficiency levels of the PSMM, with the directional vector towards the PS minimum point, for each group of observations, are presented in Table 6.7[22]. The inefficiency level of each farm in each group of observations represents the minimal distance from its observed data point to the minimum PS frontier of that group by given output and input phosphorus contents. The average PS inefficiency, TIE, and AIE of each group of observations are given in the fifth column of Table 6.7. The number of efficient farms that lie on the PS efficiency, TE, and AE frontiers for each group of observations is shown in the fourth column of Table 6.7. The results show that only one farm in each group of observations is PS, technically, and allocatively efficient. The PSMM results of jasmine rice farms in the Northern region are used as an example, demonstrating how to interpret the results of TIE and AIE for each group of observations using the PSMM. The number of TE farms of jasmine rice in the Northern region is 8, indicating that 1 farm is PS efficient and 7 farms are technically efficient but PS inefficient. The PS inefficiency of these 7 farms is due to allocative inefficiency of mixed

[22] The environmental efficiency measure is computed for each farm in the sample; the results of this measurement are presented in Appendix D.

phosphorus contents (these 7 farms are technically efficient farms when TE scores are estimated, using the conventional DDF model). Moreover, the number of AE farms of jasmine rice in the Northern region is 19, indicating that 1 farm is PS efficient and 18 farms are allocatively efficient but PS inefficient. The PS inefficiency of these 18 farms is due to technical reasons, i.e. wrong management practices (these 18 farms are technically inefficient farms when TE scores are estimated using the conventional DDF model).

Table 6.7 Summary statistics of phosphorus surplus inefficiency of each type of rice farms in each region

Type of rice	**Regions**	**Inefficiency**	**No. of frontier farms**	**Mean**	**Std. dev.**	**Min.**	**Max.**
Jasmine	North	PS inefficiency	1	27.73	17.27	0	56.80
		TIE	8	17.52	17.53	0	56.80
		AIE	19	10.22	19.07	0	53.38
	Northeast	PS inefficiency	1	26.29	28.72	0	131.21
		TIE	11	24.86	28.88	0	131.21
		AIE	116	1.43	7.91	0	66.19
	Central	PS inefficiency	1	32.01	28.24	0	99.54
		TIE	6	29.06	29.09	0	99.54
		AIE	22	2.95	11.35	0	58.54
Non-jasmine	North	PS inefficiency	1	60.72	44.46	0	169.84
		TIE	12	54.01	47.07	0	169.84
		AIE	62	6.71	22.26	0	114.01
	Northeast	PS inefficiency	1	16.07	16.33	0	58.83
		TIE	7	12.71	14.60	0	58.83
		AIE	24	3.36	11.92	0	52.39
	Central	PS inefficiency	1	108.65	80.59	0	396.30
		TIE	11	101.75	80.87	0	396.30
		AIE	144	6.90	37.00	0	325.30
	South	PS inefficiency	1	27.96	27.37	0	112.64
		TIE	11	22.50	23.93	0	103.00
		AIE	51	5.46	20.65	0	112.64
Glutinous	North	PS inefficiency	1	11.22	8.49	0	34.65
		TIE	10	8.20	7.81	0	25.44
		AIE	25	3.02	7.88	0	34.65
	Northeast	PS inefficiency	1	19.68	17.33	0	71.49
		TIE	13	18.35	17.61	0	71.49
		AIE	106	1.33	6.28	0	43.10

Source: Author's analysis of sample data (the total number of observations of jasmine rice North, jasmine rice Northeast, jasmine rice Central, non-jasmine rice North, non-jasmine rice Northeast, non-jasmine rice Central, non-jasmine rice South, glutinous rice North, and glutinous rice Northeast is 26, 126, 27, 73, 30, 154, 61, 34, and 118, respectively).

The average level of PS inefficiency of jasmine rice farms in the Northern region is 27.73 kg/farm, while the PS efficient farm discharged PS 1.77 kg/farm. This indicates that jasmine rice farmers in the Northern region discharged an average PS of 29.5 kg/farm or 23.05 kg/ha.

The average level of PS inefficiency of jasmine rice farms in the North-eastern region is 26.29 kg/farm, while the PS efficient farm discharged PS 0.82 kg/farm. This indicates that jasmine rice farmers in the North-eastern region discharged an average PS of 27.11 kg/farm or 19.34 kg/ha. The average level of PS inefficiency of jasmine rice farms in the Central region is 32.01 kg/farm, while the PS efficient farm discharged PS 0.04 kg/farm. This indicates that jasmine rice farmers in the Central region discharged an average PS of 32.05 kg/farm or 19.19 kg/ha. Thus, on average, jasmine rice farmers in the Northern region discharged more PS into the environment than the jasmine rice farmers in the North-eastern and Central and regions.

The average level of PS inefficiency of non-jasmine rice farms in the Northern region is 60.72 kg/farm, while the PS efficient farm discharged PS 1.02 kg/farm. This indicates that non-jasmine rice farmers in the Northern region discharged an average PS of 61.74 kg/farm or 19.48 kg/ha. The average level of PS inefficiency of non-jasmine rice farms in the North-eastern region is 16.07 kg/farm, while the PS efficient farm discharged PS 0.93 kg/farm. This indicates that non-jasmine rice farmers in the North-eastern region discharged an average PS of 17 kg/farm or 26.56 kg/ha. The average level of PS inefficiency of non-jasmine rice farms in the Central region is 108.65 kg/farm, while the PS efficient farm discharged PS 0.34 kg/farm. This indicates that non-jasmine rice farmers in the Central region discharged an average PS of 109 kg/farm or 28.68 kg/ha. The average level of PS inefficiency of non-jasmine rice farms in the Southern region is 27.96 kg/farm, while the PS efficient farm discharged PS 3.2 kg/farm. This indicates that non-jasmine rice farmers in the Southern region discharged an average PS of 31.16 kg/farm or 28.07 kg/ha. Therefore, on average, non-jasmine rice farmers in the Northern region discharged less PS per hectare into the environment than non-jasmine rice farmers in the Northern, North-eastern and Southern regions.

The average level of PS inefficiency of glutinous rice farms in the Northern region is 11.22 kg/farm, while the PS efficient farm discharged PS 0.32 kg/farm. This indicates that glutinous rice farmers in the Northern region discharged an average PS of 11.54 kg/farm or 16.25 kg/ha. The average level of PS inefficiency of glutinous rice farms in North-eastern region is 11.69 kg/farm, while the PS efficient farm discharged PS 0.27 kg/farm. This indicates that glutinous rice farmers in the North-eastern region discharged an average PS of 11.96 kg/farm or 10.97 kg/ha. Thus, the glutinous rice farmers in Northern region are less PS efficient than glutinous rice farmers in the North-eastern region.

Considering the PS efficiency of Thai rice farmers within each region, in the Northern region, jasmine rice farmers discharged more PS per hectare into the environment than non-jasmine rice and glutinous rice farmers. In the North-eastern region, the average amount of PS per hectare discharged by glutinous rice farms is less than that discharged by jasmine rice and non-jasmine rice farms. In the Central region, jasmine rice farms discharged a smaller average amount of PS per hectare into the environment than non-jasmine rice farms.

Furthermore, glutinous rice farmers in the North-eastern region are the most PS efficient of the Thai rice farming system as they discharged the lowest amount of PS into the environment compared to the other 8 observed groups. On the other hand, non-jasmine rice farmers in the North-eastern, Central, and Southern regions are the most PS inefficient of the Thai rice farming system as they discharged the largest amount of PS into the environment compared to the other 6 observed groups.

6.4 The improvement of output produced and inputs used by different efficiency measures

Tables 6.8 - 6.16 compare the improvement of rice output and the combination of inputs used per hectare that would enable the average farm in each observed group to produce on the frontiers according to the various efficiency measures, including DDF1 – DDF4, NSMM, and PSMM. The NS and PS produced per hectare of the average farms and the percentage change of NS and PS with different directions of improvement compared to the average farm in each group of observations are also presented in the last four rows of each Table.

Table 6.8 shows that the improvement of jasmine rice output and the combination of inputs used per hectare of the average farm in the Northern region for all directional vectors towards the TE frontiers (DDF1-DDF3 directions) can lead to the reduction of NS and PS discharged into the environment. However, the approach of the farm's efficiency towards the profit maximisation frontier (DDF4) increases the amounts of NS and PS discharged into the environment by 487% and 131%, respectively. The approach of the farm's efficiency towards the NS minimisation frontier (NSMM) results in a reduction of NS by 57% and no PS being discharged into the environment, but its output is 6.4% lower than that of the average farm. Furthermore, the farm's approach towards the PS minimisation frontier (PSMM) results in a reduction of PS by 40% and no NS being discharged into the environment.

Table 6.8 Average improvement of inputs used and jasmine rice produced per hectare required to be technically, profit, NS, and PS efficient for farms in the Northern region

Description	Unit	Mean[1/]	DDF1	DDF2	DDF3	DDF4	NSMM	PSMM
Rice output	Kg	3,107.3	3,107.3	3,213.9	3,154.5	3,347.5	2,907.0	3,640.0
Planted area	Ha/Farm	1.7	1.6	1.7	1.6	4.7	0.4	0.3
Seed	Kg	121.5	118.1	121.5	119.6	135.0	78.7	78.8
Bio-fertiliser	Kg	2,316.2	2,252.7	2,316.2	2,281.0	0.0	15,730.4	0.0
N-fertiliser	Kg	44.6	43.4	44.6	44.0	104.7	36.2	18.6
P-fertiliser	Kg	17.8	17.3	17.8	17.5	33.8	0.0	14.2
K-fertiliser	Kg	5.6	5.5	5.6	5.5	0.0	0.0	14.2
Pesticide	Kg	16.0	15.5	16.0	15.7	2.7	3.1	6.3
Human labour	Baht	7,647.3	7,437.8	7,647.3	7,531.0	4,165.7	7,166.8	7,257.9
Machinery	Baht	3,746.5	3,643.9	3,746.5	3,689.6	2,185.9	3,775.3	5,046.8
Fuel	Litre	4.2	4.1	4.2	4.1	0.0	0.0	6.3
Other cost	Baht	796.6	774.8	796.6	784.5	176.4	1,573.0	3,280.4
NS	Kg	11.80	10.54	10.63	10.58	69.31	5.07	-20.61
PS	Kg	11.83	11.34	11.62	11.46	27.33	-5.66	7.08
% change of NS			-10.68	-9.93	-10.33	487.37	-57.00	-274.67
% change of PS			-4.18	-1.80	-3.12	131.01	-147.81	-40.18

Note: 1/ denotes the average value of rice output and inputs used for the jasmine rice North sample.

Table 6.9 Average improvement of inputs used and jasmine rice produced per hectare required to be technically, profit, NS, and PS efficient for farms in the North-eastern region

Description	Unit	Mean[1/]	DDF1	DDF2	DDF3	DDF4	NSMM	PSMM
Rice output	Kg	2,062.5	2,062.5	2,391.3	2,206.5	2,013.4	2,400.0	2,019.2
Planted area	Ha/Farm	1.6	1.4	1.6	1.5	8.9	0.5	1.0
Seed	Kg	146.7	128.4	146.7	136.5	93.8	140.6	62.7
Bio-fertiliser	Kg	3,427.7	3,000.3	3,427.7	3,188.5	0.0	0.0	3,919.3
N-fertiliser	Kg	44.1	38.6	44.1	41.0	48.0	25.0	14.8
P-fertiliser	Kg	20.6	18.0	20.6	19.2	16.4	12.5	4.7
K-fertiliser	Kg	16.0	14.0	16.0	14.9	26.9	12.5	4.7
Pesticide	Kg	2.7	2.3	2.7	2.5	0.0	0.0	0.0
Human labour	Baht	8,036.5	7,034.3	8,036.5	7,475.5	5,817.8	5,490.6	7,497.4
Machinery	Baht	3,574.7	3,128.9	3,574.7	3,325.2	3,439.1	3,125.0	2,821.9
Fuel	Litre	5.0	4.4	5.0	4.7	0.0	0.0	0.0
Other cost	Baht	820.1	717.8	820.1	762.9	105.7	0.0	219.5
NS	Kg	23.03	17.33	19.41	18.25	26.92	0.15	-6.70
PS	Kg	16.76	14.15	16.10	15.01	12.54	7.98	0.79
% change of NS			-24.76	-15.70	-20.73	16.91	-99.36	-129.11
% change of PS			-15.54	-3.92	-10.42	-25.15	-52.37	-95.29

Note: 1/ denotes the average value of rice output and inputs used for the jasmine rice Northeast sample.

Table 6.9 shows that the improvement of jasmine rice output and the combination of inputs used per hectare of the average farm in the North-eastern region for all directions to the efficiency frontiers can lead to the reduction of NS and PS discharged into the environment, except the farm's approach towards the profit maximisation frontier, which would lead to a 20% increase in NS discharged into the environment.

Table 6.10 Average improvement of inputs used and jasmine rice produced per hectare required to be technically, profit, NS, and PS efficient for farms in the Central region

Description	Unit	Mean[1/]	DDF1	DDF2	DDF3	DDF4	NSMM	PSMM
Rice output	Kg	2,388.8	2,388.8	2,627.0	2,492.8	2,580.6	2,095.8	2,586.2
Planted area	Ha/Farm	3.1	2.8	3.1	2.9	10.9	1.7	1.2
Seed	Kg	146.8	135.5	146.8	140.4	98.7	125.1	100.2
Bio-fertiliser	Kg	463.1	427.3	463.1	442.9	0.0	0.0	0.0
N-fertiliser	Kg	37.2	34.3	37.2	35.5	19.7	22.2	33.1
P-fertiliser	Kg	16.8	15.5	16.8	16.1	24.7	27.8	5.0
K-fertiliser	Kg	3.8	3.5	3.8	3.7	0.0	0.0	5.0
Pesticide	Kg	2.1	1.9	2.1	2.0	1.8	0.0	5.0
Human labour	Baht	4,360.9	4,023.8	4,360.9	4,171.2	6,123.6	4,344.5	4,320.8
Machinery	Baht	3,637.2	3,356.0	3,637.2	3,478.9	3,124.3	2,815.3	3,945.1
Fuel	Litre	0.9	0.8	0.9	0.9	0.0	0.0	0.0
Other cost	Baht	149.8	138.2	149.8	143.3	0.0	0.0	0.0
NS	Kg	12.50	9.50	9.88	9.67	-7.57	0.57	5.71
PS	Kg	12.30	10.98	11.82	11.35	19.70	23.86	0.04
% change of NS			-23.98	-20.96	-22.64	-160.56	-95.46	-54.29
% change of PS			-10.73	-3.87	-7.73	60.19	94.01	-99.70

Note: 1/ denotes the average value of rice output and inputs used for the jasmine rice Central sample.

Table 6.10 shows that the improvement of jasmine rice output and the combination of inputs used per hectare of the average farm in the Central region for all directions to the efficiency frontiers can lead to the reduction of NS and PS discharged into the environment, except that the farm's efficiency approach towards the profit maximisation and NS minimisation frontiers leads to the increase of PS discharged into the environment.

Table 6.11 shows that the improvement of non-jasmine rice output and the combination of inputs used per hectare of the average farm in the Northern region for all directions to the efficiency frontiers can lead to the reduction of NS and PS discharged into the environment.

Table 6.12 indicates that the improvement of non-jasmine rice output and the combination of inputs used per hectare of the average farm in the North-eastern region for all directions to the efficiency frontiers can lead to the reduction of NS and PS discharged into the environment, except that when the farm approaches the profit maximisation frontier, there is an increase in PS discharged into the environment, and its approach to the PS minimisation frontier leads to a large amount of NS being discharged into the environment.

Table 6.11 Average improvement of inputs used and non-jasmine rice produced per hectare required to be technically, profit, NS, and PS efficient for farms in the Northern region

Description	Unit	Mean1/	DDF1	DDF2	DDF3	DDF4	NSMM	PSMM
Rice output	Kg	3,643.7	3,643.7	3,821.9	3,726.4	3,723.8	3,355.7	3,947.4
Planted area	Ha/Farm	3.3	3.1	3.3	3.2	12.9	1.5	0.4
Seed	Kg	172.7	165.4	172.7	168.8	156.2	117.4	92.8
Bio-fertiliser	Kg	1,727.7	1,654.6	1,727.7	1,688.5	0.0	117.4	0.0
N-fertiliser	Kg	72.8	69.7	72.8	71.2	71.9	36.0	35.4
P-fertiliser	Kg	17.5	16.8	17.5	17.1	0.0	0.0	10.4
K-fertiliser	Kg	2.5	2.4	2.5	2.5	0.0	0.0	26.0
Pesticide	Kg	14.0	13.4	14.0	13.7	2.4	2.6	0.0
Human labour	Baht	7,029.8	6,732.5	7,029.8	6,870.3	5,435.8	4,059.8	13,747.2
Machinery	Baht	3,368.8	3,226.3	3,368.8	3,292.3	3,748.8	2,817.3	4,331.0
Fuel	Litre	10.4	9.9	10.4	10.1	3.6	0.0	0.0
Other cost	Baht	493.9	473.0	493.9	482.7	0.0	160.4	77.3
NS	Kg	34.65	31.48	32.69	32.04	32.61	0.38	-6.95
PS	Kg	10.60	9.84	10.24	10.03	-7.14	-6.48	2.69
% change of NS			-9.12	-5.66	-7.52	-5.88	-98.91	-120.07
% change of PS			-7.14	-3.36	-5.39	-167.31	-161.10	-74.66

Note: 1/ denotes the average value of rice output and inputs used for the non-jasmine rice North sample.

Table 6.12 Average improvement of inputs used and non-jasmine rice produced per hectare required to be technically, profit, NS, and PS efficient for farms in the North-eastern region

Description	Unit	Mean1/	DDF1	DDF2	DDF3	DDF4	NSMM	PSMM
Rice output	Kg	2,230.2	2,230.2	2,357.1	2,285.3	2,737.6	2,046.5	2,222.2
Planted area	Ha/Farm	1.01	0.97	1.01	0.99	2.63	0.43	0.27
Seed	Kg	148.7	141.9	148.7	145.0	156.3	62.0	95.2
Bio-fertiliser	Kg	5,758.8	5,494.5	5,758.8	5,616.6	0.0	0.0	0.0
N-fertiliser	Kg	48.2	46.0	48.2	47.0	17.5	24.8	166.6
P-fertiliser	Kg	20.1	19.2	20.1	19.6	21.9	12.4	7.7
K-fertiliser	Kg	15.5	14.8	15.5	15.1	0.0	12.4	15.7
Pesticide	Kg	3.0	2.9	3.0	3.0	0.0	0.0	0.0
Human labour	Baht	7,438.2	7,096.8	7,438.2	7,254.5	4,448.4	4,364.0	7,505.9
Machinery	Baht	3,669.0	3,500.6	3,669.0	3,578.3	3,750.2	2,356.6	2,095.2
Fuel	Litre	4.0	3.8	4.0	3.9	2.2	0.0	0.0
Other cost	Baht	545.4	520.4	545.4	531.9	306.3	62.0	39.7
NS	Kg	25.32	23.03	23.92	23.48	-10.89	2.98	143.20
PS	Kg	15.93	14.99	15.67	15.31	16.71	8.43	3.45
% change of NS			-9.04	-5.51	-7.26	-143.02	-88.21	465.57
% change of PS			-5.88	-1.59	-3.85	4.94	-47.09	-78.34

Note: 1/ denotes the average value of rice output and inputs used for the non-jasmine rice Northeast sample.

Table 6.13 indicates that the improvement of non-jasmine rice output and the combination of inputs used per hectare of the average farm in the Central region for all directions to the efficiency frontiers can lead to the reduction of NS and PS discharged into the environment, except that the farm's approach towards the profit maximisation frontier leads to the increase of NS and PS discharged into the environment, and the farm's approach towards the NS minimisation frontier leads to an increase in the PS discharged into the environment.

Table 6.13 Average improvement of inputs used and non-jasmine rice produced per hectare required to be technically, profit, NS, and PS efficient for farms in the Central region

Description	**Unit**	**Mean[1/]**	**DDF1**	**DDF2**	**DDF3**	**DDF4**	**NSMM**	**PSMM**
Rice output	Kg	3,863.3	3,863.3	4,438.1	4,092.7	4,186.8	3,763.4	4,788.7
Planted area	Ha/Farm	4.28	3.85	4.28	4.03	20.66	0.93	1.42
Seed	Kg	174.5	156.9	174.5	164.1	144.0	137.3	233.8
Bio-fertiliser	Kg	1,879.0	1,689.6	1,879.0	1,767.4	0.0	2.5	7,794.2
N-fertiliser	Kg	81.7	73.5	81.7	76.8	121.2	39.9	36.6
P-fertiliser	Kg	30.6	27.5	30.6	28.7	44.2	49.9	9.4
K-fertiliser	Kg	2.1	1.9	2.1	2.0	0.0	0.0	9.4
Pesticide	Kg	9.3	8.4	9.3	8.8	3.1	2.5	5.8
Human labour	Baht	6,010.2	5,404.4	6,010.2	5,653.2	5,766.9	5,492.2	6,436.7
Machinery	Baht	3,274.1	2,944.1	3,274.1	3,079.7	3,312.0	4,680.9	4,053.0
Fuel	Litre	25.7	23.1	25.7	24.2	0.3	0.0	39.0
Other cost	Baht	175.0	157.4	175.0	164.6	0.0	0.0	0.0
NS	Kg	41.12	32.69	34.80	33.63	76.77	0.06	-13.47
PS	Kg	23.18	20.06	22.03	20.88	36.06	42.67	0.24
% change of NS			-20.50	-15.38	-18.22	86.69	-99.86	-132.76
% change of PS			-13.44	-4.96	-9.90	55.61	84.12	-98.95

Note: 1/ denotes the average value of rice output and inputs used for the non-jasmine rice Central sample.

Table 6.14 Average improvement of inputs used and non-jasmine rice produced per hectare required to be technically, profit, NS, and PS efficient for farms in the Southern region

Description	**Unit**	**Mean[1/]**	**DDF1**	**DDF2**	**DDF3**	**DDF4**	**NSMM**	**PSMM**
Rice output	Kg	2,787.5	2,787.5	3,200.9	2,959.2	3,462.4	3,043.5	3,481.5
Planted area	Ha/Farm	1.81	1.62	1.81	1.70	9.30	0.92	0.54
Seed	Kg	177.5	158.7	177.5	166.6	156.2	234.8	157.1
Bio-fertiliser	Kg	952.1	851.2	952.1	893.4	0.0	0.0	0.0
N-fertiliser	Kg	48.0	42.9	48.0	45.0	125.8	31.3	10.1
P-fertiliser	Kg	27.0	24.2	27.0	25.4	0.0	39.1	12.6
K-fertiliser	Kg	1.2	1.1	1.2	1.1	0.0	0.0	0.0
Pesticide	Kg	6.8	6.1	6.8	6.4	6.2	1.2	0.0
Human labour	Baht	8,939.5	7,991.9	8,939.5	8,388.9	4,699.8	3,882.6	5,081.7
Machinery	Baht	4,404.6	3,937.7	4,404.6	4,133.3	3,124.9	3,131.2	3,456.4
Fuel	Litre	5.6	5.0	5.6	5.2	3.9	0.0	0.0
Other cost	Baht	345.8	309.1	345.8	324.5	54.7	313.1	0.0
NS	Kg	19.26	13.97	14.71	14.30	89.41	0.42	-26.51
PS	Kg	21.81	18.91	20.98	19.78	-6.61	33.52	5.93
% change of NS			-27.47	-23.61	-25.77	364.19	-97.82	-237.65
% change of PS			-13.31	-3.79	-9.31	-130.32	53.71	-72.83

Note: 1/ denotes the average value of rice output and inputs used for the non-jasmine rice South sample.

Table 6.15 Average improvement of inputs used and glutinous rice produced per hectare required to be technically, profit, NS, and PS efficient for farms in the Northern region

Description	Unit	Mean[1/]	DDF1	DDF2	DDF3	DDF4	NSMM	PSMM
Rice output	Kg	3,354.7	3,354.7	3,424.1	3,386.2	3,750.0	3,750.0	2,790.7
Planted area	Ha/Farm	0.91	0.89	0.91	0.90	1.40	1.20	0.43
Seed	Kg	100.2	98.5	100.2	99.3	44.7	53.7	62.0
Bio-fertiliser	Kg	1,185.1	1,164.6	1,185.1	1,174.0	4,471.7	0.0	0.0
N-fertiliser	Kg	36.7	36.1	36.7	36.4	34.5	41.1	5.0
P-fertiliser	Kg	13.8	13.6	13.8	13.7	17.0	0.0	6.2
K-fertiliser	Kg	2.9	2.9	2.9	2.9	20.0	0.0	0.0
Pesticide	Kg	12.3	12.1	12.3	12.2	15.2	20.1	0.0
Human labour	Baht	10,055.2	9,881.3	10,055.2	9,960.7	7,700.3	12,713.1	16,163.3
Machinery	Baht	4,627.6	4,547.5	4,627.6	4,584.1	4,382.3	5,634.4	4,961.2
Fuel	Litre	9.8	9.7	9.8	9.7	0.0	0.0	0.0
Other cost	Baht	893.2	877.8	893.2	884.8	17.9	1,091.1	1,550.4
NS	Kg	0.94	0.29	0.18	0.24	-6.27	0.48	-25.06
PS	Kg	7.30	7.05	7.16	7.10	9.55	-7.39	0.75
% change of NS			-69.59	-81.20	-74.69	-766.78	-48.77	-2,764.15
% change of PS			-3.32	-1.90	-2.67	30.86	-201.34	-89.69

Note: 1/ denotes the average value of rice output and inputs used for the glutinous rice North sample.

Table 6.16 Average improvement of inputs used and glutinous rice produced per hectare required to be technically, profit, NS, and PS efficient for farms in the North-eastern region

Description	Unit	Mean[1/]	DDF1	DDF2	DDF3	DDF4	NSMM	PSMM
Rice output	Kg	2,108.7	2,108.7	2,292.6	2,193.7	2,019.5	2,381.7	2,187.5
Planted area	Ha/Farm	1.26	1.16	1.26	1.20	1.64	1.31	0.80
Seed	Kg	157.9	146.1	157.9	151.6	99.2	155.9	157.2
Bio-fertiliser	Kg	4,004.4	3,704.5	4,004.4	3,843.0	5,666.4	0.0	0.0
N-fertiliser	Kg	52.2	48.3	52.2	50.1	61.2	24.9	268.0
P-fertiliser	Kg	19.1	17.7	19.1	18.4	11.3	21.8	4.4
K-fertiliser	Kg	20.3	18.8	20.3	19.5	0.0	6.2	11.0
Pesticide	Kg	3.0	2.8	3.0	2.9	4.5	7.8	1.6
Human labour	Baht	8,442.3	7,809.9	8,442.3	8,102.0	5,711.3	13,300.0	7,354.5
Machinery	Baht	3,551.6	3,285.6	3,551.6	3,408.5	1,869.9	4,987.8	3,143.0
Fuel	Litre	3.2	3.0	3.2	3.1	0.0	15.6	0.0
Other cost	Baht	873.0	807.6	873.0	837.8	1,180.9	576.7	157.2
NS	Kg	30.75	26.71	28.72	27.64	40.07	0.46	245.68
PS	Kg	15.24	13.78	14.87	14.28	7.49	17.37	0.34
% change of NS			-13.14	-6.58	-10.11	30.33	-98.52	699.05
% change of PS			-9.56	-2.41	-6.26	-50.82	14.01	-97.77

Note: 1/ denotes the average value of rice output and inputs used for the glutinous rice Northeast sample.

Table 6.14 indicates that the improvement of non-jasmine rice output and the combination of inputs used per hectare of the average farm in the Southern region for all directions to the efficiency frontiers can lead to the reduction of NS and PS discharged into the environment, except that the farm's approach towards the profit maximisation frontier leads to an increase in NS discharged into the environment, and the farm's approach towards the NS minimisation frontier leads to an increase in PS discharged into the environment.

Table 6.15 indicates that the improvement of glutinous rice output and the combination of inputs used per hectare of the average farm in the Northern region for all directions to the efficiency frontiers can lead to the reduction of NS and PS discharged into the environment, except that the farm's approach towards the profit maximisation frontier leads to an increase in PS discharged into the environment.

Table 6.16 indicates that the improvement of glutinous rice produced and the combination of inputs used per hectare of the average farm in the North-eastern region with all directions to the efficiency frontiers can lead to the reduction of NS and PS discharged into the environment, except that the farm's approach towards the profit maximisation and PS minimisation frontiers leads to an increase in NS discharged into the environment and the farm's approach towards the NS minimisation frontier leads to an increase in PS discharged into the environment.

6.5 Technical, profit and environmental best practice farms

Table 6.17 – Table 6.25 present the average rice output per hectare and the average input used to produce a tonne of rice output on the technical best practice farms (TBPFs), which construct the PPF for directions DDF1 – DDF3 (the fourth column), the average rice output per hectare and the average input used to produce a tonne of rice on the profit efficiency BPF, which construct the profit maximisation frontier (the fifth column), the average rice output per hectare and the average input used to produce a tonne of rice on the NS efficiency BPF, which construct the NS minimisation frontier (the sixth column), and the average rice output per hectare and the average input used to produce a tonne of rice on the PS efficiency BPF, which construct the PS minimisation frontier (the seventh column), compared to the average farms (the third column) in the 9 observed groups. The NS and PS discharged into the environment when the average farms and the BPFs produce a tonne of rice are presented in the third and fourth rows from the end of each Table. The percentage change of NS and PS of the BPFs compared to the average farms when they produce a tonne of rice are also presented in the last two rows of each Table. Since the TBPFs which create the PPF of each sample using the DDF1 to DDF3 measures are the same farms, the average inputs and output are the same across these three measures.

Table 6.17 Comparison of jasmine rice produced per hectare and inputs used per tonne of jasmine rice on the average sample farms, technical, profit maximisation, NS minimisation, and PS minimisation BPFs in the Northern region

Description	Unit	Mean1/	DDF1-DDF3	DDF4	NSMM	PSMM
Rice output	Kg/ha	3,107.29	3,186.95	3,347.55	2,906.98	3,640.00
Planted area	Ha	0.32	0.31	0.30	0.34	0.27
Seed	Kg	39.09	38.22	40.34	27.06	21.66
Bio-fertiliser	Kg	745.40	716.99	0.00	5,411.26	0.00
N-fertiliser	Kg	14.37	13.57	31.26	12.45	5.10
P-fertiliser	Kg	5.73	4.49	10.08	0.00	3.90
K-fertiliser	Kg	1.81	0.88	0.00	0.00	3.90
Pesticide	Kg	5.14	4.62	0.81	1.08	1.74
Human labour	Baht	2,461.08	2,376.76	1,244.40	2,465.37	1,993.93
Machinery	Baht	1,205.73	1,145.03	652.99	1,298.70	1,386.48
Fuel	Litre	1.35	1.38	0.00	0.00	1.74
Other cost	Baht	256.37	205.22	52.69	541.13	901.21
NS per ton of rice	Kg	3.80	2.99	20.71	1.75	-5.66
PS per ton of rice	Kg	3.81	2.56	8.17	-1.95	1.94
% change of NS			-21.17	445.21	-54.04	-249.11
% change of PS			-32.68	114.43	-151.10	-48.94

Note: 1/ denotes the average value of rice output and inputs used on the jasmine rice North sample farms.

Table 6.18 Comparison of jasmine rice produced per hectare and inputs used per tonne of jasmine rice on average sample farms, technical, profit maximisation, NS minimisation, and PS minimisation BPFs in the North-eastern region

Description	Unit	Mean1/	DDF1-DDF3	DDF4	NSMM	PSMM
Rice output	Kg	2,062.50	2,189.56	2,013.42	2,400.00	2,019.23
Planted area	Ha	0.48	0.46	0.50	0.42	0.50
Seed	Kg	71.14	51.63	46.58	58.59	31.06
Bio-fertiliser	Kg	1,661.93	1,106.68	0.00	0.00	1,941.00
N-fertiliser	Kg	21.38	19.52	23.86	10.42	7.34
P-fertiliser	Kg	9.98	9.44	8.14	5.21	2.33
K-fertiliser	Kg	7.78	6.06	13.35	5.21	2.33
Pesticide	Kg	1.29	1.56	0.00	0.00	0.00
Human labour	Baht	3,896.47	2,974.03	2,889.50	2,287.76	3,712.98
Machinery	Baht	1,733.20	1,415.53	1,708.07	1,302.08	1,397.51
Fuel	Litre	2.44	0.77	0.00	0.00	0.00
Other cost	Baht	397.63	184.48	52.48	0.00	108.70
NS	Kg	11.17	9.09	13.37	0.06	-3.32
PS	Kg	8.13	7.54	6.23	3.33	0.39
% change of NS			-18.62	19.76	-99.45	-129.74
% change of PS			-7.16	-23.33	-59.07	-95.19

Note: 1/ denotes the average value of rice output and inputs used on the jasmine rice Northeast sample farms

Table 6.17 shows that the TBPFs, the profit efficiency BPF, and the PS efficiency BPF of the jasmine rice North sample produced more jasmine rice per hectare than the average farm, while the NS efficiency BPF produced less jasmine rice per hectare than the average farm. Moreover, all the BPFs of the jasmine rice North sample used less seed, N fertiliser, and P fertiliser than the average farm to produce a tonne of jasmine rice, except the profit efficiency BPF. As a result, the BPFs, except the profit efficiency BPF, discharged less NS and PS into the environment than the average farm when producing a tonne of jasmine rice.

Table 6.18 shows that the TBPFs and the NS efficiency BPF of the jasmine rice Northeast sample produced more jasmine rice per hectare than the average farm, while the profit efficiency BPF and the PS efficiency BPF produced less jasmine rice per hectare than the average farm. Moreover, the BPFs of the jasmine rice Northeast sample used less seed, N fertiliser, and P fertiliser than the average farm to produce a tonne of jasmine rice, except the profit efficiency BPF, which used higher N fertiliser than the average farm. As a result, the BPFs discharged less NS and PS into the environment than the average farm when producing a tonne of jasmine rice, except the profit efficiency BPF, which discharged more NS into the environment than the average farm when producing a tonne of jasmine rice.

Table 6.19 Comparison of jasmine rice produced per hectare and inputs used per tonne of jasmine rice on average sample farms, technical, profit maximisation, NS minimisation, and PS minimisation BPFs in the Central region

Description	Unit	Mean1/	DDF1-DDF3	DDF4	NSMM	PSMM
Rice output	Kg	2,388.85	2,457.95	2,580.65	2,095.81	2,586.21
Planted area	Ha/Farm	0.42	0.41	0.39	0.48	0.39
Seed	Kg	61.46	50.87	38.23	59.70	38.74
Bio-fertiliser	Kg	193.84	105.26	0.00	0.00	0.00
N-fertiliser	Kg	15.56	11.25	7.65	10.61	12.78
P-fertiliser	Kg	7.03	5.58	9.56	13.27	1.94
K-fertiliser	Kg	1.60	1.02	0.00	0.00	1.94
Pesticide	Kg	0.87	0.56	0.70	0.00	1.94
Human labour	Baht	1,825.51	1,744.25	2,372.88	2,072.95	1,670.70
Machinery	Baht	1,522.56	1,391.31	1,210.65	1,343.28	1,525.42
Fuel	Litre	0.37	0.61	0.00	0.00	0.00
Other cost	Baht	62.71	27.61	0.00	0.00	0.00
NS	Kg	5.23	0.81	-2.93	0.27	2.21
PS	Kg	5.15	3.69	7.63	11.39	0.01
% change of NS			-84.53	-156.06	-94.82	-57.77
% change of PS			-28.42	48.29	121.14	-99.73

Note: 1/ denotes the average value of rice output and inputs used on the jasmine rice Central sample farms.

Table 6.19 shows that the TBPFs, the profit efficiency BPF, and the PS efficiency BPF of the jasmine rice Central sample produced more jasmine rice per hectare than the average farm, while the NS efficiency BPF produced less jasmine rice per hectare than the average farm. Furthermore, the BPFs of the jasmine rice Central sample used less seed, N fertiliser, and P fertiliser than the average farm to produce a tone of jasmine rice, except the profit efficiency BPF and the NS efficiency BPF, which used more P fertiliser than the average farm. As a result, the BPFs discharged less NS and PS into the environment than the average farm when producing a tonne of jasmine rice, except the profit efficiency BPF and the NS efficiency BPF, which discharged more PS into the environment than the average farm when producing a tonne of jasmine rice.

Table 6.20 shows that the TBPFs, the profit efficiency BPF, and the PS efficiency BPF of the non-jasmine rice North sample produced more non-jasmine rice per hectare than the average farm, while the NS efficiency BPF produced less non-jasmine rice per hectare than the average farm. The results also indicate that the BPFs of the non-jasmine rice North sample used less seed, nitrogen fertiliser, and phosphorus fertiliser than the average farm to produce a tonne of non-jasmine rice. As a result, the BPFs discharged less NS and PS into the environment than the average farm when producing a tonne of non-jasmine rice.

Table 6.20 Comparison of non-jasmine rice produced per hectare and inputs used per tonne of non-jasmine rice on average sample farms, technical, profit maximisation, NS minimisation, and PS minimisation BPFs in the Northern region

Description	**Unit**	**Mean[1/]**	**DDF1-DDF3**	**DDF4**	**NSMM**	**PSMM**
Rice output	Kg	3,643.73	3,735.81	3,723.82	3,355.70	3,947.37
Planted area	Ha/Farm	0.27	0.27	0.27	0.30	0.25
Seed	Kg	47.41	41.84	41.95	34.98	23.51
Bio-fertiliser	Kg	474.15	544.23	0.00	34.98	0.00
N-fertiliser	Kg	19.99	15.85	19.30	10.73	8.98
P-fertiliser	Kg	4.81	2.95	0.00	0.00	2.63
K-fertiliser	Kg	0.69	0.33	0.00	0.00	6.58
Pesticide	Kg	3.85	2.56	0.65	0.77	0.00
Human labour	Baht	1,929.29	1,984.05	1,459.73	1,209.83	3,482.63
Machinery	Baht	924.53	896.76	1,006.71	839.55	1,097.18
Fuel	Litre	2.85	1.72	0.98	0.00	0.00
Other cost	Baht	135.56	121.05	0.00	47.81	19.59
NS	Kg	9.51	5.31	8.76	0.11	-1.76
PS	Kg	2.91	1.03	-1.92	-1.93	0.68
% change of NS			-44.11	-7.91	-98.81	-118.52
% change of PS			-64.49	-165.87	-166.35	-76.61

Note: 1/ denotes the average value of rice output and inputs used on the non-jasmine rice North sample farms.

Table 6.21 shows that the TBPFs and the profit efficiency BPF of the non-jasmine rice Northeast sample produced more non-jasmine rice per hectare than the average farm, while the NS efficiency BPF and the PS efficiency BPF produced less non-jasmine rice per hectare than the average farm. The results also indicate that the BPFs of the non-jasmine rice Northeast sample used less seed, N fertiliser, and P fertiliser than the average farm to produce a tonne of non-jasmine rice, except the PS efficiency BPF, which used more N fertiliser than the average farm. As a result, the BPFs discharged less NS and PS into the environment than the average farm when producing a tonne of non-jasmine rice, except the PS efficiency BPF, which discharged 467.6% more NS into the environment than the average farm when producing a tonne of non-jasmine rice.

Table 6.21 Comparison of non-jasmine rice produced per hectare and inputs used per tonne of non-jasmine rice on average sample farms, technical, profit maximisation, NS minimisation, and PS minimisation BPFs in the North-eastern region

Description	**Unit**	**Mean[1/]**	**DDF1-DDF3**	**DDF4**	**NSMM**	**PSMM**
Rice output	Kg	2,230.17	2,308.38	2,737.64	2,046.51	2,222.22
Planted area	Ha/Farm	0.45	0.43	0.37	0.49	0.45
Seed	Kg	66.67	61.13	57.08	30.31	42.85
Bio-fertiliser	Kg	2,582.23	2,264.67	0.00	0.00	0.00
N-fertiliser	Kg	21.62	16.25	6.39	12.13	74.97
P-fertiliser	Kg	9.01	5.70	7.99	6.06	3.47
K-fertiliser	Kg	6.93	4.28	0.00	6.06	7.07
Pesticide	Kg	1.36	1.20	0.00	0.00	0.00
Human labour	Baht	3,335.26	2,965.10	1,624.89	2,132.42	3,377.65
Machinery	Baht	1,645.15	1,450.07	1,369.86	1,151.51	942.85
Fuel	Litre	1.78	1.70	0.80	0.00	0.00
Other cost	Baht	244.56	140.68	111.87	30.31	17.85
NS	Kg	11.35	5.92	-3.98	1.46	64.44
PS	Kg	7.14	3.83	6.10	4.12	1.55
% change of NS			-47.87	-135.05	-87.15	467.59
% change of PS			-46.41	-14.52	-42.34	-78.26

Note: 1/ denotes the average value of rice output and inputs used on the non-jasmine rice Northeast sample farms.

Table 6.22 shows that the TBPFs, the profit efficiency BPF and the PS efficiency BPF of the non-jasmine rice Central sample produced more non-jasmine rice per hectare than the average farm, while the NS efficiency BPF produced less non-jasmine rice per hectare than the average farm. The TBPFs and PS efficiency BPF used less N fertiliser and P fertiliser than the average farm to produce a tonne of non-jasmine rice, resulting in a reduction of NS and PS discharged into the environment. The profit BPF applied more N fertiliser and P fertiliser than the average farm, resulting in greater discharges of NS and PS. Moreover, the NS efficiency BPF applied a very small amount of N fertiliser, but applied more P fertiliser than the average farm, resulting in a higher discharge of PS than that of the average farm.

Table 6.22 Comparison of non-jasmine rice produced per hectare and inputs used per tonne of non-jasmine rice on average sample farms, technical, profit maximisation, NS minimisation, and PS minimisation BPFs in the Central region

Description	Unit	Mean1/	DDF1-DDF3	DDF4	NSMM	PSMM
Rice output	Kg	3,863.27	4,249.71	4,186.83	3,763.44	4,788.73
Planted area	Ha/Farm	0.26	0.24	0.24	0.27	0.21
Seed	Kg	45.16	39.58	34.39	36.48	48.83
Bio-fertiliser	Kg	486.37	703.97	0.00	0.66	1,627.60
N-fertiliser	Kg	21.15	17.63	28.96	10.61	7.65
P-fertiliser	Kg	7.91	5.91	10.55	13.27	1.95
K-fertiliser	Kg	0.56	0.31	0.00	0.00	1.95
Pesticide	Kg	2.41	2.23	0.75	0.66	1.22
Human labour	Baht	1,555.73	1,439.63	1,377.39	1,459.37	1,344.14
Machinery	Baht	847.50	690.69	791.04	1,243.78	846.35
Fuel	Litre	6.66	7.26	0.08	0.00	8.14
Other cost	Baht	45.30	30.13	0.00	0.00	0.00
NS	Kg	10.64	7.06	18.34	0.02	-2.81
PS	Kg	6.00	3.99	8.61	11.34	0.05
% change of NS			-33.66	72.26	-99.85	-126.43
% change of PS			-33.57	43.58	89.00	-99.16

Note: 1/ denotes the average value of rice output and inputs used on the non-jasmine rice Central sample farms.

Table 6.23 Comparison of non-jasmine rice produced per hectare and inputs used per tonne of non-jasmine rice on average sample farms, technical, profit maximisation, NS minimisation, and PS minimisation BPFs in the Southern region

Description	Unit	Mean1/	DDF1-DDF3	DDF4	NSMM	PSMM
Rice output	Kg	2,787.50	2,952.93	3,462.37	3,043.48	3,481.48
Planted area	Ha/Farm	0.36	0.34	0.29	0.33	0.29
Seed	Kg	63.69	60.96	45.13	77.16	45.13
Bio-fertiliser	Kg	341.55	531.56	0.00	0.00	0.00
N-fertiliser	Kg	17.21	15.32	36.33	10.29	2.89
P-fertiliser	Kg	9.70	6.04	0.00	12.86	3.61
K-fertiliser	Kg	0.43	0.10	0.00	0.00	0.00
Pesticide	Kg	2.45	1.97	1.80	0.39	0.00
Human labour	Baht	3,207.02	2,771.92	1,357.40	1,275.72	1,459.64
Machinery	Baht	1,580.13	1,449.64	902.53	1,028.81	992.78
Fuel	Litre	2.00	1.33	1.13	0.00	0.00
Other cost	Baht	124.04	80.36	15.79	102.88	0.00
NS	Kg	6.91	4.99	25.82	0.14	-7.62
PS	Kg	7.82	4.16	-1.91	11.02	1.70
% change of NS			-27.75	273.71	-98.00	-210.21
% change of PS			-46.78	-124.41	40.78	-78.25

Note: 1/ denotes the average value of rice output and inputs used on the non-jasmine rice South sample farms.

Table 6.23 shows that the TBPFs, the profit efficiency BPF, the NS efficiency BPF, and the PS efficiency BPF of the non-jasmine rice South sample produced more non-jasmine rice per hectare than the average farm. The results also indicate that the TBPFs and the PS efficiency BPF of the non-jasmine rice South sample used less seed, N fertiliser, and P fertiliser than the average farm to produce a tonne of non-jasmine rice, resulting in a reduction of NS and PS discharged into the environment. The profit efficiency BPF applied more N fertiliser than the average farm by 111.1%, resulting in a discharge of NS that was higher than that of the average farm by 273.7%. Furthermore, the NS efficiency BPF discharged NS 0.14 kg/ha, but it discharged PS 11 kg/ha which is higher than the average farm by 40.8%.

Table 6.24 Comparison of glutinous rice produced per hectare and inputs used per tonne of glutinous rice on average sample farms, technical, profit maximisation, NS minimisation, and PS minimisation BPFs in the Northern region

Description	**Unit**	**Mean1/**	**DDF1-DDF3**	**DDF4**	**NSMM**	**PSMM**
Rice output	Kg	3,354.70	3,376.12	3,750.00	3,750.00	2,790.70
Planted area	Ha/Farm	0.30	0.30	0.27	0.27	0.36
Seed	Kg	29.87	27.34	11.92	14.31	22.23
Bio-fertiliser	Kg	353.26	373.65	1,192.46	0.00	0.00
N-fertiliser	Kg	10.95	10.15	9.20	10.97	1.78
P-fertiliser	Kg	4.11	3.87	4.52	0.00	2.23
K-fertiliser	Kg	0.87	0.72	5.34	0.00	0.00
Pesticide	Kg	3.66	3.04	4.06	5.37	0.00
Human labour	Baht	2,997.35	2,842.84	2,053.42	3,390.15	5,791.84
Machinery	Baht	1,379.44	1,344.84	1,168.62	1,502.50	1,777.78
Fuel	Litre	2.93	2.66	0.00	0.00	0.00
Other cost	Baht	266.25	255.88	4.77	290.96	555.56
NS	Kg	0.28	-0.55	-1.67	0.13	-8.98
PS	Kg	2.17	1.93	2.55	-1.97	0.27
% change of NS			-296.43	-696.49	-54.17	-3,302.58
% change of PS			-11.28	17.07	-190.65	-87.61

Note: 1/ denotes the average value of rice output and inputs used on the glutinous rice North sample farms.

Table 6.24 shows that the TBPFs, the profit efficiency BPF, and the NS efficiency BPF of the glutinous rice North sample produced more glutinous rice per hectare than the average farm, while the PS efficiency BPF produced less glutinous rice per hectare than the average farm. The results also indicate that the BPFs of the glutinous rice North sample used less seed, N fertiliser, and P fertiliser than the average farm to produce a tonne of glutinous rice, except the profit efficiency BPF, which used slightly more P fertiliser than the average farm. As a result, the BPFs discharged less NS and PS into the environment than the average farm when producing a tonne of glutinous rice, except the profit efficiency BPF, which, for every tonne of glutinous rice, discharged more PS into the environment than the average farm by 17.1%.

Table 6.25 shows that the TBPFs, the NS efficiency BPF, and the PS efficiency BPF of the glutinous rice Northeast sample produced more glutinous rice per hectare than the average farm, while the profit efficiency BPF produced less glutinous rice per hectare than the average farm. The results also indicate that the TBPFs of the glutinous rice Northeast sample used less seed, nitrogen fertiliser, and phosphorus fertiliser than the average farm to produce a tonne of glutinous rice, resulting in smaller discharges of NS and PS into the environment than those produced by the average farm. The profit efficiency and PS efficiency BPFs used more N fertiliser than the average farm to produce a tonne of glutinous rice resulting in higher discharges of NS into the environment than those produced by the average farm. The NS efficiency BPF used slightly more P fertiliser than the average farm to produce a tonne of glutinous rice, resulting in higher discharges of PS into the environment than those produced by the average farm.

Table 6.25 Comparison of glutinous rice produced per hectare and inputs used per tonne of glutinous rice on average sample farms, technical, profit maximisation, NS minimisation, and PS minimisation BPFs in the North-eastern region

Description	Unit	Mean1/	DDF1-DDF3	DDF4	NSMM	PSMM
Rice output	Kg	2,108.70	2,206.00	2,019.51	2,381.68	2,187.50
Planted area	Ha/Farm	0.47	0.45	0.50	0.42	0.46
Seed	Kg	74.89	65.53	49.10	65.45	71.84
Bio-fertiliser	Kg	1,898.99	1,777.49	2,805.84	0.00	0.00
N-fertiliser	Kg	24.76	16.33	30.30	10.47	122.52
P-fertiliser	Kg	9.08	6.48	5.61	9.16	2.01
K-fertiliser	Kg	9.62	4.68	0.00	2.62	5.03
Pesticide	Kg	1.41	2.13	2.24	3.27	0.72
Human labour	Baht	4,003.55	3,608.88	2,828.06	5,584.29	3,362.07
Machinery	Baht	1,684.28	1,425.63	925.93	2,094.24	1,436.78
Fuel	Litre	1.53	0.73	0.00	6.54	0.00
Other cost	Baht	413.99	271.50	584.74	242.15	71.84
NS	Kg	14.58	6.06	19.84	0.19	112.31
PS	Kg	7.23	4.61	3.71	7.29	0.16
% change of NS			-58.47	36.08	-98.69	670.27
% change of PS			-36.15	-48.64	0.94	-97.85

Note: 1/ denotes the average value of rice output and inputs used on the glutinous rice Northeast sample farms.

6.6 Discussion

The average TE scores obtained from the DDF1 measurement (or input-oriented DEA) of the 9 observed groups of Thai rice farmers range from 87.5% to 98.3%. The average TE scores obtained from the DDF2 measurement (or output-oriented DEA) of the 9 observed groups of Thai rice farmers range from 84.1% to 97.9%. The average TE scores obtained from the DDF3 measurement of the 9 observed groups of Thai rice farmers range from 93% to 99%. The Thai rice farms' TE scores, when adjusted according to input data based on the provincial average calculated yield of rice in the wet season for the crop year 2007/08 and categorised into their regions (North, Northeast, Central, and South) and rice type (jasmine rice, non-jasmine rice, and glutinous rice), are higher than the TE scores obtained from the evaluation of TE scores of the sample for the whole country (without categorising the sample into regions and rice type). This implies that some of the expected input and output heterogeneity, and the subsequent bias in efficiency measurement, have been removed.

The results of the NSMM of 9 groups of Thai rice farmers indicate that the observed farms' average discharge of NS into the environment ranged from 20.1 kg/ha to 50.7 kg/ha. The results of the PSMM indicate that their discharge of PS into the environment averaged from 11.0 kg/ha to 28.7 kg/ha. Although this study underestimates NS and PS because of lack of information regarding the inflows of N and P nutrients (i.e. soil, bio-fertiliser, biological fixation, atmospheric deposition, precipitation, and irrigation water) and the outflows of N and P (rice straw, and soil), the amounts of NS and PS discharged into the environment from the Thai rice farming system are comparatively high. These results indicate that Thai rice farmers applied more N and P fertiliser than the crops needed. In addition, there are unobserved residual nutrients (N and P) in the soil from earlier in the sample year (in the unsurveyed dry season), so the amount of NS and PS discharged into the environment are probably higher than the NS and PS calculated in this study.

The NS and PS from rice fields are the main sources of eutrophication of surface water (Tirado et al., 2008). Gold and Sims (2005 cited in Nguyen et al., 2012, p. 371) indicate that phosphorus has more eutrophying power in the context of fresh water than nitrogen. The previous empirical studies on environmental efficiency measurement (e.g. Coelli et al., 2007; Hoang and Coelli, 2011; Nguyen et al., 2012) have assumed the weights of the eutrophying power of N and P as 1 for N and 10 for P. That is, the eutrophying power is equal to the summation of the amount of N and ten times the amount of P. If these weights are applied in this study, the eutrophying power on fresh water of the average farm averages from 129.78 kg/ha to 337.46 kg/ha. This high level is consistent with Tirado et al. (2008), who indicated that Thai rice cultivation caused problems arising from eutrophication in river, lake, coastal and marine ecosystems (as discussed in Section 2.3).

If Thai rice farmers continue to use the current level of N and P fertiliser during their cultivation period without paying attention to the impact of these inputs on the environment, the environmental problems caused by NS and PS will be more severe because approximately 20.1 - 50.7 kg of NS and 11.0 - 28.7 kg of PS per hectare of rice cultivation area will be discharged into the environment every crop year (i.e. the NS and PS from N and P fertilisers application will accumulate in the environment every year). If these environmental problems are not solved, rice will not be able to grow in Thailand in the future. Therefore, maintaining the sustainability of rice-producing environments by the efficient use of N and P fertilisers is necessary for the sustainable development of Thai rice farming.

Before the creation of effective agro-environmental policies, the technical and environmental efficiency level of Thai rice farmers must be examined across rice type and regions. Considering the efficiency level of Thai rice farmers within each rice type, with regard to jasmine rice production, the results indicate that jasmine rice farmers in the Northern region are more technically efficient, earned higher profit, and discharged a lower amount of NS (20.1 kg/ha) into the environment than jasmine rice farmers in the Central and North-eastern regions. However, they discharged a higher amount of PS (23.1 kg/ha) into the environment than jasmine rice farmers in the other two regions. The results also indicate that jasmine rice farmers in the North-eastern region are less technically efficient, obtained less profit, and discharged a higher amount of NS (35.5 kg/ha) into the environment than jasmine rice farmers in the Northern and Central regions.

For non-jasmine rice production, the results indicate that non-jasmine rice farmers in the Northern regions are more technically efficient and discharged lower amounts of PS into the environment than non-jasmine rice farmers in the other three regions. They also earned higher profits than non-jasmine rice farmers in the North-eastern and Southern regions, but earned lower profits than non-jasmine rice farmers in the Central region. However, they discharged the highest amount of NS (50.66 kg/ha) into the environment compared to non-jasmine rice farmers in the other three regions; this is also the highest amount of NS discharged by any of the 9 observed groups. While non-jasmine rice farmers in the Southern region are less technically efficient than non-jasmine rice farmers in the other three regions, they obtained higher profits (11,702 Baht/ha) than non-jasmine rice farmers in the North-eastern region (1,536.9 Baht/ha). Furthermore, non-jasmine rice farmers in the Central region earned the highest profit compared to non-jasmine rice farmers in the other three regions and this is also the highest profit obtained by any of the 9 observed groups. On the other hand, non-jasmine rice farmers in the North-eastern region earned lower profits than the non-jasmine rice farmers in the other three regions, even though their average TE score is high.

With regard to glutinous rice production, the TE results indicate that glutinous rice farmers in the Northern region are more technically efficient and NS efficient than glutinous rice farmers in the North-eastern region. Glutinous rice farmers in the Northern region earned an average profit of 681.63 Baht/ha, while glutinous rice farmers in the North-eastern region suffered a loss of 6,930.35 Baht/ha. Furthermore, the glutinous rice farmers in the Northern region obtained the highest average TE scores compared to the other 8 groups of Thai rice farmers. However, they earned the lowest average profit compared to jasmine rice and non-jasmine rice farmers.

Considering the efficiency level of Thai rice farmers within each region, in the Northern region, glutinous rice farmers are more technically and PS efficient than jasmine rice and non-jasmine rice farmers. However, they earned lower profits than jasmine rice and non-jasmine rice farmers. Jasmine rice farmers are more NS efficient but less PS efficient than non-jasmine rice and glutinous rice farmers. On the other hand, non-jasmine rice farmers are more profit efficient than jasmine rice and glutinous rice farmers. In the North-eastern region, non-jasmine rice farmers are more technically efficient than glutinous rice and jasmine rice farmers. However, jasmine rice farmers are more profit efficient than non-jasmine rice and glutinous rice farmers. The average amounts of NS discharged by jasmine rice, non-jasmine rice, and glutinous rice farmers are nearly the same. Glutinous rice farmers are more PS efficient than jasmine rice and non-jasmine rice farmers, but they suffered a loss of 6,930.35 Baht/ha. In addition, jasmine rice farmers in the Central region are more technically, NS, and PS efficient than non-jasmine rice farmers in Central region, but they earned lower profits than non-jasmine rice farmers.

Considering the efficiency level of Thai rice farmers for the whole country, glutinous rice farmers in the Northern region are more TE than the other groups of Thai rice farmers, but they earned a very low profit of 681.63 Baht/ha. On the other hand, jasmine rice farmers in the North-eastern region are less TE than the other groups and earned a low profit of 1,536.91 Baht/ha. Non-jasmine rice farmers in the Central and Northern regions earned the highest profit of 13,779.97 and 13,328.56 Baht/ha, respectively. However, they are the most NS inefficient as they discharged the largest amount of NS into the environment compared to the other 7 groups of Thai rice farmers. Glutinous rice farmers in the North-eastern region are the most PS efficient for Thai rice farming system as they discharged the lowest amount of PS into the environment compared to the other 8 observed groups. However, they had the lowest profit efficiency and suffered a loss of 6,930.35 Baht/ha. The glutinous rice farmers are also less profit efficient compared with jasmine rice and non-jasmine rice farmers. Furthermore, jasmine rice farmers in the Northern region are the most NS efficient in the Thai rice farming system as they discharged the lowest amount of NS into the environment compared to the other 8 observed groups. In addition, non-jasmine rice farmers in the North-eastern, Central, and Southern regions are the most PS inefficient in the Thai rice farming system as they discharged the largest amount of PS into the environment compared to the other 6 observed groups.

The improvement of rice output and the combination of inputs used per hectare required to enable the average farms to produce on the frontiers constructed by the BPFs according to the NSMM, the PSMM, and the DDF1 – DDF4 measures have been compared. The improvements in the TE of the 9 groups of Thai rice farmers according to DDF1 – DDF3 results in this study would result in both higher profits (as farmers either pay lower production costs or earn more income) and lower amounts of NS and PS discharged into the environment: these measures could be used for sustainable intensification strategies.

The improvements in the profit efficiency of the 9 groups of Thai rice farmers, according to DDF4 measurements in this study would result in higher profit. However, improvements in the profit efficiency of non-jasmine rice farmers in the Northern region would also result in lower amounts of both NS and PS being discharged into the environment: this could be used for sustainable intensification strategies. On the other hand, improvements in the profit efficiency of jasmine rice farmers in the Northern region and non-jasmine rice farmers in the Central region would result in greater amounts of NS and PS being discharged into the environment. Furthermore, improvements of the profit efficiency of the other 6 groups of Thai rice farmers would result in either lower or higher amounts of NS and PS being discharged into the environment.

Improvements in the NS efficiency of the 9 observed groups of Thai rice farmers, according to NSMM results in this study, would result in both higher profits (as farmers applied less chemical fertiliser to their crop, thus reducing production costs) and lower amounts of NS and PS discharged into the environment, apart from the jasmine rice Central, non-jasmine rice Central, non-jasmine rice South, and glutinous rice Northeast farms, whose discharges of PS into the environment are higher than the average farms in their groups. However, the improvement of NS efficiency is all that the jasmine rice Northeast and glutinous rice North groups need to produce higher rice output per hectare and reduce the amounts of NS and PS discharged into the environment: these examples could be used for sustainable intensification strategies.

The improvements in the PS efficiency of the 9 observed groups of Thai rice farming systems, according to PSMM figures in this study, would result in both higher profits (as farmers applied less chemical fertiliser to their crop, thus reducing production costs) and lower amounts of NS and PS discharged into the environment, apart from non-jasmine rice and glutinous rice farms in the Northeast region, whose discharges of NS into the environment are higher than the average farms in their groups.

The average inputs used to produce a tonne of paddy rice on the average farm, the TBPFs, the profit efficiency BPF, the NS efficiency BPF, and the PS efficiency BPF of each group of observations have been compared. The results indicate that the TBPFs of the 9 observed groups; the profit efficiency BPFs of non-jasmine North and non-jasmine Northeast; the NS efficiency BPFs of jasmine rice North, jasmine rice Northeast, non-jasmine rice North, non-jasmine rice Northeast, and glutinous rice North; and the PS efficiency BPFs of jasmine rice North, jasmine rice Northeast, jasmine rice Central, non-jasmine rice North, non-jasmine rice Central, non-jasmine rice South, and glutinous rice North can earn higher profits by using fewer inputs, especially inputs detrimental to the environment like nitrogen and phosphorus fertilisers, than the average farms in their respective groups, which also results in lower amounts of NS and PS being discharged into the environment, compared to the average farms in their respective groups. Thus, these BPFs can be used as benchmark farms to reduce environmental problems caused by the overuse of fertiliser when planning sustainable intensification agricultural development policy.

6.7 Conclusions

The technical efficiency of the 9 observed groups of Thai rice farmers was investigated using the DDF1-DDF3 measures. The results indicate that Thai rice farmers have average TE scores ranged from 84.1% to 99%, depending on which directional vector is chosen. The results of TE analysis also indicate that the adjustment of input data by the provincial average calculated yield of rice in the wet season for the crop year 2007/08 and the categorisation of sample data into regions (North, Northeast, Central, and South) and rice type (jasmine rice, non-jasmine rice, and glutinous rice) can help to remove some of the expected input and output heterogeneity and subsequent bias in efficiency measurement. Furthermore, the profit efficiency of the 9 observed groups of Thai rice farmers was investigated using the DDF4 measure. The results indicate that the average profit of Thai rice farmers ranged from 681.63 to 13,779.97 Baht/ha, but glutinous rice farmers in the North-eastern region suffered a loss of 6,930.35 Baht/ha.

Two models, namely the NSMM with the directional vector towards the nitrogen surplus minimum point and the PSMM with the directional vector towards the phosphorus surplus minimum point, were applied to measure the environmental efficiency of Thai rice farming using the directional nutrient surplus efficiency measure. The results indicate that the amount of NS discharged into the environment by the observed Thai rice farmers averages from 20.1 kg/ha to 50.7 kg/ha, and the PS discharged into the environment averages from 11.0 kg/ha to 28.7 kg/ha. These results also indicate that the average eutrophying effect of Thai rice farming on fresh water ranges from 129.78 kg/ha to 337.46 kg/ha.

The technical, profit, NS, and PS efficiency scores of the 9 observed groups of Thai rice farmers have been compared across rice type, regions, and country. The improvement of rice output and the combination of inputs used per hectare required to enable the average farms of 9 groups of Thai rice farmers to produce on the frontiers constructed by the BPFs according to the NSMM, the PSMM, and the DDF1 – DDF4 measurements have been compared with their actual performance. Furthermore, the average inputs used to produce a tonne of paddy rice on the average farm, the TBPFs, the profit efficiency BPF, the NS efficiency BPF, and the PS efficiency BPF in each observed group have been compared. The results indicate that the TBPFs of the 9 observed groups; the profit efficiency BPFs of the non-jasmine North and non-jasmine Northeast; the NS efficiency BPFs of the jasmine rice North, jasmine rice Northeast, non-jasmine rice North, non-jasmine rice Northeast, and glutinous rice North; and the PS efficiency BPFs of the jasmine rice North, jasmine rice Northeast, jasmine rice Central, non-jasmine rice North, non-jasmine rice Central, non-jasmine rice South, and glutinous rice North can be used as benchmark farms to reduce environmental problems caused by the overuse of fertiliser when planning sustainable intensification agricultural development policy. Thus, the environmental problems caused by Thai rice farming systems can be solved by adopting the methods of these best practice farms.

Chapter 7

Summary, Discussion and Conclusion

Rice is the staple food for people in Asia and Africa (GRiSP, 2013), areas where the FAO (2009) predicted most growth of the world population would occur. Thailand is the world's leading rice exporter and the sixth largest rice producing country in the world after China, India, Indonesia, Bangladesh, and Vietnam (FAO, 2016). Each year Thailand exports approximately 10 million tonnes of milled rice to other countries, which accounts for approximately 25% of the world's rice exports. The top ten importers of rice from Thailand are China, the U.S.A., the Philippines, Benin, Nigeria, South Africa, Malaysia, Hong Kong, Cote d'Ivoire, and Japan (OAE, 2015). The majority of these countries are located in the regions where high population growth is predicted. The intensive use of agrochemicals aims to boost rice productivity, yet it creates severe environmental problems: water pollution with nitrates and eutrophication of river, lake, coastal and marine ecosystems (as discussed in Section 2.3). If these environmental problems caused by rice cultivation are not solved, Thailand may not be able to produce enough rice to meet future global rice demand, and this will affect world food security. Further, the intensive use of chemical fertilisers increases the costs of agricultural production, sometimes with few commensurate benefits for farmers. This is a particular problem for farmers in Thailand, where chemical fertilisers are expensive, in part because the country has to import them from other countries.

Understanding the extent to which rice production in Thailand is technically and environmentally efficient is an important step towards enabling Thailand to design and implement policies that improve the efficiency of input use, especially nitrogen and phosphorus nutrients from chemical fertiliser and manure. This can reduce rice cultivation's negative impacts on the environment, reduce production costs, and reduce adverse health effects on farmers and their customers.

7.1 Contribution of this thesis

This thesis makes several contributions to the literature that have important policy implications. Firstly, previous studies have measured the technical efficiency level of rice production in Thailand using the input-oriented DEA approach (Taraka et al., 2010; Kiatpathomchai, 2008; Krasachat, 2004). This study adds to the existing literature of the TE of rice production in Thailand by estimating, for the first time, the TE of rice production at farm level using an output-oriented DEA and DDF with different directions of improvement towards the PPF. The results from the DDF1 – DDF3 measures for each group of observations indicate that the technically efficient farms in each observed group are the same farms across the DDF1 – DDF3 measures, implying that different TE measurements (i.e. different directional vectors) do not change the ranking of technically efficient farms in the observation. The results indicate that 70% of the jasmine rice North sample, 26% of the jasmine rice Northeast sample, 55% of the jasmine rice Central sample, 55% of the non-jasmine rice North sample, 64% of the non-jasmine rice Northeast sample, 40% of the non-jasmine rice Central sample, 46% of the non-jasmine rice South sample, 78% of the glutinous rice North sample, and 34% of the glutinous rice Northeast sample are technically efficient. However, the technical inefficiency scores of technically inefficient farms appear to depend on the particular model used. This implies that the rank of technically inefficient farms varies depends on the specific model, in particular assumptions about the direction of improvement towards the PPF.

This finding raises the issue of how policy makers can best identify and target those farms that have the greatest potential to improve the efficiency of their use of purchased inputs. Moreover, calculating the improvement of inputs used and output produced per hectare required to make the average farm in each observed group technically efficient using the DDF model with the direction towards observed farms' output produced holding all inputs fixed (or output-oriented DEA model), and the DDF model with the direction towards observed farms' inputs used and output produced to the PPF (DDF3 model), suggests higher potential profit for farmers than that using the input-oriented DEA model. Thus, the selection of the directional improvement of TE (i.e. model specification) of the DDF approach is has important implications for the direction of policy.

Secondly, this research contributes to the DDF and environmental efficiency literature by estimating the environmental efficiency of the sustainable intensification of Thai rice farming systems by proposing a new efficiency measurement, within the theoretical context of DDF, that has not been undertaken before. A great deal of research has investigated the environmental performance of the production processes by incorporating the negative impact of the production process on the environment, either as detrimental inputs (e.g. Chung et al., 1997; Reinhard et al., 2000; Shaik et al., 2002; De Koeijer et al, 2002; Areal et al, 2012) or as undesirable outputs (e.g. Färe et al., 1989; Shaik et al., 2002; Färe et al., 2005, Picazo-Tadeo et al., 2005; Macpherson et al., 2010; Färe et al., 2012; Toma et al., 2013), into traditional methods of productivity and efficiency analysis (i.e. Stochastic Production Frontier, DEA, and DDF approaches). Unlike these earlier studies, this research does not incorporate the MBC as either new input or new output variables into the traditional efficiency methods. Instead, it focuses on minimising the nutrient balance, a novel contribution to this literature.

Specifically, in this thesis, "the directional nutrient surplus efficiency measure" is determined, which shows how to minimise surplus nutrients in the production process: in the case of Thai rice farming, this means minimising the nitrogen and phosphorus surplus. The environmental efficiency measurement proposed by Coelli et al. (2007) can be used to minimise the nutrient content of inputs. The minimum nutrient content in each farm's inputs is measured by employing the input-oriented DEA method, which is similar to the cost-minimising DEA method. Then the environmental efficiency scores of each farm are calculated as "the ratio of minimum nutrients over observed nutrients" (Coelli et al., 2007, p. 7). In contrast, the environmental efficiency measurement approach used in this research demonstrates how to minimise the surplus of the specific nutrients (nitrogen and phosphorus) by incorporating the MBC into the DDF in a similar manner to that in which price data is normally incorporated. Using the directional nutrient surplus efficiency measure demonstrates how nitrogen and phosphorus surpluses can be minimised simultaneously, reducing nitrogen and phosphorus contents in inputs and expanding rice output. This new approach can be applied to the evaluation of the environmental performance of other production processes.

Thirdly, this study adds to the existing literature on the environmental efficiency of rice production in Thailand by estimating, for the first time, the nitrogen surplus efficiency and phosphorus surplus efficiency (i.e. environmental efficiency) of rice production in Thailand by incorporating the MBC into the DDF with the direction towards the nitrogen surplus minimising frontier and phosphorus surplus minimising frontier, respectively. This study shows that a farm's efficiency ranking changes when nitrogen and phosphorus surpluses are included in the efficiency analysis. The improvement of the environmental performance of Thai rice farming system towards either nitrogen or phosphorus minimising frontiers through a reduction of nitrogen and phosphorus surplus from rice cultivation can increase farmers' profit in addition to having environmental benefits.

Finally, this research contributes to the improvement of surveys for the national Thai input survey of rice and other agricultural production. The questionnaire would provide much greater scope for analysis if questions were added concerning demographic variables and farm characteristics. These might variously include socio-economic factors such as farmers' age, farmers' experience, educational level of farmers, number of family members, farm size, rice monoculture, source of funds; agricultural extension variables such as whether a farmer is a member of agricultural cooperative, whether the farmer has received a government extension visit; and environmental variables such as soil type, soil nutrients testing, and farmers' views on inorganic fertilisers. These data would allow researchers to investigate factors affecting the technical and environmental inefficiency of rice and other agricultural production systems in Thailand. This information could be used to provide insights into farmers' management practices, which are important for designing effective agro-environmental policies. In order to understand why farmers overuse chemical fertiliser and manure, the questionnaire could include questions on such topics as the strategies used by farmers to decide whether to apply chemical fertilisers, and their reasons for using large amounts of fertiliser.

7.2 Understanding the findings of this thesis

The analysis in this thesis suggests that a large number of farms apply excessive quantities of fertiliser, resulting in reduced profits and environmental damage caused by run-off, as well as compromising farmers' health. 767 farmers (69.0% of the total observation) applied nutrients containing excessive quantities of nitrogen, while 775 farmers (69.7% of the total observation) applied nutrients containing excessive quantities of phosphorus (Table 5.7 Chapter 5). This raises the question of why farmers are behaving as they do, and whether any negative consequences would arise from policy makers encouraging farmers to reduce their use of inputs as part of a sustainable intensification strategy, whether with respect to reducing input usage or expanding output through more efficient input use.

This research provides information on the efficiency level of farmers in Thailand, indicating the percentage by which farmers can reduce their inputs usage, and the percentage by which farmers can expand their output if they perform efficiently. However, the use of secondary data precludes an exploration of the reasons why Thai farmers overuse chemical fertiliser and manure. This thesis provides a comprehensive review of the literature in order to build an understanding of the general rationale for farmers' overuse of fertiliser (as discussed in Section 2.4), but solid evidence for this is not available. The literature suggests that Thai farmers overuse chemical fertiliser and manure due to uncertainty about soil quality, uncertain weather, and their belief in the agronomic advice given by government extension officers.

Farmers lack information on the soil quality of their fields. They learn how to identify soil quality and health, and what nutrients are lacking, from their experience. This includes examining the appearance of the soil and plants, the health of the animals, and the quality of the water. However, they do not know exactly how much nutrients need to be applied. Thus, farmers reduce their risk of low productivity and low profit by applying an equal or greater amount of fertiliser, in relation to previous practice, or applying the same amount as neighbouring farmers. This finding from the literature supports the need for a site-specific soil nutrient testing policy to help farmers apply nutrients containing nitrogen and phosphorus efficiently. Furthermore, farmers face uncertain weather, which affects a crop's capacity to absorb nutrients during the rice cultivation period. A risk-averse farmer may apply more fertiliser than necessary for normal growing conditions in order to reduce risk caused by uncertain weather if he considers fertiliser as a risk-reducing input. However, if a risk-averse farmer considers fertiliser as a risk-enhancing input, his fertiliser application rate will lower than that of risk-neutral farmers.

Thus, this research provides a further step towards the design of an effective sustainable development policy for Thai rice farming systems. If the reasons behind the behaviour of farmers can be identified, an effective policy to reduce the negative effect of the overuse of inorganic fertiliser on the environment can be designed.

7.3 Summary of the objectives of this study

The overall objective of this research was to provide insight into the extent to which agricultural inputs are over-applied, to the detriment of health, the environment, and the economy. The objective was achieved through the implementation of novel approaches to measuring the technical and environmental efficiencies of rice farming systems at farm level in Thailand. Technical efficiency is estimated using DEA and DDF models. Environmental efficiency, which focuses on minimising nitrogen and phosphorus surpluses in rice farming systems by improving efficiency in the use of nutrients containing nitrogen and phosphorus, is estimated using the directional nutrient surplus efficiency measure. Data for this study come from the national Thai input survey of rice farming systems cultivated during the wet season crop for the crop year 2008/09. The input data of the observed Thai rice farmers was adjusted by the relative index number of the provincial average calculated yield of rice in the wet season for the crop year 2007/08 and the yield of the sample farms, in order to capture the differences in soil fertility across the sample: that would help to remove some of the expected input heterogeneity and the subsequent bias in the efficiency measurement. Then the observed Thai rice farmers were put into 4 categories, according to their regions (North, Northeast, Central, and South) in order to capture the differences in climate and soil across the sample, and then split by rice type (jasmine rice, non-jasmine rice, and glutinous rice): that would help to remove some of the expected input and output heterogeneity and the subsequent bias in the efficiency measurement. Consequently, 9 groups of Thai rice farmers are observed in this research: jasmine rice North, jasmine rice Northeast, jasmine rice Central, non-jasmine rice North, non-jasmine rice Northeast, non-jasmine rice Central, non-jasmine rice South, glutinous rice North, and glutinous rice Northeast. The total number of observations for the technical and environmental efficiency analysis of each group is presented in Table 5.7. The total number of observations for TE analysis is 1,112 farms, the total number of observations for NS efficiency analysis is 646 farms, and the total number of observations for PS efficiency analysis is 649 farms. All details regarding the sources of data, the methods of building the data analysed in this analysis, data cleaning, and the descriptive statistics used for this research were presented in Chapter 5.

This study provides answers to three main questions (as outlined in Section 1.4) which correspond to the objectives of this study.

7.4 Technical efficiency of Thai rice production

Research question 1: To what extent do Thai rice farmers use an efficient combination of inputs for producing rice? Sub-question: What are the existing technical efficiency levels of rice production in Thailand?

This research question is assessed through a comparison of the technical efficiency of Thai rice farmers using the input-oriented DEA, output-oriented DEA, and DDF approaches. The main objectives associated with this research question are to minimise all inputs to produce the same level of rice output, to maximise rice output by using the same level of inputs, and to reduce all inputs and increase rice output simultaneously. The estimation of efficiency scores reveals the number of farms in the sample that produce on the PPF and the distance of the inefficient farms' production from this frontier.

In Chapter 6 Section 6.2, three DDF models (DDF1 – DDF3) were used to estimate the TE level of the 9 observed groups of Thai rice farmers, and one DDF model (DDF4) was used to estimate the profit efficiency level of these 9 groups of observations. The results of the technical efficiency analysis suggest that 70%, 26%, 55%, 55%, 64%, 40%, 46%, 78%, and 34% of the total observations of jasmine rice North, jasmine rice Northeast, jasmine rice

Central, non-jasmine rice North, non-jasmine rice Northeast, non-jasmine rice Central, non-jasmine rice South, glutinous rice North, and glutinous rice Northeast, respectively, produce on the PPF. However, only one farm in each observed group produces on the profit maximising frontier.

The average TIE scores obtained from the DDF1 measurement (or input-oriented DEA) of 9 groups of Thai rice farmers range from 1.7% to 12.5%. This indicates that rice farmers would be able to reduce their current amount of inputs on average from 1.7% to 12.5% to obtain their current levels of rice output if they were to operate efficiently. The average TIE scores obtained from the DDF2 measurement (or output-oriented DEA range from 2.1% to 15.9%. This indicates that rice farmers could expand rice output on average from 2.1% to 15.9% by using the same level of inputs if they were to operate efficiently. The average TIE scores obtained from the DDF3 range from 1% to 7%. This indicates that rice farmers could expand rice output on average from 1% to 7%, while they could contract their current amount of inputs on average from 1% to 7% if they were to operate efficiently. Moreover, the average SEs of these 9 groups are greater than 0.95. This indicates that the average scale inefficiencies are less than 5%, which is quite small. The majority of Thai rice farmers across all types of rice and regions operated close to the optimal scale size (CRS), except the majority of jasmine rice and glutinous rice farmers in the North-eastern region, who operated above the optimal scale (DRS).

The average level of profit inefficiency obtained from the DDF4 measurement of 9 groups of Thai rice farmers ranges from 19,854 to 309,428. This indicates that the average farms in these 9 groups could increase their profit by 19,854 to 309,428 Baht/farm if they were to operate profit efficiently. These average levels of profit inefficiency also indicate that Thai rice farmers earned profits averaging from 681.63 to 13,779.97 Baht/ha, except glutinous rice farmers in the North-eastern region, who suffered an average loss of 6,930.35 Baht/ha.

The results from the DDF1 – DDF3 measurements of each group indicate that the technically efficient farms in each observed group remain the same, implying that different TE measurements (i.e. different directional vectors) do not change the status of the technically efficient farms in the observation. However, the technical inefficiency scores of technically inefficient farms vary depending on which directional vector is chosen. Thus, the rank of technically inefficient farms varies when changing the direction of improvement towards the production possibility frontier. Moreover, the results of the DDF4 measures indicate that the majority of Thai rice farmers in these 9 observed groups operated far from the efficiency benchmarks constructed by their profit efficiency best practice farms.

Research question 2: How can an efficiency analysis of rice farming systems in Thailand be developed to accommodate and explore the problem of excess nutrient application on rice fields? Sub-question: How can the environmental impact of rice cultivation be assessed?

The main objective is to develop an approach to measuring agricultural environmental efficiency by adjusting traditional methods of technical efficiency analysis through the incorporation of environmental concerns (nutrient surplus) into the model. The nutrient surpluses from rice cultivation that cause environmental problems are nitrogen and phosphorus surplus. Hence, this study focused on the evaluation of nitrogen and phosphorus surplus efficiency of Thai rice farmers for the environmental efficiency analysis.

7.5 The directional nutrient surplus efficiency measure

This study proposes the directional nutrient surplus efficiency measure within the theoretical context of the DDF to evaluate the environmental performance of Thai rice farming systems (as discussed in Chapter 4 Section 4.9). This measure is applied to evaluate the nitrogen and phosphorus surplus efficiency in this study in order to investigate the environmental performance of Thai rice farming systems in Chapter 6. The directional nutrient surplus efficiency measure provides more choice of directional vector, and assumes a nutrient surplus minimising behaviour in order to determine the difference between observed and minimal nutrient surplus along an optimal direction that projects any farm towards the nutrient surplus minimising benchmark. Hence, the nutrient surplus inefficiency level of a farm represents the minimal distance from its observed data point to the minimum nutrient surplus frontier by given output and input nutrient contents. Moreover, the directional nutrient surplus efficiency measure is able to classify the nutrient surplus inefficiency of a farm as either technical (if the farm is located below the technical efficiency frontier, i.e. a technically inefficient farm) or allocative (if the farm is located on the technical efficiency frontier, i.e. a technically efficient farm).

Research question 3: What scope is there for Thai farmers to produce the same or higher rice output using fewer inputs, particularly environmentally damaging inputs? Sub-question: What is the current nitrogen and phosphorus use efficiency of Thai rice farmers?

The main purposes of this research question are to evaluate the environmental efficiency of rice farming practice in Thailand using the directional nutrient surplus efficiency measure, and to compare the technical and environmental inefficiencies of Thai rice farming. A nitrogen surplus minimising frontier and a phosphorus surplus minimising frontier are constructed to estimate and compare the effects of Thai farmers' use of nitrogen and phosphorus across the country. This measure enables the current level of nitrogen and phosphorus surpluses, which cause the Thai rice farming system's negative impacts on the environment, to be ascertained.

7.6 Environmental efficiency of Thai rice farming

The nutrient surpluses from rice cultivation that cause environmental problems are nitrogen and phosphorus. Two models, namely the nitrogen surplus minimisation model (NSMM) with the directional vector towards the nitrogen surplus minimum point, and the phosphorus surplus minimisation model (PSMM) with the directional vector towards the phosphorus surplus minimum point, are applied to measure the environmental efficiencies of 9 groups of Thai rice farmers using the directional nutrient surplus efficiency measure. The results, showing the environmental efficiencies of these 9 groups, are presented in Chapter 6 Section 6.3.

The average level of NS inefficiency obtained from the NSMM measures of 9 groups of Thai rice farmers range from 20.2 to 193.8. This indicates that the average farms in these groups could reduce the amount of NS discharged into the environment by 20.2 to 193.8 kg/farm if the farmers were to operate NS efficiently. These average levels of NS inefficiency also indicate that the amount of NS discharged into the environment by Thai rice farmers averaged from 20.1 to 50.7 kg/ha. The average level of PS inefficiency obtained from the PSMM measures of these 9 groups ranged from 11.2 to 108.7. This indicates that the average farms of these 9 groups of Thai rice farmers could reduce the amount of PS discharged into the environment by 11.2 to 108.7 kg/farm if the farmers were to operate PS efficiently. These average level of PS inefficiency also indicate that the amount of PS discharged into the environment by Thai rice farmers averaged from 11.0 to 28.7 kg/ha.

7.7 The improvement of output produced and inputs used by different efficiency measures

The comparisons of the improvement of rice output and the combination of inputs used per hectare required to enable the average farms to produce on the frontiers constructed by the

BPFs according to the NSMM, the PSMM, and the DDF1 – DDF4 measures are provided in Chapter 6 Section 6.4. The improvements in the TE of the 9 groups of Thai rice farmers according to DDF1 – DDF3 results in this study would result in both higher profits (as farmers either pay lower production costs or earn more income) and lower amounts of NS and PS discharged into the environment: these measures could be used for sustainable intensification strategies.

The improvements in the profit efficiency of the 9 groups of Thai rice farmers, according to DDF4 measurements in this study, would result in higher profit. However, improvements in the profit efficiency of non-jasmine rice farmers in the Northern region would also result in lower amounts of both NS and PS being discharged into the environment: this could be used for sustainable intensification strategies. On the other hand, improvements in the profit efficiency of jasmine rice farmers in the Northern region and non-jasmine rice farmers in the Central region would result in greater amounts of NS and PS being discharged into the environment. Furthermore, improvements of the profit efficiency of the other 6 groups of Thai rice farmers would result in either lower or higher amounts of NS and PS being discharged into the environment.

Improvements in the NS efficiency of the 9 observed groups of Thai rice farmers, according to NSMM results in this study, would result in both higher profits (as farmers applied less chemical fertiliser to their crop, thus reducing production costs) and lower amounts of NS and PS discharged into the environment, apart from the jasmine rice Central, non-jasmine rice Central, non-jasmine rice South, and glutinous rice Northeast farms, whose discharges of PS into the environment are higher than the average farms in their groups. However, the improvement of NS efficiency is all that the jasmine rice Northeast and glutinous rice North groups need to produce higher rice output per hectare and reduce the amounts of NS and PS discharged into the environment: these examples could be used for sustainable intensification strategies.

The improvements in the PS efficiency of the 9 observed groups of Thai rice farming systems, according to PSMM figures in this study, would result in both higher profits (as farmers applied less chemical fertiliser to their crop, thus reducing production costs) and lower amounts of NS and PS discharged into the environment, apart from non-jasmine rice and glutinous rice farms in the Northeast region, whose discharges of NS into the environment are higher than the average farms in their groups.

7.8 Technical, profit, nitrogen surplus, and phosphorus surplus best practice farms

The average inputs used to produce a tonne of paddy rice on the average farm, the TBPFs, the profit efficiency BPF, the NS efficiency BPF, and the PS efficiency BPF of each group of observations have been compared in Chapter 6 Section 6.5. The results indicate that the TBPFs of the 9 observed groups; the profit efficiency BPFs of the non-jasmine North and non-jasmine Northeast regions; the NS efficiency BPFs of the jasmine rice North, jasmine rice Northeast, non-jasmine rice North, non-jasmine rice Northeast, and glutinous rice North regions; and the PS efficiency BPFs of the jasmine rice North, jasmine rice Northeast, jasmine rice Central, non-jasmine rice North, non-jasmine rice Central, non-jasmine rice South, and glutinous rice North regions can earn higher profits by using fewer inputs, especially inputs detrimental to the environment like nitrogen and phosphorus fertilisers, than the average farms in their respective groups, which also results in lower amounts of NS and PS being discharged into the environment, compared to the average farms in their respective groups. Thus, these BPFs can be used as benchmarks for the reduction of environmental problems caused by the overuse of fertiliser when planning sustainable agricultural intensification development policy.

7.9 Discussion and conclusions

The technical efficiency of the 9 observed groups of Thai rice farmers was investigated using the DDF1-DDF3 measures. The average TE scores obtained from the DDF1 measurement (or input-oriented DEA) of the 9 observed groups of Thai rice farmers range from 87.5% to 98.3%. These average TE scores, using the input-oriented DEA models in this study, give average values of TE scores, based on Thai rice production analysis, which are similar to those in some previous studies (e.g. Kiatpathomchai, 2008), but higher than in those of Krasachart, (2004) and Taraka et al. (2010). The average TE scores obtained from the DDF2 measurement (or output-oriented DEA) of the 9 observed groups of Thai rice farmers range from 84.1% to 97.9%. The average TE scores obtained from the DDF3 measurement of the 9 observed groups of Thai rice farmers range from 93% to 99%. The Thai rice farms' TE scores, when adjusted according to input data based on the provincial average calculated yield of rice in the wet season for the crop year 2007/08 and categorised into their regions (North, Northeast, Central, and South) and rice type (jasmine rice, non-jasmine rice, and glutinous rice), are higher than the TE scores obtained from the evaluation of TE scores of the sample for the whole country (without categorising the sample into regions and rice type). This implies that some of the expected input and output heterogeneity, and the subsequent bias in efficiency measurement, have been removed. Furthermore, the profit efficiency of the 9 observed groups of Thai rice farmers was investigated using the DDF4 measure. The results indicate that the average profit of Thai rice farmers ranged from 681.63 to 13,779.97 Baht/ha, but glutinous rice farmers in the North-eastern region suffered a loss of 6,930.35 Baht/ha.

The environmental efficiency of Thai rice farming systems has been investigated using the directional nutrient surplus efficiency measure. The results of this study suggest how NS and PS discharged from the Thai rice farming system can be reduced without compromising yields or profit. The results of the NSMM and PSMM of 9 groups of Thai rice farmers indicate that the amount of NS discharged into the environment by the observed Thai rice farmers averages from 20.1 kg/ha to 50.7 kg/ha, and the PS discharged into the environment averages from 11.0 kg/ha to 28.7 kg/ha. The NS and PS from rice fields are the main sources of eutrophication of surface water (Tirado et al., 2008). Gold and Sims (2005 cited in Nguyen et al., 2012, p. 371) indicate that phosphorus has more eutrophying power in the context of fresh water than nitrogen. The previous empirical studies on environmental efficiency measurement (e.g. Coelli et al., 2007; Hoang and Coelli, 2011; Nguyen et al., 2012; Hoang and Alauddin, 2012) have calculated the eutrophying power of N and P by the summation of the amount of N and ten times the amount of P. Thus, the eutrophying power on fresh water of the average farm in this study averages from 129.78 kg/ha to 337.46 kg/ha. This high level is consistent with Tirado et al. (2008), who indicated that Thai rice cultivation caused problems arising from eutrophication in river, lake, coastal and marine ecosystems (as discussed in Section 2.3).

Although this study underestimates NS and PS because of lack of information regarding the inflows of N and P nutrients (i.e. soil, bio-fertiliser, biological fixation, atmospheric deposition, precipitation, and irrigation water) and the outflows of N and P (rice straw, and soil), the amounts of NS and PS discharged into the environment from the Thai rice farming system are comparatively high. These results suggest that Thai rice farmers applied more N and P fertiliser than the crops needed. In addition, there are unobserved residual nutrients (N and P) in the soil from earlier in the sample year (in the unsurveyed dry season), so the amount of NS and PS discharged into the environment are probably higher than the NS and PS calculated in this study. The overuse of these fertilisers not only creates severe environmental problems, but also increases production costs.

If Thai rice farmers continue to use their current level of N and P fertiliser, the environmental problems caused by NS and PS will be more severe. Simultaneously increasing production efficiency and improving the environmental performance of Thai rice farming systems are the common goals of sustainable intensification. Thus, the estimation undertaken in this thesis of specific inputs, namely nitrogen and phosphorus, which used in excess can harm the environment, can provide insights into the development of targets and strategies designed to improve sustainable agricultural intensification.

The technical and environmental efficiency levels of Thai rice farmers were examined across rice type, regions, and country. Considering the efficiency level of Thai rice farmers within each rice type, with regard to jasmine rice production, the results indicate that jasmine rice farmers in the Northern region are more technically efficient, earned higher profits, and discharged a lower amount of NS into the environment than jasmine rice farmers in the Central and North-eastern regions. However, they discharged a higher amount of PS into the environment than jasmine rice farmers in the other two regions. The results also indicate that jasmine rice farmers in the North-eastern region are less technically efficient, obtained less profit, and discharged a higher amount of NS into the environment than jasmine rice farmers in the Northern and Central regions. This is due to the fact that the average yield of jasmine rice produced in the North-eastern region is lower than that in the Northern and Central regions by 34% and 14%, but the N fertiliser application rate of jasmine rice farmers in the North-eastern region is nearly the same as that of jasmine rice farmers in the Northern region and higher than that of jasmine rice farmers in the Central region by 16% (Table 5.4 Chapter 5). Moreover, Limtong (2012) indicates that soil in the North-eastern region has low fertility compared to the Northern, Central, and Southern regions.

For non-jasmine rice production, the results indicate that non-jasmine rice farmers in the Northern region are more technically efficient and discharged lower amounts of PS into the environment than non-jasmine rice farmers in the other three regions. They also earned higher profits than non-jasmine rice farmers in the North-eastern and Southern regions, but earned lower profits than non-jasmine rice farmers in the Central region. However, they discharged the highest amount of NS into the environment compared to non-jasmine rice farmers in the other three regions; this is also the highest amount of NS discharged by any of the 9 observed groups. While non-jasmine rice farmers in the Southern region are less technically efficient than non-jasmine rice farmers in the other three regions, they obtained higher profits than non-jasmine rice farmers in the North-eastern region. Furthermore, non-jasmine rice farmers in the Central region earned the highest profit compared to non-jasmine rice farmers in the other three regions and this is also the highest profit obtained by any of the 9 observed groups. On the other hand, non-jasmine rice farmers in the North-eastern region earned lower profits than the non-jasmine rice farmers in the other three regions, even though their average TE score is high.

With regard to glutinous rice production, the TE results indicate that glutinous rice farmers in the Northern region are more technically efficient and NS efficient than glutinous rice farmers in the North-eastern region. Glutinous rice farmers in the Northern region earned an average profit of 681.63 Baht/ha, while glutinous rice farmers in the North-eastern region suffered a loss of 6,930.35 Baht/ha. Furthermore, the glutinous rice farmers in the Northern region obtained the highest average TE scores compared to the other 8 groups of Thai rice farmers. However, they earned the lowest average profit compared to jasmine rice and non-jasmine rice farmers.

Considering the efficiency level of Thai rice farmers within each region, in the Northern region, glutinous rice farmers are more technically and PS efficient than jasmine rice and non-jasmine rice farmers. However, they earned lower profits than jasmine rice and non-jasmine rice farmers. Jasmine rice farmers are more NS efficient but less PS efficient than non-jasmine rice and glutinous rice farmers. On the other hand, non-jasmine rice farmers are more profit efficient than jasmine rice and glutinous rice farmers. In the North-eastern region, non-jasmine rice farmers are more technically efficient than glutinous rice and jasmine rice farmers. However, jasmine rice farmers are more profit efficient than non-jasmine rice and glutinous rice farmers. The average amounts of NS discharged by jasmine rice, non-jasmine rice, and glutinous rice farmers are nearly the same. Glutinous rice farmers are more PS efficient than jasmine rice and non-jasmine rice farmers, but they suffered a loss of 6,930.35 Baht/ha. In addition, jasmine rice farmers in the Central region are more technically, NS, and PS efficient than non-jasmine rice farmers in Central region, but they earned lower profits than non-jasmine rice farmers.

Considering the efficiency level of Thai rice farmers for the whole country, glutinous rice farmers in the Northern region are more TE than the other groups of Thai rice farmers, but they earned a very low profit of 681.63 Baht/ha. On the other hand, jasmine rice farmers in the North-eastern region are less TE than the other groups and earned a low profit of 1,536.91 Baht/ha. Non-jasmine rice farmers in the Central and Northern regions earned the highest profit of 13,779.97 and 13,328.56 Baht/ha, respectively. However, they are the most NS inefficient as they discharged the largest amount of NS into the environment compared to the other 7 groups of Thai rice farmers. Glutinous rice farmers in the North-eastern region are the most PS efficient of the Thai rice farming system as they discharged the lowest amount of PS into the environment compared to the other 8 observed groups. However, they had the lowest profit efficiency and suffered a loss of 6,930.35 Baht/ha. The glutinous rice farmers are also less profit efficient compared with jasmine rice and non-jasmine rice farmers. Furthermore, jasmine rice farmers in the Northern region are the most NS efficient in the Thai rice farming system as they discharged the lowest amount of NS into the environment compared to the other 8 observed groups. In addition, non-jasmine rice farmers in the North-eastern, Central, and Southern regions are the most PS inefficient in the Thai rice farming system as they discharged the largest amount of PS into the environment compared to the other 6 observed groups.

7.10 Implications for Thai rice policy

7.10.1 Adopting the methods of the best practice farms

The average inputs used to produce a tonne of paddy rice on the average farm, the TBPFs, the profit efficiency BPF, the NS efficiency BPF, and the PS efficiency BPF in each observed group indicate that the TBPFs of the 9 observed groups of Thai rice farmers; the profit efficiency BPFs of the non-jasmine North and non-jasmine Northeast; the NS efficiency BPFs of the jasmine rice North, jasmine rice Northeast, non-jasmine rice North, non-jasmine rice Northeast, and glutinous rice North regions; and the PS efficiency BPFs of the jasmine rice North, jasmine rice Northeast, jasmine rice Central, non-jasmine rice North, non-jasmine rice Central, non-jasmine rice South, and glutinous rice North regions can earn higher profits by using fewer inputs, especially inputs detrimental to the environment like nitrogen and phosphorus fertilisers, than the average farms in their respective groups, which also results in lower amounts of NS and PS being discharged into the environment, compared to the average farms in their respective groups. This implies that the input used by these BPFs can lead to their use as benchmark farms to reduce environmental problems caused by the overuse of fertiliser when planning sustainable intensification agricultural development policy. An environmental efficiency development policy can use theses BPFs as model farms for Thai rice farmers to learn how to improve management practices for nitrogen and phosphorus use in order to achieve higher environmental efficiency, or even to become environmentally efficient. Thus, the environmental problems caused by Thai rice farming systems can be solved by adopting the methods of these best practice farms.

7.10.2 Environmental tax policy

The material balance condition (MBC) work offered a particularly useful dual interpretation of the results: that the zero balance condition mirrors, and is applied in the same way as, the ratio of prices in the profit maximisation case.

The profit function is defined by $\pi(p,w) = py - wx$

where p = output price, w = input price, y = output quantity, and x = input quantity.

When we set zero profit $0 = py - wx$, we will get $y = (w/p)x$

Thus, the slope of profit maximisation is the ratio of input and output prices.

The nutrient surplus is defined by $N(a_N, b_N) = a_N x - b_N y$

where b_N = output nutrients, a_N = input nutrients, y = output quantity, and x = input quantity.

When we set zero balance condition $0 = a_N x - b_N y$, we will get $y = (a_N/b_N)x$

Thus, the slope of the MBC minimisation case is the ratio of input and output nutrients.

This means that the slope of the zero balance condition can be interpreted as the price ratio that sets the MB to zero. Thus, the Pigouvian Tax equivalent could be imposed in order to reduce the negative externalities (i.e. nitrogen and phosphorus surpluses) caused by rice cultivation. The Pigouvian tax is defined as “a tax levied on each unit of an externality-generator’s output in an amount equal to the marginal damage at the efficient level of output” (Rosench5, 2017, p. 2).

A calculation of the Pigouvian Tax equivalent on Thai rice production can be explained using Figure 7.1 in the case of NS. The figure presents the graphical representation of a NS (negative externality problem) caused by a Thai rice farmer. The horizontal axis measures the amount of rice output produced by the farmer (kg/farm) and the vertical axis measures monetary units (Baht/kg). The marginal private benefit curve, which is assumed to be equal to the marginal social benefit, represents the marginal benefit to the farmer from each level of rice produced; it declines as the amount of rice output increases. The marginal cost to the farm as rice output increases is represented by the marginal private cost curve. As more output is produced, more NS is discharged into the environment, leading to the higher negative effects which are represented by the marginal damage cost curve, i.e. the externality. Furthermore, the marginal social cost curve, which is constructed by the summation of the marginal private cost and the marginal damage cost to the environment, represents the total marginal cost for society as a whole.

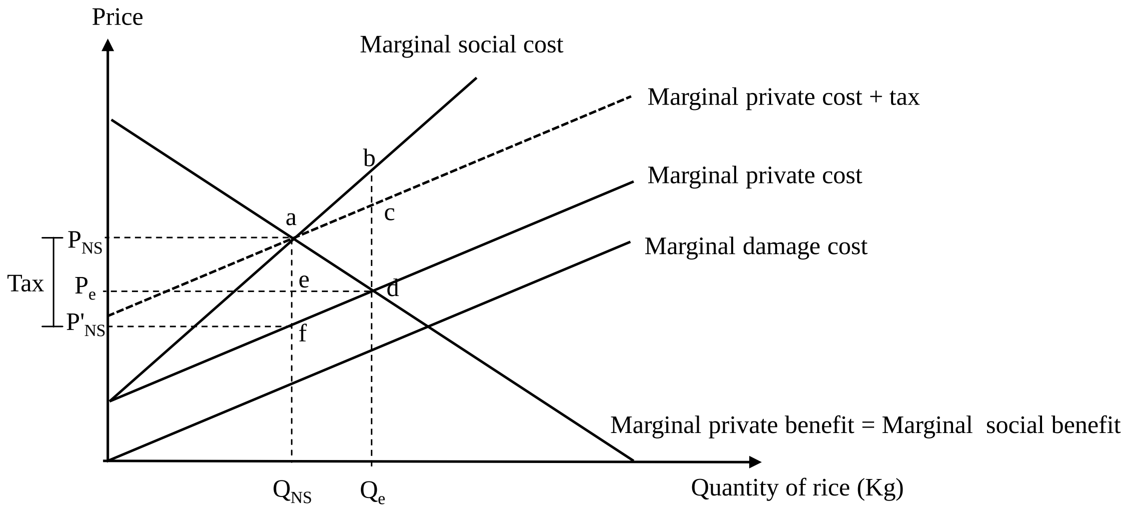

Figure 7.1 The Pigouvian Tax equivalent for Thai rice production (Adapted from Policonomics, 2017).

A farm maximises profit where private marginal cost equals marginal private benefit, i.e., the farm's rice output is Q_e kg/farm at a price P_e. At Q_e the marginal social cost is greater than the marginal social benefit, i.e., this is inefficient. Thus, the social welfare loss is equal to the area *abd*. In order to reduce the NS discharged into the environment, the Pigouvian tax could be imposed. This tax would decrease the rice output to Q_{NS} kg/farm (the rice output produced by the NS efficient farm for each group of observations), where the marginal social cost equals the marginal social benefit, and increase the price to P_{NS}, thus achieving a socially efficient equilibrium. The tax would be $P_{NS} - P'_{NS}$ per unit, with total tax revenues of $(P_{NS} - P'_{NS}) \times Q_{NS}$ or the area $afP_{NS}\,P'_{NS}$. This increases the farmer's cost to the marginal social cost at Q_{NS}. The farmer pays a tax equal to $(P_e - P'_{NS}) \times Q_{NS}$ or the area $efP_e\,P'_{NS}$, while the consumers pay a tax equal to $(P_{NS} - P_e) \times Q_{NS}$ or the area $aeP_{NS}\,P_e$. Therefore, the negative effects of the NS (externality) are eliminated using a Pigouvian tax.

For the reduction of the negative effects of the NS from rice cultivation, the Pigouvian tax needed to produce a zero balance of NS for the 9 observed groups of Thai rice farmers is presented in Table 7.1. Q_e represents the rice output per hectare of the average farm (kg/ha) for each group, Q_{NS} represents the rice output per hectare of the NS efficient farm (kg/ha) for each group, P_e is the production cost of the average farm (Baht/kg) for each group, P_{NS} is the production cost of the average farm for each group if it were to operate NS efficiently (Baht/kg), and P'_{NS} is the production cost of the average farm for each group when producing a rice output of Q_{NS} kg/ha. The average farmer of each group pays a tax equal to $P_e - P'_{NS}$ Baht/kg or $(P_e - P'_{NS}) \times Q_{NS}$ Baht/ha, while the consumers pay a tax equal to $P_{NS} - P_e$ Baht/kg or $(P_{NS} - P_e) \times Q_{NS}$ Baht/ha. The Pigouvian tax that the average farmers and consumers for each group have to pay is presented in the last two columns of Table 7.1. The positive values of the Pigouvian tax imply that farmers and consumers have to pay this tax to the government in order to incentivise farmers to become NS efficient farmers (get lower production with lower NS discharged into the environment). On the other hand, the negative values of the Pigouvian tax imply that the government has to subsidise production costs in order to incentivise farmers to become NS efficient farmers (get higher production with lower NS discharged into the environment).

Table 7.1 The Pigouvian tax needed to produce a zero balance of NS in Thai rice production

Rice type	Region	Q_e	Q_{NS}	P_e	P'_{NS}	P_{NS}	Tax	
							Farmer	Consumer
		kg/ha	kg/ha	Baht/kg	Baht/kg	Baht/kg	Baht/ha	Baht/ha
Jasmine rice	North	3,107	2,907	12.88	12.05	13.44	2,414	1,610
	Northeast	2,062	2,400	14.87	17.30	12.52	-5,839	-5,630
	Central	2,389	2,096	9.09	7.97	10.01	2,337	1,931
Non-jasmine rice	North	3,644	3,356	10.40	9.58	10.74	2,758	1,151
	Northeast	2,230	2,047	16.67	15.30	17.26	2,809	1,221
	Central	3,863	3,763	15.75	15.34	15.70	1,531	-155
	South	2,787	3,043	8.71	9.51	8.09	-2,435	-1,878
Glutinous rice	North	3,355	3,750	9.90	11.07	8.68	-4,374	-4,583
	Northeast	2,109	2,382	12.16	13.74	10.45	-3,750	-4,073

For the reduction of the negative effects of the PS from rice cultivation, the Pigouvian tax needed to produce a zero balance of PS for the 9 observed groups of Thai rice farmers are presented in Table 7.2. Q_e represents the rice output per hectare of the average farm (kg/ha) for each group, Q_{PS} represents the rice output per hectare of the PS efficient farm (kg/ha) for each group, P_e is the production cost of the average farm (Baht/kg) for each group, P_{PS} is the production cost of the average farm for each group if it were to operate PS efficiently (Baht/kg), and P'_{PS} is production cost of the average farm for each group when producing a rice output of Q_{PS} kg/ha. The average farmer of each group pays a tax equal to $P_e - P'_{PS}$ Baht/kg or $(P_e - P'_{PS}) \times Q_{PS}$ Baht/ha, while the consumers pay a tax equal to $P_{PS} - P_e$ Baht/kg or $(P_{PS} - P_e) \times Q_{PS}$ Baht/ha. The Pigouvian tax that the average farmers and consumers for each group have to pay is presented in the last two columns of Table 7.2. The positive values of the Pigouvian tax imply that farmers and consumers have to pay this tax to the government (get lower production with lower PS discharged into the environment). On the other hand, the negative values of the Pigouvian tax imply that the government has to subsidise production costs in order to incentivise farmers to become PS efficient farmers (get higher production with lower PS discharged into the environment).

Table 7.2 The Pigouvian tax needed to produce a zero balance of PS in Thai rice production

Rice type	Region	Q_e	Q_{PS}	P_e	P'_{PS}	P_{PS}	Tax	
							Farmer	Consumer
		kg/ha	kg/ha	Baht/kg	Baht/kg	Baht/kg	Baht/ha	Baht/ha
Jasmine rice	North	3,107	3,640	12.88	15.09	10.76	-8,040	-7,717
	Northeast	2,062	2,019	14.87	14.56	14.23	630	-1,292
	Central	2,389	2,586	9.09	9.84	7.98	-1,942	-2,855
Non-jasmine rice	North	3,644	3,947	10.40	11.26	9.22	-3,420	-4,665
	Northeast	2,230	2,222	16.67	16.61	16.24	132	-950
	Central	3,863	4,789	15.75	19.52	12.80	-18,062	-14,087
	South	2,787	3,481	8.71	10.88	6.79	-7,550	-6,693
Glutinous rice	North	3,355	2,791	9.90	8.24	11.60	4,645	4,749
	Northeast	2,109	2,188	12.16	12.62	11.54	-994	-1,354

7.10.3 Soil fertility improvement

The results of the efficiency analysis in this study show that the average TE scores of the 9 observed groups of Thai rice farmers are high compared to those in the previous studies. However, rice farmers in the North-eastern region obtained the lowest profit compared to rice farmers in the other three regions. This is due to the fact that the soil in the North-eastern region is low in fertility compared to the other three regions, while the soil in the Northern and Central regions is more fertile than in the Southern and North-eastern regions (Limtong, 2012). Thus, soil fertility measuring and improvement form the most important strategy for achieving sustainable intensification, especially in the North-eastern region of Thailand. If the land has good soil fertility and good ecosystem services, less inorganic fertiliser is required when cultivating rice. Rice plants can use inflows of N and P nutrients from natural processes for their growth. Therefore, high soil fertility is crucial for sustainable intensification development. It is the most important element for the cultivation of rice, as well as other agricultural crops.

A site-specific soil nutrients testing policy is necessary for efficient use of nitrogen and phosphorus nutrients (i.e. nutrient management). This is because the general fertiliser application rate recommended by the government is not suitable for the whole country. Some areas need less N and P nutrients than the recommended rate, which leads to the problem of NS and PS being discharged into the environment and unnecessarily high production costs on some farms. On the other hand, some areas need more N and P nutrients than the current recommended application rate, which leads to the problem of low productivity. Note that the recommended rates of N, P and K fertiliser for Thai rice farmers are 75, 18.75, 0 kg/ha, respectively (this application rate is recommend by the site- specific nutrient management of the Rice Department, Ministry of Agriculture and Cooperative, Thailand, cited in Cheun-im et al., 2010, p. 1).

Furthermore, farmers could improve soil fertility without using inorganic fertilisers by using organic fertiliser, and introducing legume-based crop rotation or mixed crops. Farmers should not burn rice straw in their fields after harvesting because rice straw burning results in the loss of plant nutrients (such as N, K, and sulphur) and negatively affects the organic carbon and microbial population in the soil, as well as creating air pollution (Tipayarom and Oanh, 2007; Ahmed et al., 2015). Tipayarom and Oanh (2007) state that open rice straw burning after harvesting is a common practice for Thai rice farmers and other Asian countries. More importantly, the government could train farmers to produce organic fertiliser themselves, to introduce legume-based crop rotation and mixed crops into their farm management, and to understand the negative effect of rice straw burning and the positive effect of abandoning their custom of burning rice straw in favour of incorporating it into the soil to improve its fertility.

7.11 Implication for future research

As discussed in Chapter 3, the evaluation of the environmental performance of the production processes has been investigated by incorporating the negative impact of production processes on the environment both in terms of detrimental inputs (e.g. Chung et al., 1997; Reinhard et al., 2000; Shaik et al., 2002; De Koeijer et al, 2002; Areal et al, 2012) and undesirable outputs (e.g. Färe et al., 1989; Shaik et al., 2002; Färe et al., 2005, Picazo-Tadeo et al., 2005; Macpherson et al., 2010; Färe et al., 2012; Toma et al., 2013) into traditional methods of productivity and efficiency analysis (i.e. Stochastic Production Frontier, DEA, and DDF approaches). Coelli et al. (2007) proposed a new environmental efficiency measure that incorporates the MBC into the input-oriented DEA model in a similar manner to that by which price data is normally incorporated (i.e. the cost-minimising DEA approach). The environmental efficiency score of each farm is calculated by "the ratio of minimum nutrients over observed nutrients". Thus, the environmental efficiency measurement proposed by Coelli et al. (2007) can be used to minimise the total amount of nutrients in inputs while fixing the same level of outputs. Unlike the environmental measurement proposed by Coelli et al. (2007), this study attempts to minimise the surplus of nitrogen and phosphorus nutrients within the theoretical context of the DDF, in which nitrogen and phosphorus surpluses can be minimised by simultaneously reducing nitrogen and phosphorus inputs and expanding rice output (as discussed in Chapter 4 Section 4.9). This measure is named “the directional nutrient surplus efficiency measure”. Thus, the new approach for nutrient surplus efficiency measures proposed in this study can be applied to the evaluation of the environmental performance of the production processes.

7.12 Limitations of the study

The limitations of this study are as follows:

1) This study used secondary data, resulting in a lack of important information related to farm size, farmers’ age, farmers’ experience, and the educational level of farmers, all of which are useful to determine factors affecting the efficiency of Thai rice farming systems. This is because this information was not included in the national Thai input survey for the crop year 2008/09. Therefore, this research was unable to investigate factors affecting the technical and environmental inefficiencies of Thai rice farmers.

2) None of the proxies from statistical reports and previous research could be used as the representative for all N and P inflows from natural processes (i.e. N and P contents in soil, biological fixation, atmospheric deposition, precipitation, and irrigation water) and outflows (quantity of rice straw produced by each farm, and soil) in Thailand for each farm in the sample. Consequently, nitrogen and phosphorus surpluses in this study were calculated from nitrogen and phosphorus contents in manure, chemical fertilisers, and paddy rice. The omission of nitrogen and phosphorus inflow variables (soil, bio-fertiliser, biological fixation, atmospheric deposition, precipitation, in irrigation water) and outflow variables (rice straw, and soil) leads to the underestimation of nitrogen and phosphorus surpluses on each farm. However, the rank of NS and PS efficiency in the sample does not change if a proxy of inflow variables and a proxy of outflow variables are the same across all farms in the sample. If information on all N and P inflows from natural processes and outflows for each farm were available, the estimation of nitrogen and phosphorus surpluses from the Thai rice farming system would be more precise.

3) The efficiency analysis in this study was based on cross-sectional data. If the panel data of Thai rice farmers were available, the analysis of the improvement of Thai rice farmers’ efficiency would be more precise.

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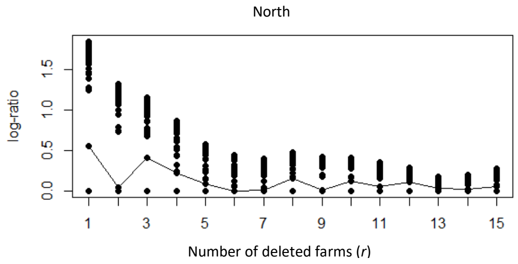
Appendices

Appendix A Identifying outliers using the data cloud method for technical efficiency analysis

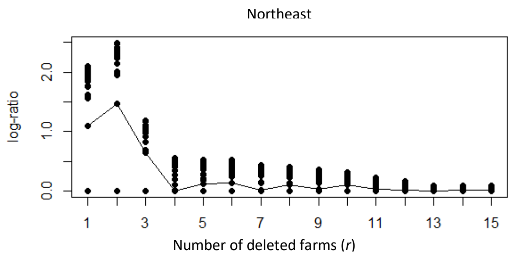
Jasmine rice farms

Log-ratio plot for outlier identification for each group of observations

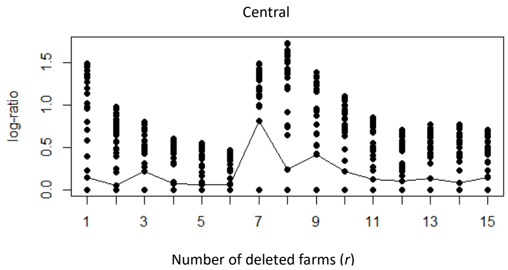
The values of $R^{(r)}_{min}$ and the farm number to be deleted in each group of observations



r	Deleted observations (North)														$R^{(r)}_{min}$
1	34														0.1304
2	35	34													0.0283
3	**35**	**70**	**34**												**0.0063**
4	16	35	70	34											0.0021
5	16	69	35	70	34										0.0008
6	16	75	60	35	70	34									0.0003
7	16	75	60	69	35	70	34								0.0001
8	**33**	**16**	**75**	**60**	**69**	**35**	**70**	**34**							**0.0001**
9	33	7	16	75	60	69	35	70	34						0.0000
10	**33**	**15**	**7**	**16**	**75**	**60**	**69**	**35**	**70**	**34**					**0.0000**
11	55	33	15	7	16	75	60	69	35	70	34				0.0000
12	**55**	**33**	**15**	**12**	**7**	**16**	**75**	**60**	**69**	**35**	**70**	**34**			**0.0000**
13	55	33	53	15	12	7	16	75	60	69	35	70	34		0.0000
14	38	57	33	15	41	12	7	16	75	60	69	35	70	34	0.0000
15	46	38	57	33	15	41	12	7	16	75	60	69	35	70	34	0.0000



r	Deleted observations (Northeast)															$R^{(r)}_{min}$
1	173															0.1081
2	**169**	**173**														**0.0079**
3	169	94	173													0.0021
4	169	167	94	173												0.0011
5	169	189	167	94	173											0.0004
6	**169**	**93**	**189**	**167**	**94**	**173**										**0.0002**
7	169	93	189	167	166	94	173									0.0001
8	**169**	**93**	**189**	**167**	**178**	**166**	**94**	**173**								**0.0000**
9	169	119	93	189	167	178	166	94	173							0.0000
10	**169**	**68**	**119**	**93**	**189**	**167**	**178**	**166**	**94**	**173**						**0.0000**
11	169	68	125	119	93	189	167	178	166	94	173					0.0000
12	169	68	125	43	119	93	189	167	178	166	94	173				0.0000
13	169	68	135	125	43	119	93	189	167	178	166	94	173			0.0000
14	169	68	91	135	125	43	119	93	189	167	178	166	94	173		0.0000
15	169	68	131	91	135	125	43	119	93	189	167	178	166	94	173	0.0000

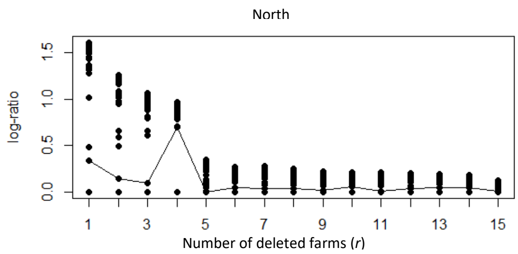


r	Deleted observations (Central)															$R^{(r)}_{min}$
1	6															0.1872
2	32	6														0.0405
3	**4**	**32**	**6**													**0.0091**
4	23	4	32	6												0.0025
5	34	3	4	32	6											0.0007
6	10	33	11	4	32	6										0.0002
7	**10**	**45**	**33**	**40**	**34**	**11**	**6**									**0.0000**
8	10	45	33	40	34	11	4	6								0.0000
9	**10**	**45**	**33**	**40**	**34**	**11**	**4**	**32**	**6**							**0.0000**
10	10	45	33	40	34	11	3	4	32	6						0.0000
11	10	45	33	40	34	11	3	23	4	32	6					0.0000
12	8	10	9	45	33	40	34	11	3	4	32	6				0.0000
13	8	10	9	45	33	40	34	11	3	23	4	32	6			0.0000
14	8	10	9	45	52	33	40	34	11	3	23	4	32	6		0.0000
15	8	10	9	45	22	52	33	40	34	11	3	23	4	32	6	0.0000

Non-jasmine rice farms

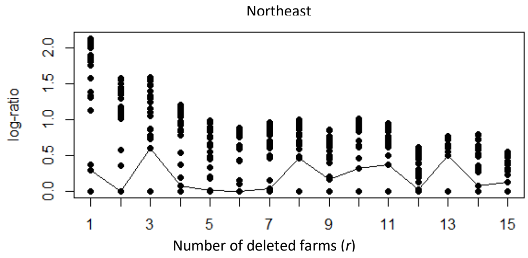
Log-ratio plot for outlier identification for each group of observations

The values of $R^{(r)}_{min}$ and the farm number to be deleted in each group of observations

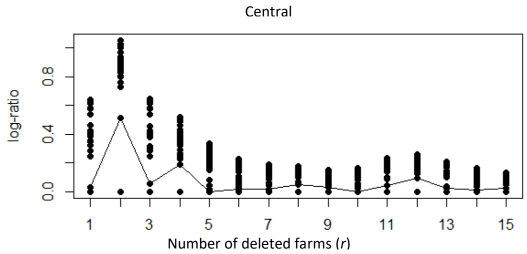


r	Deleted observations (North)															$R^{(r)}_{min}$
1	62															0.1711
2	78	62														0.0407
3	97	78	62													0.0111
4	**121**	**97**	**78**	**62**												**0.0033**
5	161	121	97	78	62											0.0020
6	161	162	121	97	78	62										0.0010
7	161	162	118	121	97	78	62									0.0006
8	151	161	162	118	121	97	78	62								0.0003
9	151	79	161	162	118	121	97	78	62							0.0002
10	**151**	**123**	**79**	**161**	**162**	**118**	**121**	**97**	**78**	**62**						**0.0001**
11	151	119	123	79	161	162	118	121	97	78	62					0.0001
12	151	119	123	75	79	161	162	118	121	97	78	62				0.0000
13	151	119	123	135	75	79	161	162	118	121	97	78	62			0.0000
14	151	119	55	123	135	75	79	161	162	118	121	97	78	62		0.0000
15	151	106	119	55	123	135	75	79	161	162	118	121	97	78	62	0.0000

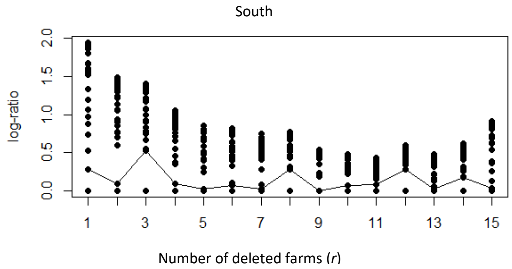
Log-ratio plot for outlier identification for each group of observations	The values of $R_{min}^{(r)}$ and the farm number to be deleted in each group of observations



r	Deleted observations (Northeast)															$R_{min}^{(r)}$
1	70															0.1003
2	62	70														0.0134
3	**62**	**16**	**70**													**0.0017**
4	17	62	16	70												0.0004
5	17	18	62	16	70											0.0001
6	32	17	18	62	16	70										0.0000
7	42	17	45	18	62	16	70									0.0000
8	**42**	**32**	**17**	**45**	**18**	**62**	**16**	**70**								**0.0000**
9	21	20	42	17	45	18	62	16	70							0.0000
10	21	20	42	32	17	45	18	62	16	70						0.0000
11	**21**	**20**	**42**	**32**	**30**	**17**	**45**	**18**	**62**	**16**	**70**					**0.0000**
12	21	50	20	42	32	30	17	45	18	62	16	70				0.0000
13	**21**	**50**	**20**	**35**	**42**	**32**	**30**	**17**	**45**	**18**	**62**	**16**	**70**			**0.0000**
14	21	50	56	20	35	42	32	30	17	45	18	62	16	70		0.0000
15	21	40	50	56	20	35	42	32	30	17	45	18	62	16	70	0.0000



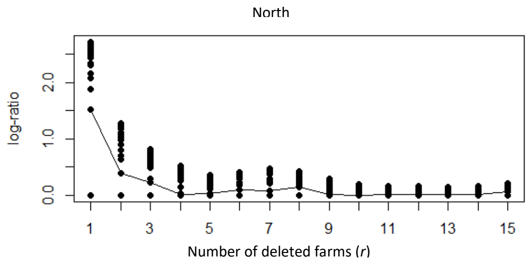
r	Deleted observations (Central)															$R_{min}^{(r)}$
1	92															0.4583
2	**209**	**208**														**0.1299**
3	209	208	92													0.0595
4	**218**	**209**	**208**	**92**												**0.0288**
5	218	209	134	208	92											0.0167
6	218	209	20	134	208	92										0.0096
7	218	34	209	20	134	208	92									0.0056
8	**218**	**34**	**209**	**20**	**133**	**134**	**208**	**92**								**0.0033**
9	218	34	209	20	190	133	134	208	92							0.0021
10	218	179	174	34	209	20	133	134	208	92						0.0013
11	218	179	174	34	209	20	190	133	134	208	92					0.0008
12	**218**	**179**	**174**	**146**	**34**	**209**	**20**	**190**	**133**	**134**	**208**	**92**				**0.0005**
13	137	218	179	174	146	34	209	20	190	133	134	208	92			0.0003
14	137	218	189	179	174	146	34	209	20	190	133	134	208	92		0.0002
15	137	218	189	201	179	174	146	34	209	20	190	133	134	208	92	0.0002



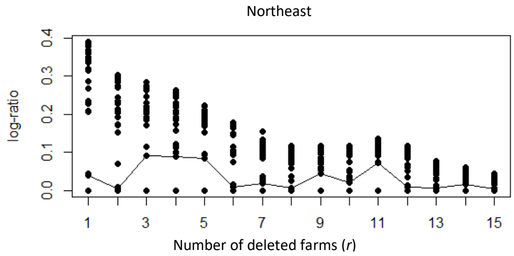
r	Deleted observations (South)															$R_{min}^{(r)}$
1	39															0.1261
2	38	39														0.0177
3	**38**	**9**	**39**													**0.0025**
4	47	38	9	39												0.0006
5	35	47	38	9	39											0.0001
6	78	35	47	38	9	39										0.0000
7	46	78	35	47	38	9	39									0.0000
8	**46**	**78**	**35**	**47**	**43**	**38**	**9**	**39**								**0.0000**
9	46	78	69	35	47	43	38	9	39							0.0000
10	34	46	78	69	35	47	43	38	9	39						0.0000
11	76	34	46	37	78	35	47	43	38	9	39					0.0000
12	**76**	**34**	**46**	**37**	**78**	**69**	**35**	**47**	**43**	**38**	**9**	**39**				**0.0000**
13	33	76	34	46	37	78	69	35	47	43	38	9	39			0.0000
14	**32**	**76**	**34**	**46**	**10**	**37**	**78**	**69**	**35**	**47**	**43**	**38**	**9**	**39**		**0.0000**
15	2	32	76	34	46	10	37	78	69	35	47	43	38	9	39	0.0000

Glutinous rice farms

Log-ratio plot for outlier identification for each group of observations	The values of $R_{min}^{(r)}$ and the farm number to be deleted in each group of observations



r	Deleted observations (North)															$R_{min}^{(r)}$
1	**46**															**0.0565**
2	6	46														0.0135
3	7	6	46													0.0048
4	76	7	6	46												0.0022
5	51	76	7	6	46											0.0010
6	**78**	**80**	**76**	**7**	**6**	**46**										**0.0004**
7	78	80	13	76	7	6	46									0.0002
8	**78**	**80**	**13**	**51**	**76**	**7**	**6**	**46**								**0.0001**
9	78	80	94	13	51	76	7	6	46							0.0000
10	1	78	80	94	13	51	76	7	6	46						0.0000
11	78	80	52	74	94	13	51	76	7	6	46					0.0000
12	35	78	80	52	74	94	13	51	76	7	6	46				0.0000
13	35	1	78	80	52	74	94	13	51	76	7	6	46			0.0000
14	35	78	98	80	99	52	74	94	13	51	76	7	6	46		0.0000
15	35	1	78	98	80	99	52	74	94	13	51	76	7	6	46	0.0000



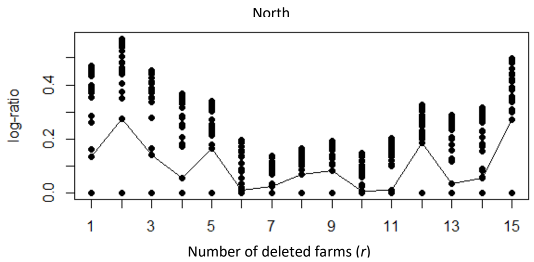
r	Deleted observations															$R_{min}^{(r)}$
1	90															0.5803
2	146	49														0.3487
3	**146**	**49**	**90**													**0.2021**
4	180	146	49	90												0.1279
5	87	180	146	49	90											0.0814
6	181	87	180	146	49	90										0.0558
7	**181**	**87**	**35**	**180**	**146**	**49**	**90**									**0.0379**
8	181	87	35	101	180	146	49	90								0.0262
9	**181**	**87**	**12**	**35**	**101**	**180**	**146**	**49**	**90**							**0.0182**
10	181	43	46	87	35	101	180	146	49	90						0.0130
11	**181**	**43**	**46**	**87**	**12**	**35**	**101**	**180**	**146**	**49**	**90**					**0.0090**
12	181	43	98	46	87	12	35	101	180	146	49	90				0.0066
13	181	43	98	46	87	118	12	35	101	180	146	49	90			0.0049
14	**181**	**43**	**98**	**46**	**87**	**71**	**118**	**12**	**35**	**101**	**180**	**146**	**49**	**90**		**0.0037**
15	181	43	98	46	74	87	71	118	12	35	101	180	146	49	90	0.0028

Appendix B Identifying outliers using the data cloud method for environmental (nitrogen surplus) efficiency analysis

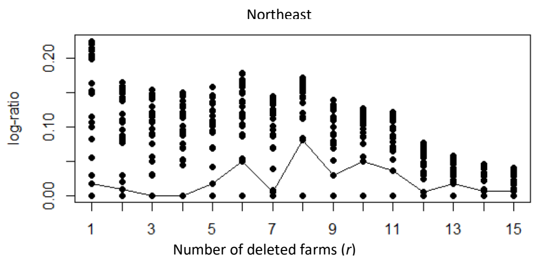
Jasmine rice farms

Log-ratio plot for outlier identification for each group of observations

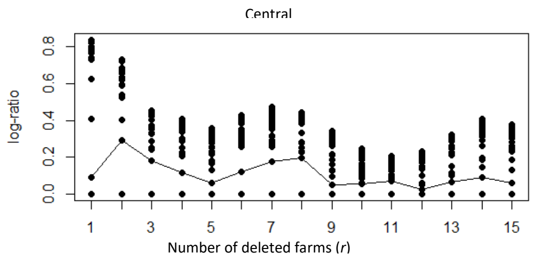
The values of $R_{min}^{(r)}$ and the farm number to be deleted in each group of observations



r	Deleted observations (North)															$R_{min}^{(r)}$
1	26															0.5848
2	**29**	**26**														**0.3050**
3	12	29	26													0.1811
4	12	13	29	26												0.1154
5	**12**	**13**	**31**	**29**	**26**											**0.0736**
6	9	12	13	31	29	26										0.0552
7	17	19	12	13	31	29	26									0.0390
8	27	9	2	12	13	31	29	26								0.0266
9	**27**	**9**	**10**	**2**	**12**	**13**	**31**	**29**	**26**							**0.0180**
10	27	9	10	2	17	12	13	31	29	26						0.0129
11	27	9	14	10	4	2	12	13	31	29	26					0.0082
12	**27**	**9**	**16**	**14**	**10**	**4**	**2**	**12**	**13**	**31**	**29**	**26**				**0.0048**
13	27	9	16	14	10	4	25	2	12	13	31	29	26			0.0031
14	27	9	16	14	10	4	6	25	2	12	13	31	29	26		0.0019
15	**27**	**9**	**16**	**14**	**10**	**4**	**11**	**6**	**25**	**2**	**12**	**13**	**31**	**29**	**26**	**0.0009**



r	Deleted observations (Northeast)															$R_{min}^{(r)}$
1	73															0.7724
2	95	66														0.5925
3	96	95	66													0.4537
4	91	95	66	73												0.3472
5	96	91	95	66	73											0.2642
6	**99**	**96**	**91**	**95**	**66**	**73**										**0.2022**
7	97	99	96	91	95	66	73									0.1623
8	**97**	**36**	**99**	**96**	**91**	**95**	**66**	**73**								**0.1245**
9	97	36	99	96	139	91	95	66	73							0.1031
10	**97**	**36**	**42**	**99**	**96**	**139**	**91**	**95**	**66**	**73**						**0.0849**
11	97	36	40	42	99	96	139	91	95	66	73					0.0713
12	27	97	36	40	42	99	96	139	91	95	66	73				0.0621
13	**85**	**27**	**97**	**36**	**40**	**42**	**99**	**96**	**139**	**91**	**95**	**66**	**73**			**0.0542**
14	109	85	27	97	36	40	42	99	96	139	91	95	66	73		0.0476
15	109	94	85	27	97	36	40	42	99	96	139	91	95	66	73	0.0419

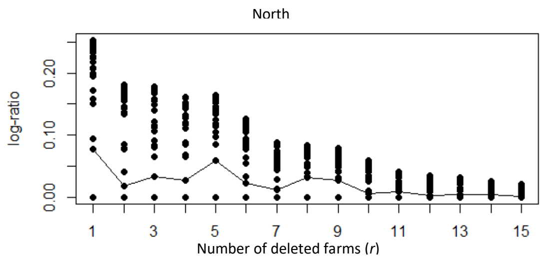


r	Deleted observations (Central)															$R_{min}^{(r)}$
1	26															0.4116
2	**27**	**26**														**0.1850**
3	33	27	26													0.1103
4	35	33	27	26												0.0680
5	34	35	33	27	26											0.0434
6	31	34	35	33	27	26										0.0250
7	31	34	17	35	33	27	26									0.0144
8	**5**	**31**	**34**	**17**	**35**	**33**	**27**	**26**								**0.0086**
9	4	5	31	34	17	35	33	27	26							0.0056
10	4	5	31	34	17	1	35	33	27	26						0.0038
11	**4**	**5**	**31**	**8**	**28**	**34**	**17**	**35**	**33**	**27**	**26**					**0.0025**
12	4	5	6	31	8	28	34	17	35	33	27	26				0.0016
13	4	5	6	31	8	28	34	17	1	35	33	27	26			0.0009
14	**4**	**5**	**30**	**6**	**31**	**8**	**28**	**34**	**17**	**1**	**35**	**33**	**27**	**26**		**0.0005**
15	4	5	30	18	6	31	8	28	34	17	1	35	33	27	26	0.0003

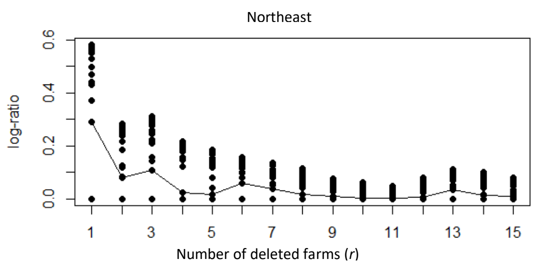
Non-jasmine rice farms

Log-ratio plot for outlier identification for each group of observations

The values of $R_{min}^{(r)}$ and the farm number to be deleted in each group of observations

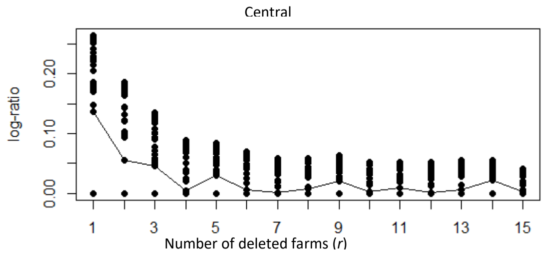


r	Deleted observations (North)															$R_{min}^{(r)}$
1	48															0.7433
2	51	48														0.5872
3	**92**	**51**	**48**													**0.4579**
4	52	92	51	48												0.3645
5	**82**	**52**	**92**	**51**	**48**											**0.2881**
6	82	19	52	92	51	48										0.2405
7	7	82	19	52	92	51	48									0.2047
8	**4**	**7**	**82**	**19**	**52**	**92**	**51**	**48**								**0.1724**
9	**107**	**4**	**7**	**82**	**19**	**52**	**92**	**51**	**48**							**0.1474**
10	107	4	23	7	82	19	52	92	51	48						0.1288
11	**107**	**2**	**4**	**23**	**7**	**82**	**19**	**52**	**92**	**51**	**48**					**0.1120**
12	85	107	2	4	23	7	82	19	52	92	51	48				0.0979
13	85	107	2	4	42	23	7	82	19	52	92	51	48			0.0855
14	85	107	44	2	4	42	23	7	82	19	52	92	51	48		0.0750
15	49	85	107	44	2	4	42	23	7	82	19	52	92	51	48	0.0658

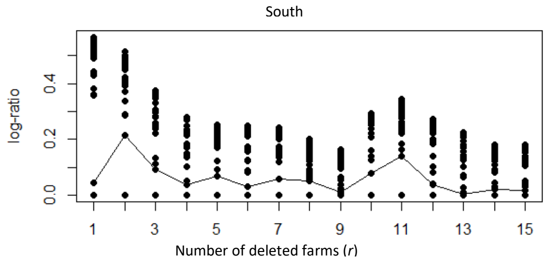


r	Deleted observations (Northeast)															$R_{min}^{(r)}$
1	28															0.5258
2	16	28														0.3691
3	**29**	**16**	**28**													**0.2477**
4	37	29	16	28												0.1830
5	37	46	29	16	28											0.1359
6	**37**	**32**	**46**	**29**	**16**	**28**										**0.1025**
7	20	37	32	46	29	16	28									0.0804
8	25	20	37	32	46	29	16	28								0.0641
9	25	47	20	37	32	46	29	16	28							0.0518
10	25	13	2	20	37	32	46	29	16	28						0.0420
11	6	25	36	47	20	37	32	46	29	16	28					0.0337
12	30	41	33	40	36	45	47	37	46	29	16	28				0.0257
13	**30**	**41**	**33**	**40**	**36**	**45**	**47**	**37**	**32**	**46**	**29**	**16**	**28**			**0.0188**
14	30	41	33	40	6	36	45	47	37	32	46	29	16	28		0.0143
15	30	41	33	40	6	36	3	45	47	37	32	46	29	16	28	0.0108

Log-ratio plot for outlier identification for each group of observations	The values of $R_{min}^{(r)}$ and the farm number to be deleted in each group of observations



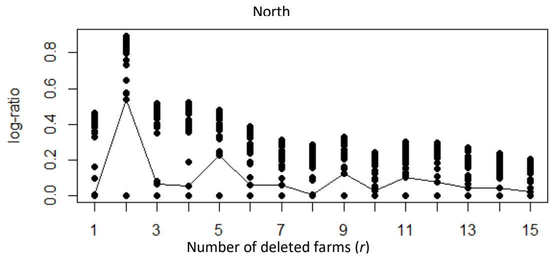
r	Deleted observations (Central)															$R_{min}^{(r)}$
1	158															0.7445
2	156	158														0.5986
3	**6**	**156**	**158**													**0.5018**
4	59	6	156	158												0.4311
5	**59**	**135**	**6**	**156**	**158**											**0.3649**
6	59	135	162	6	156	158										0.3153
7	59	135	162	102	6	156	158									0.2743
8	114	59	135	162	102	6	156	158								0.2373
9	**114**	**112**	**59**	**135**	**162**	**102**	**6**	**156**	**158**							**0.2063**
10	153	114	112	59	135	162	102	6	156	158						0.1823
11	148	153	114	112	59	135	162	102	6	156	158					0.1606
12	48	148	153	114	112	59	135	162	102	6	156	158				0.1423
13	48	80	148	153	114	112	59	135	162	102	6	156	158			0.1261
14	**48**	**80**	**110**	**148**	**153**	**114**	**112**	**59**	**135**	**162**	**102**	**6**	**156**	**158**		**0.1124**
15	138	48	80	110	148	153	114	112	59	135	162	102	6	156	158	0.1020



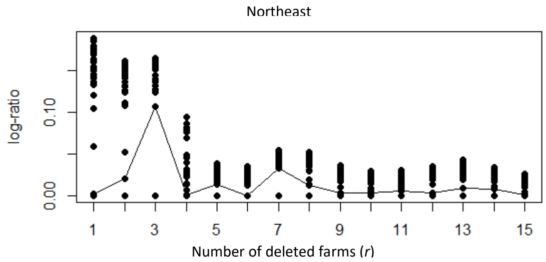
r	Deleted observations (South)															$R_{min}^{(r)}$
1	20															0.5484
2	**40**	**20**														**0.3068**
3	43	40	20													0.2030
4	47	43	40	20												0.1421
5	**47**	**4**	**43**	**40**	**20**											**0.0959**
6	38	47	4	43	40	20										0.0670
7	**38**	**47**	**34**	**4**	**43**	**40**	**20**									**0.0461**
8	23	38	47	34	4	43	40	20								0.0335
9	23	38	2	47	34	4	43	40	20							0.0240
10	48	21	23	38	2	47	4	43	40	20						0.0146
11	**48**	**21**	**23**	**38**	**2**	**47**	**34**	**4**	**43**	**40**	**20**					**0.0093**
12	48	21	23	38	2	47	42	34	4	43	40	20				0.0066
13	48	21	23	38	2	33	47	42	34	4	43	40	20			0.0047
14	**48**	**21**	**17**	**23**	**38**	**14**	**2**	**47**	**42**	**34**	**4**	**43**	**40**	**20**		**0.0033**
15	48	21	17	23	38	14	2	33	47	42	34	4	43	40	20	0.0023

Glutinous rice farms

Log-ratio plot for outlier identification for each group of observations	The values of $R_{min}^{(r)}$ and the farm number to be deleted in each group of observations



r	Deleted observations (North)															$R_{min}^{(r)}$
1	27															0.5892
2	**31**	**27**														**0.2138**
3	15	31	27													0.1191
4	32	15	31	27												0.0636
5	**32**	**28**	**15**	**31**	**27**											**0.0353**
6	26	32	28	15	31	27										0.0223
7	**26**	**32**	**23**	**28**	**15**	**31**	**27**									**0.0143**
8	30	26	32	23	28	15	31	27								0.0091
9	**30**	**26**	**25**	**32**	**23**	**28**	**15**	**31**	**27**							**0.0055**
10	24	30	26	25	32	23	28	15	31	27						0.0037
11	**30**	**26**	**2**	**25**	**32**	**1**	**23**	**28**	**15**	**31**	**27**					**0.0022**
12	30	26	2	25	3	32	1	23	28	15	31	27				0.0014
13	24	30	26	2	25	3	32	1	23	28	15	31	27			0.0009
14	**21**	**24**	**30**	**26**	**2**	**25**	**3**	**32**	**1**	**23**	**28**	**15**	**31**	**27**		**0.0006**
15	21	24	30	26	2	25	5	3	32	1	23	28	15	31	27	0.0004



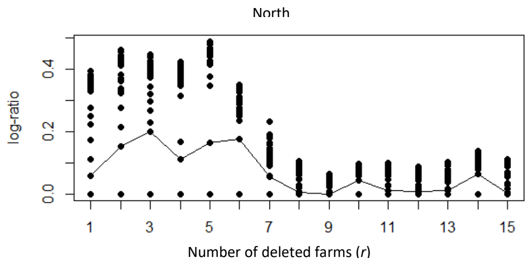
r	Deleted observations (Northeast)															$R_{min}^{(r)}$
1	16															0.7892
2	43	16														0.6187
3	**40**	**43**	**16**													**0.4847**
4	81	40	43	16												0.4222
5	41	81	40	43	16											0.3644
6	30	41	81	40	43	16										0.3152
7	**10**	**30**	**41**	**81**	**40**	**43**	**16**									**0.2664**
8	35	10	30	41	81	40	43	16								0.2299
9	35	10	30	41	74	81	40	43	16							0.2002
10	10	89	30	51	118	41	81	40	43	16						0.1735
11	35	10	89	30	51	118	41	81	40	43	16					0.1494
12	15	119	10	89	30	51	118	41	81	40	43	16				0.1281
13	**15**	**119**	**35**	**10**	**89**	**30**	**51**	**118**	**41**	**81**	**40**	**43**	**16**			**0.1095**
14	27	35	122	10	28	30	51	41	12	74	81	40	43	16		0.0943
15	27	35	122	10	28	30	51	118	41	12	74	81	40	43	16	0.0813

Appendix C Identifying outliers using the data cloud method for environmental (Phosphorus surplus) efficiency analysis

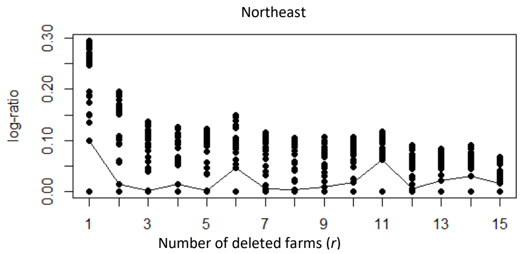
Jasmine rice farms

Log-ratio plot for outlier identification for each group of observations

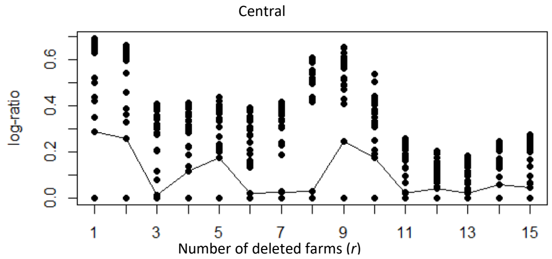
The values of $R_{min}^{(r)}$ and the farm number to be deleted in each group of observations



r	Deleted observations (North)															$R_{min}^{(r)}$
1	28															0.6357
2	32	28														0.3628
3	**21**	**32**	**28**													**0.2144**
4	20	21	32	28												0.1304
5	20	27	21	32	28											0.0740
6	**20**	**27**	**34**	**21**	**32**	**28**										**0.0489**
7	9	20	27	34	21	32	28									0.0378
8	24	9	20	27	34	21	32	28								0.0304
9	33	8	9	20	27	34	21	32	28							0.0243
10	**33**	**3**	**8**	**9**	**20**	**27**	**34**	**21**	**32**	**28**						**0.0182**
11	33	3	6	8	9	20	27	34	21	32	28					0.0141
12	10	33	3	6	8	9	20	27	34	21	32	28				0.0108
13	31	40	33	3	8	24	9	20	27	34	21	32	28			0.0079
14	**31**	**40**	**33**	**3**	**35**	**8**	**24**	**9**	**20**	**27**	**34**	**21**	**32**	**28**		**0.0056**
15	31	40	33	3	6	35	8	24	9	20	27	34	21	32	28	0.0042



r	Deleted observations (Northeast)															$R_{min}^{(r)}$
1	101															0.7203
2	74	101														0.5615
3	74	67	101													0.4440
4	**74**	**97**	**67**	**101**												**0.3460**
5	98	74	97	67	101											0.2732
6	**94**	**98**	**74**	**97**	**67**	**101**										**0.2120**
7	99	94	98	74	97	67	101									0.1714
8	35	99	94	98	74	97	67	101								0.1376
9	35	99	92	94	98	74	97	67	101							0.1106
10	35	99	92	94	98	74	41	97	67	101						0.0896
11	**35**	**99**	**92**	**94**	**98**	**140**	**74**	**41**	**97**	**67**	**101**					**0.0722**
12	116	35	99	92	94	98	140	74	41	97	67	101				0.0613
13	27	116	35	99	92	94	98	140	74	41	97	67	101			0.0510
14	**27**	**85**	**116**	**35**	**99**	**92**	**94**	**98**	**140**	**74**	**41**	**97**	**67**	**101**		**0.0427**
15	64	27	85	116	35	99	92	94	98	140	74	41	97	67	101	0.0368

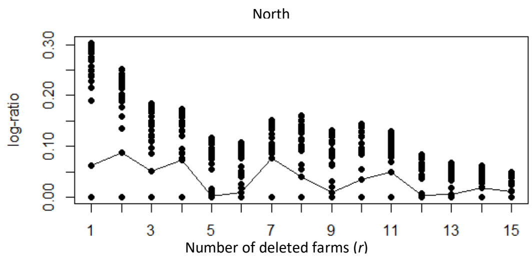


r	Deleted observations (Central)															$R_{min}^{(r)}$
1	3															0.4764
2	27	3														0.2327
3	27	28	3													0.1457
4	32	27	28	3												0.0826
5	**32**	**22**	**27**	**28**	**3**											**0.0470**
6	35	32	22	27	28	3										0.0288
7	35	32	36	22	38	27	3									0.0159
8	14	35	32	36	22	38	27	3								0.0074
9	**14**	**35**	**32**	**36**	**22**	**38**	**27**	**28**	**3**							**0.0035**
10	14	35	20	32	36	22	38	27	28	3						0.0021
11	14	26	35	20	32	36	22	38	27	28	3					0.0015
12	14	26	35	20	29	32	36	22	38	27	28	3				0.0010
13	14	26	5	35	20	29	32	36	22	38	27	28	3			0.0007
14	**14**	**7**	**26**	**5**	**35**	**20**	**29**	**32**	**36**	**22**	**38**	**27**	**28**	**3**		**0.0004**
15	14	7	26	5	35	1	20	29	32	36	22	38	27	28	3	0.0003

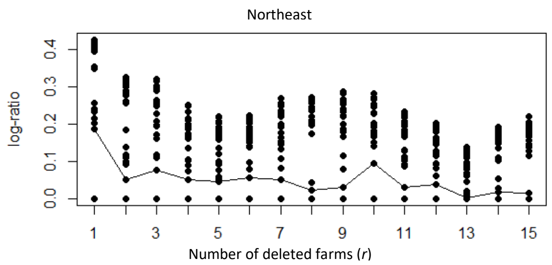
Non-jasmine rice farms

Log-ratio plot for outlier identification for each group of observations

The values of $R_{min}^{(r)}$ and the farm number to be deleted in each group of observations

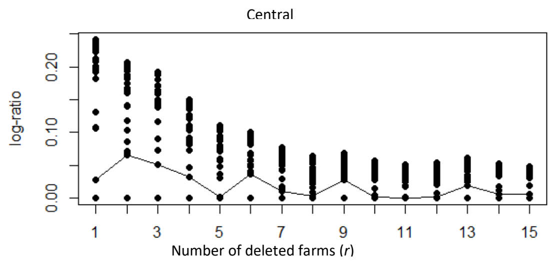


r	Deleted observations															$R_{min}^{(r)}$
1	60															0.7072
2	**40**	**60**														**0.5207**
3	84	40	60													0.4099
4	**56**	**84**	**40**	**60**												**0.3220**
5	56	35	84	40	60											0.2672
6	23	56	35	84	40	60										0.2141
7	**49**	**23**	**56**	**35**	**84**	**40**	**60**									**0.1652**
8	51	49	23	56	35	84	40	60								0.1309
9	51	49	23	4	56	35	84	40	60							0.1063
10	51	1	49	23	4	56	35	84	40	60						0.0843
11	**51**	**52**	**1**	**49**	**23**	**4**	**56**	**35**	**84**	**40**	**60**					**0.0691**
12	51	52	1	49	23	85	4	56	35	84	40	60				0.0591
13	51	52	36	1	49	23	85	4	56	35	84	40	60			0.0501
14	**51**	**52**	**36**	**1**	**49**	**23**	**85**	**81**	**4**	**56**	**35**	**84**	**40**	**60**		**0.0428**
15	51	52	36	22	1	49	23	85	81	4	56	35	84	40	60	0.0369

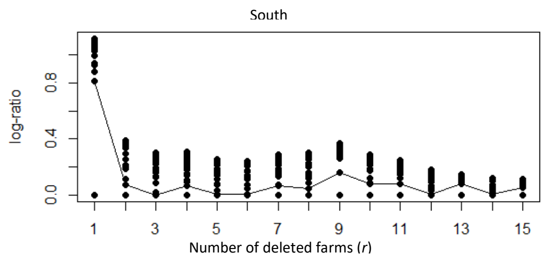


r	Deleted observations (Northeast)															$R_{min}^{(r)}$
1	24															0.6160
2	38	24														0.4157
3	**40**	**38**	**24**													**0.2633**
4	40	41	38	24												0.1772
5	40	38	25	14	24											0.1195
6	**40**	**41**	**38**	**25**	**14**	**24**										**0.0772**
7	42	40	41	38	25	14	24									0.0496
8	42	40	41	38	22	25	14	24								0.0321
9	42	40	41	6	38	22	25	14	24							0.0203
10	**39**	**42**	**40**	**41**	**6**	**38**	**22**	**25**	**14**	**24**						**0.0132**
11	27	39	42	40	41	6	38	22	25	14	24					0.0091
12	**27**	**32**	**39**	**42**	**40**	**41**	**6**	**38**	**22**	**25**	**14**	**24**				**0.0062**
13	27	32	39	42	4	40	41	6	38	22	25	14	24			0.0044
14	3	27	21	39	42	4	40	41	6	38	22	25	14	24		0.0028
15	3	27	21	32	39	42	4	40	41	6	38	22	25	14	24	0.0018

Log-ratio plot for outlier identification for each group of observations	The values of $R^{(r)}_{min}$ and the farm number to be deleted in each group of observations



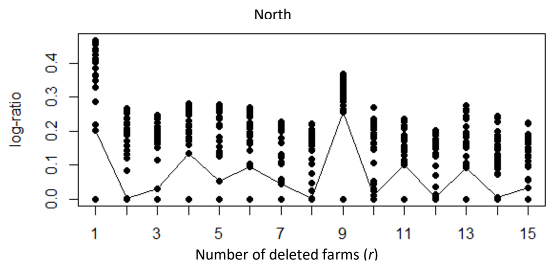
r	Deleted observations (Central)															$R^{(r)}_{min}$
1	5															0.7588
2	**151**	**5**														**0.5862**
3	149	151	5													0.4587
4	121	149	151	5												0.3741
5	121	100	149	151	5											0.3144
6	**121**	**88**	**100**	**149**	**151**	**5**										**0.2616**
7	66	121	88	100	149	151	5									0.2257
8	119	66	121	88	100	149	151	5								0.1950
9	**119**	**66**	**97**	**121**	**88**	**100**	**149**	**151**	**5**							**0.1664**
10	131	119	66	97	121	88	100	149	151	5						0.1456
11	153	131	119	66	97	121	88	100	149	151	5					0.1272
12	131	119	66	97	146	141	121	88	100	149	151	5				0.1105
13	**153**	**131**	**119**	**66**	**97**	**146**	**141**	**121**	**88**	**100**	**149**	**151**	**5**			**0.0960**
14	153	131	62	119	66	97	146	141	121	88	100	149	151	5		0.0848
15	153	131	62	154	119	66	97	146	141	121	88	100	149	151	5	0.0749



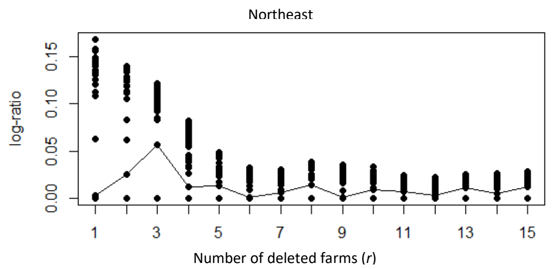
r	Deleted observations (South)															$R^{(r)}_{min}$
1	23															0.3151
2	26	23														0.2048
3	56	26	23													0.1430
4	**26**	**43**	**44**	**23**												**0.0907**
5	26	50	43	44	23											0.0630
6	56	26	50	43	44	23										0.0421
7	**24**	**56**	**26**	**50**	**43**	**44**	**23**									**0.0275**
8	24	56	26	50	2	43	44	23								0.0185
9	**24**	**56**	**26**	**4**	**50**	**2**	**43**	**44**	**23**							**0.0116**
10	24	59	56	26	4	50	2	43	44	23						0.0084
11	**46**	**24**	**59**	**56**	**26**	**4**	**50**	**2**	**43**	**44**	**23**					**0.0060**
12	46	24	59	56	26	14	4	50	2	43	44	23				0.0047
13	**46**	**24**	**59**	**20**	**56**	**26**	**14**	**4**	**50**	**2**	**43**	**44**	**23**			**0.0035**
14	27	46	24	59	20	56	26	14	4	50	2	43	44	23		0.0027
15	**27**	**46**	**19**	**24**	**59**	**20**	**56**	**26**	**14**	**4**	**50**	**2**	**43**	**44**	**23**	**0.0020**

Glutinous rice farms

Log-ratio plot for outlier identification for each group of observations	The values of $R^{(r)}_{min}$ and the farm number to be deleted in each group of observations



r	Deleted observations (North)															$R^{(r)}_{min}$
1	31															0.5936
2	49	31														0.4288
3	49	40	31													0.2953
4	**48**	**49**	**40**	**31**												**0.1993**
5	47	48	49	40	31											0.1403
6	**47**	**21**	**48**	**49**	**40**	**31**										**0.0958**
7	2	47	21	48	49	40	31									0.0676
8	39	38	47	21	48	49	40	31								0.0467
9	**2**	**39**	**38**	**47**	**21**	**48**	**49**	**40**	**31**							**0.0271**
10	2	39	38	47	18	21	48	49	40	31						0.0203
11	**2**	**39**	**38**	**47**	**24**	**18**	**21**	**48**	**49**	**40**	**31**					**0.0138**
12	2	26	39	38	47	24	18	21	48	49	40	31				0.0099
13	**2**	**25**	**39**	**38**	**47**	**9**	**24**	**18**	**21**	**48**	**49**	**40**	**31**			**0.0065**
14	10	2	25	39	38	47	9	24	18	21	48	49	40	31		0.0046
15	**4**	**2**	**26**	**25**	**39**	**38**	**47**	**9**	**24**	**18**	**21**	**48**	**49**	**40**	**31**	**0.0031**



r	Deleted observations (Northeast)															$R^{(r)}_{min}$
1	51															0.8091
2	58	51														0.6558
3	**49**	**58**	**51**													**0.5440**
4	64	49	58	51												0.4764
5	**50**	**64**	**49**	**58**	**51**											**0.4210**
6	122	50	64	49	58	51										0.3761
7	15	50	88	64	49	58	51									0.3336
8	**15**	**37**	**50**	**88**	**64**	**49**	**58**	**51**								**0.2934**
9	15	37	122	50	88	64	49	58	51							0.2617
10	**44**	**15**	**37**	**122**	**50**	**88**	**64**	**49**	**58**	**51**						**0.2326**
11	44	15	37	122	50	30	88	64	49	58	51					0.2087
12	44	15	37	122	50	17	30	88	64	49	58	51				0.1866
13	**44**	**15**	**37**	**35**	**122**	**50**	**17**	**30**	**88**	**64**	**49**	**58**	**51**			**0.1656**
14	44	34	15	37	35	122	50	17	30	88	64	49	58	51		0.1468
15	**44**	**34**	**133**	**15**	**37**	**35**	**122**	**50**	**17**	**30**	**88**	**64**	**49**	**58**	**51**	**0.1290**

Appendix D Efficiency results of each farm in the sample data

Tables D.1 to Table D.9 present the results of calculating the technical and environmental inefficiency of each farm in the Thai rice sample and its ranking using the different efficiency measures (DDF1 – DDF4, NSMM, and PSMM), the scale efficiency of each farm and its returns to scale estimated by the input-oriented DEA.

DDF1 denotes the directional distance function measure with the direction towards observed farms' individual inputs used, holding the output fixed (Input-oriented DEA). The technical inefficiency score of each farm obtained from the DDF1 model is equal to one minus the TE score of each farm obtained from the input-oriented DEA model. DDF2 denotes the directional distance function measure with the direction towards observed farms' individual output produced, holding all inputs fixed (Output-oriented DEA). The technical inefficiency score of each farm obtained from the DDF2 model is equal to the TE score of each farm obtained from the output-oriented DEA mode minus one. DDF3 denotes the directional distance function measure with the direction towards observed farms' individual inputs used and output produced. DDF4 denotes the directional distance function measure with the direction towards the profit maximisation benchmark. NSMM denotes the Nitrogen Surplus Minimisation Model. It is used to measure NS efficiency of the farmers in each group, using the directional nutrient surplus efficiency measure with the directional vector towards the nitrogen surplus minimising frontier. PSMM denotes the Phosphorus Surplus Minimisation Model. It is used to measure PS efficiency of farmers in each group, using the directional nutrient surplus efficiency measure with the directional vector towards the phosphorus surplus minimising frontier. SE, RTS, CRS, IRS, and DRS denote scale efficiency, returns to scale, constant returns to scale, increasing returns to scale and decreasing returns to scale, respectively.

Table D.1 Ranking by different efficiency measures, returns to scale, technical, environmental, and scale efficiency estimates of jasmine rice farms in the Northern region

Farm No.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
1	Chiangrai	0.014	48	0.014	48	0.007	48	97,680	26	N.A.		56.80	26	0.998	IRS
2	Chiangrai	0.000	1	0.000	1	0.000	1	94,354	23	11.18	6	18.82	9	1.000	CRS
3	Chiangrai	0.000	1	0.000	1	0.000	1	117,212	62	N.A.		N.A.		1.000	CRS
4	Chiangrai	0.000	1	0.000	1	0.000	1	103,971	44	O		O		1.000	CRS
5	*Chiangrai*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*105,438*	*49*	*0.00*	*1*	*N.A.*		*1.000*	*CRS*
6	Phayao	0.000	1	0.000	1	0.000	1	70,409	7	N.A.		26.11	16	1.000	CRS
7	Phayao	0.044	54	0.046	54	0.023	54	97,242	25	N.A.		36.50	19	0.975	DRS
8	Phayao	0.000	1	0.000	1	0.000	1	78,549	12	N.A.		52.16	22	1.000	CRS
9	Lampang	0.000	1	0.000	1	0.000	1	102,268	36	N.A.		15.65	8	1.000	CRS
10	Lampang	0.000	1	0.000	1	0.000	1	71,767	8	N.A.		O		1.000	CRS
11	Lampang	0.000	1	0.000	1	0.000	1	69,237	6	N.A.		O		1.000	CRS
12	Lampang	0.000	1	0.000	1	0.000	1	106,946	51	N.A.		N.A.		1.000	CRS
13	Lamphun	0.000	1	0.000	1	0.000	1	94,360	24	N.A.		46.28	20	1.000	CRS
14	Chiangmai	0.037	51	0.038	51	0.019	51	87,068	18	O		50.12	21	0.994	DRS
15	Chiangmai	0.043	53	0.045	53	0.022	53	104,747	46	9.73	5	25.14	15	0.957	IRS
16	Maehongson	0.110	59	0.124	59	0.058	59	107,289	53	N.A.		N.A.		0.948	IRS
17	Maehongson	0.073	58	0.079	58	0.038	58	99,414	30	N.A.		30.03	18	0.999	DRS
18	Maehongson	0.000	1	0.000	1	0.000	1	101,893	34	N.A.		9.30	3	1.000	CRS
19	Maehongson	0.000	1	0.000	1	0.000	1	107,587	55	N.A.		N.A.		1.000	CRS
20	Maehongson	0.000	1	0.000	1	0.000	1	103,214	40	N.A.		9.30	4	1.000	CRS
21	Tak	0.000	1	0.000	1	0.000	1	117,704	63	O		N.A.		1.000	CRS
22	Tak	0.201	62	0.252	62	0.112	62	102,087	35	N.A.		13.32	6	0.981	DRS
23	Tak	0.000	1	0.000	1	0.000	1	107,536	54	N.A.		N.A.		1.000	CRS
24	Kamphaengphet	0.172	61	0.208	61	0.094	61	109,059	57	19.99	10	24.12	14	0.828	IRS
25	Kamphaengphet	0.069	57	0.074	57	0.036	57	102,319	37	34.68	15	10.88	5	0.931	IRS
26	Kamphaengphet	0.000	1	0.000	1	0.000	1	74,264	10	O		N.A.		1.000	CRS
27	Kamphaengphet	0.000	1	0.000	1	0.000	1	105,999	50	O		20.18	10	1.000	CRS
28	Kamphaengphet	0.022	49	0.022	49	0.011	49	83,549	17	O		N.A.		0.982	DRS
29	Sukhothai	0.012	47	0.012	47	0.006	47	92,329	21	O		O		0.990	DRS
30	Sukhothai	0.000	1	0.000	1	0.000	1	53,227	5	O		O		1.000	CRS
31	Phrae	0.000	1	0.000	1	0.000	1	87,597	19	O		56.18	25	1.000	CRS
32	Phrae	0.000	1	0.000	1	0.000	1	103,584	43	N.A.		N.A.		1.000	CRS
33	Phrae	0.000	1	0.000	1	0.000	1	111,619	60	5.12	4	14.73	7	1.000	CRS
34	Phrae	0.047	55	0.049	55	0.024	55	105,347	48	O		O		0.997	IRS
35	*Phrae*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*108,177*	*56*	*N.A.*		*0.00*	*1*	*1.000*	*CRS*
36	Nan	0.000	1	0.000	1	0.000	1	90,917	20	2.30	3	N.A.		1.000	CRS
37	Nan	0.000	1	0.000	1	0.000	1	113,288	61	14.82	8	N.A.		1.000	CRS
38	Nan	0.269	63	0.368	63	0.155	63	110,307	59	N.A.		6.34	2	0.984	IRS
39	Nan	0.154	60	0.183	60	0.084	60	104,016	45	N.A.		N.A.		0.851	DRS
40	Nan	0.000	1	0.000	1	0.000	1	83,205	16	19.58	9	N.A.		1.000	CRS
41	Uttaradit	0.000	1	0.000	1	0.000	1	107,001	52	0.77	2	N.A.		1.000	CRS
42	Uttaradit	0.000	1	0.000	1	0.000	1	99,226	28	36.59	16	N.A.		1.000	CRS
43	Uttaradit	0.000	1	0.000	1	0.000	1	100,935	32	24.24	11	N.A.		1.000	CRS
44	Uttaradit	0.000	1	0.000	1	0.000	1	82,521	15	68.57	21	N.A.		1.000	CRS
45	Uttaradit	0.000	1	0.000	1	0.000	1	102,793	39	47.60	19	N.A.		1.000	CRS
46	Phitsanulok	0.350	64	0.538	64	0.212	64	110,100	58	O		O		0.963	DRS
47	*Phichit*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*0*	*1*	*O*		*O*		*1.000*	*CRS*
48	Phichit	0.000	1	0.000	1	0.000	1	46,371	3	O		52.72	23	1.000	CRS
49	Phichit	0.000	1	0.000	1	0.000	1	53,132	4	N.A.		53.38	24	1.000	CRS
50	Phichit	0.000	1	0.000	1	0.000	1	81,958	14	33.86	14	O		1.000	CRS
51	Phichit	0.000	1	0.000	1	0.000	1	103,476	42	N.A.		N.A.		1.000	CRS
52	Phichit	0.063	56	0.067	56	0.033	56	119,770	64	O		O		0.937	DRS
53	Uthaithani	0.000	1	0.000	1	0.000	1	72,660	9	49.29	20	N.A.		1.000	CRS
54	Uthaithani	0.000	1	0.000	1	0.000	1	34,162	2	O		N.A.		1.000	CRS
55	Uthaithani	0.000	1	0.000	1	0.000	1	78,775	13	N.A.		O		1.000	CRS
56	Uthaithani	0.040	52	0.042	52	0.020	52	75,115	11	42.32	18	O		0.989	DRS
57	Uthaithani	0.000	1	0.000	1	0.000	1	99,295	29	N.A.		O		1.000	CRS
58	Phetchabun	0.000	1	0.000	1	0.000	1	101,062	33	N.A.		N.A.		1.000	CRS
59	Phetchabun	0.000	1	0.000	1	0.000	1	92,448	22	N.A.		N.A.		1.000	CRS
60	Phetchabun	0.000	1	0.000	1	0.000	1	103,389	41	27.55	13	21.07	12	1.000	CRS
61	Phetchabun	0.023	50	0.024	50	0.012	50	104,899	47	24.81	12	22.56	13	1.000	CRS
62	Phetchabun	0.000	1	0.000	1	0.000	1	98,038	27	14.35	7	29.10	17	1.000	CRS
63	Phetchabun	0.000	1	0.000	1	0.000	1	100,876	31	40.41	17	20.32	11	1.000	CRS
64	Phetchabun	0.009	46	0.009	46	0.004	46	102,769	38	N.A.		O		0.994	IRS

Note that DDF1 – DDF3 models are estimated under the assumption of CRS; DDF4, NSMM and PSMM are estimated under the assumption of VRS. N.A. denotes the farm had negative NS or negative PS. O denotes the farm is an outlier for NSMM or PSMM.

Table D.2 Ranking by different efficiency measures, returns to scale, technical, environmental, and scale efficiency estimates of jasmine rice farms in the North-eastern region

Farm No.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
1	Loei	0.208	147	0.262	147	0.116	147	89,593	41	N.A.		N.A.		0.943	IRS
2	Loei	0.207	146	0.261	146	0.116	146	89,829	42	N.A.		N.A.		0.956	IRS
3	Loei	0.203	136	0.255	136	0.113	136	98,194	108	1.32	9	1.59	11	0.858	IRS
4	Loei	0.204	139	0.256	139	0.113	139	98,580	112	1.29	8	6.35	36	0.899	IRS
5	Loei	0.203	137	0.255	137	0.113	137	97,966	106	1.37	10	6.94	38	0.797	IRS
6	Loei	0.205	143	0.258	143	0.114	143	87,756	32	N.A.		N.A.		0.953	IRS
7	Loei	0.203	138	0.255	138	0.113	138	96,434	92	2.72	17	4.31	27	0.953	IRS
8	Nongbualamphu	0.000	1	0.000	1	0.000	1	94,190	67	N.A.		N.A.		1.000	CRS
9	Nongbualamphu	0.275	171	0.380	171	0.160	171	100,375	138	2.80	18	11.37	51	0.927	IRS
10	Nongbualamphu	0.270	169	0.370	169	0.156	169	101,150	146	50.87	87	49.40	106	0.991	IRS
11	Nongbualamphu	0.260	167	0.352	167	0.150	167	82,637	19	173.66	120	66.19	113	0.898	DRS
12	Nongbualamphu	0.114	79	0.128	79	0.060	79	101,769	153	N.A.		N.A.		0.886	IRS
13	Nongbualamphu	0.239	162	0.314	162	0.136	162	93,047	59	71.04	96	N.A.		0.861	DRS
14	Nongbualamphu	0.267	168	0.364	168	0.154	168	84,634	26	N.A.		4.11	26	0.954	DRS
15	Nongbualamphu	0.275	172	0.380	172	0.160	172	100,676	140	10.07	30	16.96	69	0.946	IRS
16	Nongbualamphu	0.245	165	0.325	165	0.140	165	99,771	127	1.01	5	0.68	4	0.755	IRS
17	Nongbualamphu	0.274	170	0.377	170	0.159	170	99,281	120	1.50	12	1.53	10	0.808	IRS
18	Udonthani	0.211	152	0.267	152	0.118	152	101,279	147	2.03	13	4.46	28	0.868	IRS
19	Udonthani	0.095	76	0.104	76	0.050	76	98,270	109	1.15	7	N.A.		0.953	IRS
20	Udonthani	0.000	1	0.000	1	0.000	1	96,794	95	5.55	21	N.A.		1.000	CRS
21	Udonthani	0.000	1	0.000	1	0.000	1	97,614	100	21.86	57	14.13	58	1.000	CRS
22	Udonthani	0.168	114	0.201	114	0.092	114	98,951	116	23.18	60	22.54	78	0.995	DRS
23	Udonthani	0.204	142	0.256	142	0.113	142	100,783	143	6.13	24	7.97	45	0.928	IRS
24	Udonthani	0.207	144	0.260	144	0.115	144	94,494	71	N.A.		3.75	24	0.981	IRS
25	Udonthani	0.209	150	0.263	150	0.116	150	105,861	172	74.17	98	19.64	72	0.999	DRS
26	Udonthani	0.208	148	0.262	148	0.116	148	101,756	152	12.94	35	16.18	66	0.993	DRS
27	Udonthani	0.164	113	0.196	113	0.089	113	95,901	82	N.A.		5.79	35	0.984	IRS
28	Udonthani	0.156	111	0.184	111	0.084	111	103,532	165	115.50	112	21.25	76	0.973	DRS
29	Udonthani	0.204	141	0.256	141	0.113	141	102,244	155	2.31	15	3.46	19	0.934	IRS
30	Udonthani	0.211	153	0.267	153	0.118	153	100,200	133	16.58	45	0.70	5	0.949	IRS
31	Udonthani	0.203	135	0.254	135	0.113	135	99,420	121	0.92	4	N.A.		0.855	IRS
32	Nongkhai	0.280	178	0.388	178	0.163	178	106,840	175	31.05	69	2.32	13	1.000	CRS
33	Nongkhai	0.277	173	0.384	173	0.161	173	115,585	185	152.00	119	28.99	85	1.000	CRS
34	Nongkhai	0.277	175	0.384	175	0.161	175	103,345	164	15.01	40	41.17	99	0.994	IRS
35	Nongkhai	0.279	177	0.386	177	0.162	177	113,596	182	O		52.03	109	0.978	DRS
36	Nongkhai	0.278	176	0.385	176	0.162	176	106,610	174	87.62	102	O		0.945	DRS
37	Nongkhai	0.280	179	0.390	179	0.163	179	113,107	181	46.65	84	86.55	118	1.000	CRS
38	Nongkhai	0.277	174	0.384	174	0.161	174	103,269	163	39.52	76	92.45	120	0.922	DRS
39	Sakonnakhon	0.190	127	0.235	127	0.105	127	75,124	9	9.13	29	60.82	112	0.913	DRS
40	Sakonnakhon	0.187	121	0.231	121	0.103	121	76,648	11	16.19	43	28.30	84	0.813	DRS
41	Sakonnakhon	0.190	125	0.234	125	0.105	125	43,991	5	57.97	88	109.97	125	0.810	DRS
42	Sakonnakhon	0.188	122	0.232	122	0.104	122	116,475	186	45.10	83	86.03	117	1.000	CRS
43	Sakonnakhon	0.189	124	0.234	124	0.105	124	88,330	36	77.23	99	5.78	34	0.984	DRS
44	Sakonnakhon	0.142	97	0.165	97	0.076	97	35,706	3	O		O		0.858	DRS
45	Sakonnakhon	0.190	126	0.235	126	0.105	126	100,215	134	141.36	117	16.31	67	0.999	IRS
46	Sakonnakhon	0.122	84	0.139	84	0.065	84	91,586	52	41.48	81	22.87	79	0.974	DRS
47	Nakhonphanom	0.297	181	0.422	181	0.174	181	100,370	137	N.A.		N.A.		0.843	DRS
48	Nakhonphanom	0.225	160	0.290	160	0.127	160	88,684	37	N.A.		1.41	7	0.875	DRS
49	Nakhonphanom	0.239	163	0.315	163	0.136	163	95,699	79	23.27	61	8.96	48	0.998	DRS
50	Nakhonphanom	0.310	183	0.449	183	0.183	183	84,613	25	O		N.A.		0.690	DRS
51	Nakhonphanom	0.341	189	0.517	189	0.205	189	110,335	178	66.87	93	11.46	52	1.000	CRS
52	Nakhonphanom	0.340	188	0.516	188	0.205	188	106,157	173	O		O		0.830	DRS
53	Nakhonphanom	0.340	185	0.514	185	0.205	185	103,044	160	10.27	31	N.A.		0.976	IRS
54	Nakhonphanom	0.147	105	0.172	105	0.079	105	95,925	83	N.A.		4.92	30	0.991	DRS
55	Nakhonphanom	0.323	184	0.478	184	0.193	184	102,019	154	109.67	109	7.42	42	0.903	DRS
56	Nakhonphanom	0.306	182	0.441	182	0.181	182	95,567	78	6.07	23	3.51	21	0.989	DRS
57	Nakhonphanom	0.288	180	0.405	180	0.168	180	94,833	75	16.10	42	5.50	33	0.999	DRS
58	Nakhonphanom	0.340	187	0.515	187	0.205	187	94,868	76	N.A.		N.A.		0.997	IRS
59	Nakhonphanom	0.340	186	0.514	186	0.205	186	94,785	74	N.A.		N.A.		0.999	IRS
60	Mukdahan	0.168	116	0.202	116	0.092	116	98,780	114	N.A.		N.A.		1.000	CRS
61	Mukdahan	0.000	1	0.000	1	0.000	1	85,399	28	5.10	20	13.77	57	1.000	CRS
62	Mukdahan	0.199	132	0.249	132	0.111	132	70,614	8	40.22	78	N.A.		0.801	DRS
63	Mukdahan	0.208	149	0.262	149	0.116	149	92,971	58	N.A.		14.35	61	0.988	IRS
64	Mukdahan	0.209	151	0.264	151	0.117	151	95,742	81	N.A.		0.24	3	0.976	IRS
65	Mukdahan	0.207	145	0.261	145	0.115	145	97,299	98	23.91	63	9.32	49	0.997	DRS
66	Mukdahan	0.212	154	0.270	154	0.119	154	96,593	94	34.36	70	15.19	64	0.988	IRS
67	Yasothon	0.240	164	0.316	164	0.136	164	97,757	104	N.A.		3.49	20	0.979	IRS
68	Yasothon	0.000	1	0.000	1	0.000	1	97,620	101	N.A.		6.79	37	1.000	CRS
69	Yasothon	0.000	1	0.000	1	0.000	1	90,575	46	N.A.		N.A.		1.000	CRS

Table D.2 Continued

Farm No.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
70	Yasothon	0.247	166	0.328	166	0.141	166	102,311	156	N.A.		N.A.		0.976	IRS
71	Yasothon	0.139	93	0.161	93	0.075	93	101,518	151	19.44	54	23.04	80	0.861	IRS
72	Yasothon	0.223	159	0.287	159	0.125	159	100,103	130	13.56	36	17.92	71	0.916	IRS
73	Amnatcharoen	0.144	100	0.168	100	0.078	100	101,030	144	28.02	66	44.22	102	0.951	IRS
74	Amnatcharoen	0.000	1	0.000	1	0.000	1	39,306	4	N.A.		N.A.		1.000	CRS
75	Amnatcharoen	0.154	110	0.182	110	0.083	110	114,235	183	73.77	97	56.34	111	0.959	DRS
76	Amnatcharoen	0.000	1	0.000	1	0.000	1	97,577	99	N.A.		8.82	47	1.000	CRS
77	Amnatcharoen	0.013	57	0.013	57	0.007	57	103,244	162	29.07	67	39.69	95	0.996	IRS
78	Amnatcharoen	0.043	65	0.045	65	0.022	65	100,571	139	58.60	89	2.90	16	0.957	DRS
79	Amnatcharoen	0.201	133	0.252	133	0.112	133	79,835	15	N.A.		32.40	87	0.799	DRS
80	Amnatcharoen	0.192	128	0.238	128	0.106	128	101,474	150	19.37	53	N.A.		0.861	IRS
81	Amnatcharoen	0.180	119	0.220	119	0.099	119	98,629	113	35.64	72	51.67	108	0.994	DRS
82	Ubonratchathani	0.128	87	0.146	87	0.068	87	107,381	176	61.41	90	97.14	121	0.995	DRS
83	Ubonratchathani	0.193	129	0.239	129	0.107	129	94,328	68	2.56	16	N.A.		0.983	IRS
84	Ubonratchathani	0.140	95	0.163	95	0.075	95	99,509	123	0.47	2	7.02	39	0.988	IRS
85	Ubonratchathani	0.051	70	0.054	70	0.026	70	100,751	141	14.33	39	N.A.		0.949	IRS
86	Ubonratchathani	0.000	1	0.000	1	0.000	1	96,169	88	11.33	34	1.53	9	1.000	CRS
87	Ubonratchathani	0.181	120	0.221	120	0.100	120	96,167	87	97.74	105	25.24	82	0.998	DRS
88	Ubonratchathani	0.000	1	0.000	1	0.000	1	90,747	47	N.A.		N.A.		1.000	CRS
89	Ubonratchathani	0.000	1	0.000	1	0.000	1	97,745	103	89.94	103	12.45	54	1.000	CRS
90	*Ubonratchathani*	*0.144*	*99*	*0.168*	*99*	*0.077*	*99*	*0*	*1*	*O*		*O*		*0.856*	*DRS*
91	Ubonratchathani	0.000	1	0.000	1	0.000	1	95,930	84	17.84	49	N.A.		1.000	CRS
92	Ubonratchathani	0.117	81	0.133	81	0.062	81	94,701	72	77.73	100	31.91	86	0.924	DRS
93	Ubonratchathani	0.199	131	0.248	131	0.110	131	90,093	43	16.69	46	12.59	55	1.000	DRS
94	Ubonratchathani	0.179	117	0.218	117	0.098	117	101,301	148	17.64	48	5.10	31	0.987	IRS
95	*Ubonratchathani*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*86,033*	*29*	*N.A.*		*0.00*	*1*	*1.000*	*CRS*
96	Ubonratchathani	0.148	106	0.174	106	0.080	106	102,347	157	48.86	85	33.27	89	0.980	DRS
97	Ubonratchathani	0.150	107	0.176	107	0.081	107	97,669	102	142.57	118	37.79	93	0.972	DRS
98	Sisaket	0.047	68	0.049	68	0.024	68	101,131	145	O		O		1.000	IRS
99	Sisaket	0.000	1	0.000	1	0.000	1	88,061	35	193.69	121	N.A.		1.000	CRS
100	Sisaket	0.045	67	0.047	67	0.023	67	94,332	69	115.42	111	0.22	2	0.983	DRS
101	Sisaket	0.011	56	0.011	56	0.006	56	93,197	60	23.40	62	40.73	97	0.989	DRS
102	Sisaket	0.000	1	0.000	1	0.000	1	92,438	56	22.15	58	40.99	98	1.000	CRS
103	Sisaket	0.000	1	0.000	1	0.000	1	92,122	55	41.20	79	50.42	107	1.000	CRS
104	Sisaket	0.000	1	0.000	1	0.000	1	79,650	14	69.88	94	68.76	114	1.000	CRS
105	Sisaket	0.044	66	0.046	66	0.023	66	105,766	171	115.02	110	53.44	110	1.000	IRS
106	Sisaket	0.000	1	0.000	1	0.000	1	84,411	24	102.10	107	105.94	123	1.000	CRS
107	Sisaket	0.000	1	0.000	1	0.000	1	89,109	38	N.A.		N.A.		1.000	CRS
108	Sisaket	0.037	64	0.038	64	0.019	64	96,184	89	42.40	82	44.73	104	0.988	IRS
109	Sisaket	0.021	61	0.021	61	0.011	61	94,036	65	28.00	65	19.95	73	0.998	IRS
110	*Sisaket*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*92,804*	*57*	*0.00*	*1*	*3.17*	*17*	*1.000*	*CRS*
111	Surin	0.000	1	0.000	1	0.000	1	84,067	21	O		O		1.000	CRS
112	Surin	0.033	63	0.034	63	0.017	63	91,607	53	0.68	3	3.55	22	0.994	IRS
113	Surin	0.019	59	0.019	59	0.009	59	92,001	54	40.18	77	21.64	77	0.988	DRS
114	Surin	0.000	1	0.000	1	0.000	1	84,246	22	16.34	44	17.32	70	1.000	CRS
115	Surin	0.002	51	0.002	51	0.001	51	91,127	48	22.60	59	16.95	68	0.998	DRS
116	Surin	0.067	74	0.072	74	0.035	74	94,359	70	206.88	122	87.64	119	0.976	DRS
117	Surin	0.000	1	0.000	1	0.000	1	79,604	13	N.A.		3.17	18	1.000	CRS
118	Surin	0.000	1	0.000	1	0.000	1	95,990	85	O		O		1.000	CRS
119	Surin	0.000	1	0.000	1	0.000	1	91,543	51	N.A.		N.A.		1.000	CRS
120	Surin	0.031	62	0.032	62	0.016	62	89,386	40	65.18	91	40.03	96	0.988	DRS
121	Buriram	0.000	1	0.000	1	0.000	1	130,245	189	N.A.		O		1.000	CRS
122	Buriram	0.000	1	0.000	1	0.000	1	90,374	45	N.A.		N.A.		1.000	CRS
123	Buriram	0.018	58	0.018	58	0.009	58	114,405	184	N.A.		N.A.		0.982	DRS
124	Buriram	0.000	1	0.000	1	0.000	1	93,670	62	N.A.		N.A.		1.000	CRS
125	Buriram	0.083	75	0.091	75	0.043	75	81,417	16	232.53	124	2.39	14	0.917	DRS
126	Buriram	0.101	78	0.112	78	0.053	78	76,138	10	236.66	125	108.43	124	0.946	DRS
127	Buriram	0.056	71	0.060	71	0.029	71	64,903	7	O		O		0.944	DRS
128	Buriram	0.000	1	0.000	1	0.000	1	26,274	2	O		O		1.000	CRS
129	Buriram	0.000	1	0.000	1	0.000	1	89,223	39	O		O		1.000	CRS
130	Buriram	0.131	91	0.151	91	0.070	91	95,476	77	36.09	73	33.16	88	0.955	DRS
131	Buriram	0.145	101	0.169	101	0.078	101	120,952	188	O		O		0.897	DRS
132	Buriram	0.065	72	0.070	72	0.034	72	91,464	50	21.29	56	14.19	59	1.000	DRS
133	Buriram	0.000	1	0.000	1	0.000	1	86,617	30	8.27	26	80.42	115	1.000	CRS
134	Buriram	0.115	80	0.130	80	0.061	80	91,175	49	N.A.		1.49	8	0.996	IRS
135	Buriram	0.143	98	0.167	98	0.077	98	100,278	135	66.08	92	39.27	94	0.999	IRS
136	Mahasarakham	0.146	102	0.171	102	0.079	102	96,292	91	N.A.		N.A.		0.854	IRS
137	Mahasarakham	0.152	108	0.179	108	0.082	108	100,062	128	6.70	25	4.05	25	0.916	IRS
138	Mahasarakham	0.146	104	0.171	104	0.079	104	99,231	119	3.92	19	3.65	23	0.906	IRS
139	Mahasarakham	0.156	112	0.185	112	0.085	112	100,760	142	N.A.		N.A.		0.997	IRS

Table D.2 Continued

Farm No.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
140	Mahasarakham	0.121	83	0.138	83	0.064	83	99,107	118	19.26	51	11.12	50	0.959	IRS
141	Mahasarakham	0.146	103	0.171	103	0.079	103	100,097	129	N.A.		N.A.		0.854	IRS
142	Mahasarakham	0.125	85	0.143	85	0.067	85	93,637	61	97.01	104	N.A.		0.875	DRS
143	Mahasarakham	0.152	109	0.180	109	0.082	109	86,804	31	2.16	14	14.21	60	0.962	DRS
144	Mahasarakham	0.141	96	0.164	96	0.076	96	99,047	117	N.A.		N.A.		0.898	IRS
145	Roiet	0.129	89	0.148	89	0.069	89	103,712	166	37.80	75	20.02	74	0.929	IRS
146	Roiet	0.130	90	0.149	90	0.070	90	93,942	64	N.A.		N.A.		0.986	IRS
147	Roiet	0.000	1	0.000	1	0.000	1	82,357	17	240.29	126	43.22	101	1.000	CRS
148	Roiet	0.128	86	0.146	86	0.068	86	104,390	167	8.94	28	14.64	63	0.916	IRS
149	Roiet	0.128	88	0.147	88	0.068	88	103,207	161	N.A.		N.A.		0.872	DRS
150	Kalasin	0.000	1	0.000	1	0.000	1	87,766	33	1.40	11	42.80	100	1.000	CRS
151	Kalasin	0.010	55	0.010	55	0.005	55	96,568	93	10.82	32	24.97	81	0.990	IRS
152	Kalasin	0.000	1	0.000	1	0.000	1	88,049	34	11.08	33	35.22	92	1.000	CRS
153	Kalasin	0.000	1	0.000	1	0.000	1	47,393	6	107.29	108	O		1.000	CRS
154	Kalasin	0.000	1	0.000	1	0.000	1	93,779	63	131.63	116	N.A.		1.000	CRS
155	Kalasin	0.004	54	0.004	54	0.002	54	102,492	158	35.20	71	33.55	90	0.996	IRS
156	Kalasin	0.000	1	0.000	1	0.000	1	99,556	125	N.A.		N.A.		1.000	CRS
157	Kalasin	0.000	1	0.000	1	0.000	1	77,760	12	N.A.		14.41	62	1.000	CRS
158	Kalasin	0.003	53	0.004	53	0.002	53	99,535	124	N.A.		N.A.		0.997	IRS
159	Kalasin	0.000	1	0.000	1	0.000	1	83,530	20	N.A.		N.A.		1.000	CRS
160	Kalasin	0.003	52	0.003	52	0.002	52	101,393	149	N.A.		7.35	40	1.000	IRS
161	Khonkaen	0.099	77	0.110	77	0.052	77	102,859	159	8.70	27	13.55	56	0.941	IRS
162	Khonkaen	0.047	69	0.050	69	0.024	69	95,725	80	120.21	113	44.66	103	0.972	DRS
163	Khonkaen	0.000	1	0.000	1	0.000	1	100,346	136	24.47	64	N.A.		1.000	CRS
164	Khonkaen	0.000	1	0.000	1	0.000	1	99,425	122	29.53	68	33.99	91	1.000	CRS
165	Khonkaen	0.065	73	0.070	73	0.034	73	105,426	170	124.81	114	103.87	122	0.975	DRS
166	Khonkaen	0.000	1	0.000	1	0.000	1	96,269	90	18.70	50	7.95	44	1.000	CRS
167	Khonkaen	0.001	50	0.001	50	0.000	50	98,549	111	N.A.		1.91	12	0.999	IRS
168	Khonkaen	0.020	60	0.020	60	0.010	60	94,121	66	1.04	6	20.63	75	0.993	DRS
169	Khonkaen	0.000	1	0.000	1	0.000	1	98,424	110	N.A.		N.A.		1.000	CRS
170	Chaiyaphum	0.231	161	0.300	161	0.130	161	109,577	177	70.39	95	25.41	83	0.987	DRS
171	Chaiyaphum	0.179	118	0.219	118	0.099	118	96,158	86	N.A.		N.A.		0.983	DRS
172	Chaiyaphum	0.000	1	0.000	1	0.000	1	98,183	107	6.03	22	2.42	15	1.000	CRS
173	Chaiyaphum	0.204	140	0.256	140	0.113	140	105,225	169	N.A.		N.A.		0.977	DRS
174	Chaiyaphum	0.121	82	0.137	82	0.064	82	104,841	168	41.31	80	15.68	65	0.990	DRS
175	Chaiyaphum	0.000	1	0.000	1	0.000	1	100,138	132	19.27	52	N.A.		1.000	CRS
176	Chaiyaphum	0.000	1	0.000	1	0.000	1	100,112	131	N.A.		4.73	29	1.000	CRS
177	Chaiyaphum	0.000	1	0.000	1	0.000	1	97,789	105	16.75	47	12.12	53	1.000	CRS
178	Chaiyaphum	0.201	134	0.252	134	0.112	134	97,271	97	N.A.		N.A.		0.991	DRS
179	Nakhonratchasima	0.194	130	0.241	130	0.108	130	94,783	73	84.65	101	1.08	6	0.995	DRS
180	Nakhonratchasima	0.000	1	0.000	1	0.000	1	84,394	23	15.18	41	45.20	105	1.000	CRS
181	Nakhonratchasima	0.215	156	0.274	156	0.121	156	97,101	96	50.71	86	81.66	116	0.982	DRS
182	Nakhonratchasima	0.188	123	0.232	123	0.104	123	98,918	115	14.28	38	8.25	46	0.898	IRS
183	Nakhonratchasima	0.168	115	0.202	115	0.092	115	99,712	126	14.08	37	5.45	32	0.958	IRS
184	Nakhonratchasima	0.216	158	0.276	158	0.121	158	119,346	187	219.62	123	N.A.		0.954	DRS
185	Nakhonratchasima	0.214	155	0.273	155	0.120	155	110,743	179	130.34	115	7.37	41	1.000	CRS
186	Nakhonratchasima	0.139	94	0.161	94	0.075	94	84,774	27	20.34	55	7.55	43	0.861	DRS
187	Nakhonratchasima	0.137	92	0.159	92	0.074	92	90,234	44	37.63	74	N.A.		0.863	DRS
188	Nakhonratchasima	0.216	157	0.275	157	0.121	157	112,767	180	98.65	106	131.21	126	0.945	DRS
189	Nakhonratchasima	0.000	1	0.000	1	0.000	1	82,575	18	O		O		1.000	CRS

Note that DDF1 – DDF3 models are estimated under the assumption of CRS; DDF4, NSMM and PSMM are estimated under the assumption of VRS. N.A. denotes the farm had negative NS or negative PS. O denotes the farm is an outlier for NSMM or PSMM.

Table D.3 Ranking by different efficiency measures, returns to scale, technical, environmental, and scale efficiency estimates of jasmine rice farms in the Central region

Farm No.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
1	Saraburi	0.000	1	0.000	1	0.000	1	81,064	40	O		7.14	4	1.000	CRS
2	Saraburi	0.000	1	0.000	1	0.000	1	86,077	49	N.A.		12.51	9	1.000	CRS
3	*Saraburi*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*0*	*1*	*N.A.*		*O*		*1.000*	*CRS*
4	*Saraburi*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*78,889*	*33*	*5.68*	*6*	*0.00*	*1*	*1.000*	*CRS*
5	Lopburi	0.135	42	0.156	42	0.072	42	70,119	23	17.30	9	N.A.		0.984	DRS
6	Lopburi	0.000	1	0.000	1	0.000	1	32,363	5	N.A.		N.A.		1.000	CRS
7	Lopburi	0.074	36	0.080	36	0.038	36	68,832	21	O		N.A.		0.958	DRS
8	Lopburi	0.000	1	0.000	1	0.000	1	62,300	14	O		N.A.		1.000	CRS
9	Chainat	0.000	1	0.000	1	0.000	1	76,587	29	N.A.		N.A.		1.000	CRS
10	Chainat	0.097	40	0.107	40	0.051	40	68,529	20	O		O		0.903	DRS
11	Chainat	0.089	38	0.098	38	0.047	38	80,012	36	40.71	16	40.49	19	0.996	DRS
12	Chainat	0.096	39	0.106	39	0.051	39	68,312	19	O		O		0.904	DRS
13	Suphanburi	0.196	44	0.244	44	0.109	44	92,195	56	94.29	19	68.79	24	0.958	DRS
14	Suphanburi	0.089	37	0.097	37	0.046	37	82,015	44	4.08	4	7.15	5	0.955	IRS
15	Suphanburi	0.198	45	0.247	45	0.110	45	84,181	47	79.91	17	N.A.		0.983	DRS
16	Suphanburi	0.206	46	0.260	46	0.115	46	79,221	34	30.37	14	22.36	14	0.991	DRS
17	Suphanburi	0.228	48	0.295	48	0.128	48	94,600	57	20.27	10	4.61	3	0.831	IRS
18	Suphanburi	0.124	41	0.142	41	0.066	41	59,727	12	N.A.		N.A.		0.876	DRS
19	Suphanburi	0.228	49	0.296	49	0.129	49	88,978	55	22.93	12	19.78	13	0.978	IRS
20	Nakhonnayok	0.000	1	0.000	1	0.000	1	76,909	30	33.61	15	10.73	8	1.000	CRS
21	Nakhonnayok	0.000	1	0.000	1	0.000	1	61,490	13	106.53	22	N.A.		1.000	CRS
22	Nakhonnayok	0.000	1	0.000	1	0.000	1	16,093	3	O		O		1.000	CRS
23	Prachinburi	0.000	1	0.000	1	0.000	1	81,410	42	160.07	23	99.54	27	1.000	CRS
24	Prachinburi	0.000	1	0.000	1	0.000	1	81,390	41	27.65	13	79.63	25	1.000	CRS
25	Prachinburi	0.000	1	0.000	1	0.000	1	81,785	43	1.20	2	41.08	20	1.000	CRS
26	Prachinburi	0.000	1	0.000	1	0.000	1	86,079	50	5.59	5	31.87	15	1.000	CRS
27	Prachinburi	0.012	35	0.012	35	0.006	35	86,497	52	22.06	11	50.69	22	0.988	IRS
28	Chachoengsao	0.000	1	0.000	1	0.000	1	68,926	22	N.A.		O		1.000	CRS
29	*Chachoengsao*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*79,252*	*35*	*0.00*	*1*	*39.81*	*18*	*1.000*	*CRS*
30	Sakaeo	0.000	1	0.000	1	0.000	1	22,263	4	N.A.		O		1.000	CRS
31	Sakaeo	0.000	1	0.000	1	0.000	1	80,325	37	N.A.		N.A.		1.000	CRS
32	Sakaeo	0.219	47	0.281	47	0.123	47	73,002	28	N.A.		34.44	17	0.834	DRS
33	Sakaeo	0.307	57	0.442	57	0.181	57	87,714	53	11.82	8	16.19	12	0.998	DRS
34	Sakaeo	0.000	1	0.000	1	0.000	1	59,603	11	N.A.		58.54	23	1.000	CRS
35	Sakaeo	0.243	54	0.320	54	0.138	54	88,742	54	N.A.		N.A.		0.810	DRS
36	Sakaeo	0.318	58	0.466	58	0.189	58	86,451	51	104.98	21	O		0.839	DRS
37	Sakaeo	0.261	55	0.352	55	0.150	55	67,872	18	N.A.		N.A.		0.739	DRS
38	Chanthaburi	0.264	56	0.359	56	0.152	56	97,675	58	O		O		0.963	IRS
39	Chanthaburi	0.233	51	0.304	51	0.132	51	63,992	15	O		O		0.767	DRS
40	Chanthaburi	0.241	53	0.317	53	0.137	53	72,426	26	O		O		0.850	DRS
41	Chanthaburi	0.234	52	0.305	52	0.132	52	80,674	38	100.40	20	12.90	10	0.935	DRS
42	Chanthaburi	0.231	50	0.301	50	0.131	50	78,206	31	O		96.34	26	0.837	DRS
43	Trat	0.000	1	0.000	1	0.000	1	49,932	10	O		O		1.000	CRS
44	Chonburi	0.000	1	0.000	1	0.000	1	72,863	27	3.81	3	34.08	16	1.000	CRS
45	Chonburi	0.000	1	0.000	1	0.000	1	64,107	16	N.A.		9.26	7	1.000	CRS
46	Chonburi	0.000	1	0.000	1	0.000	1	40,458	7	N.A.		O		1.000	CRS
47	Chonburi	0.000	1	0.000	1	0.000	1	1,816	2	O		N.A.		1.000	CRS
48	Chonburi	0.000	1	0.000	1	0.000	1	46,051	8	N.A.		N.A.		1.000	CRS
49	Kanchanaburi	0.000	1	0.000	1	0.000	1	85,597	48	N.A.		N.A.		1.000	CRS
50	Kanchanaburi	0.000	1	0.000	1	0.000	1	70,344	24	N.A.		N.A.		1.000	CRS
51	Kanchanaburi	0.000	1	0.000	1	0.000	1	36,269	6	O		O		1.000	CRS
52	Kanchanaburi	0.000	1	0.000	1	0.000	1	78,278	32	N.A.		16.11	11	1.000	CRS
53	Kanchanaburi	0.159	43	0.189	43	0.086	43	46,981	9	O		O		0.841	DRS
54	Ratchaburi	0.003	34	0.003	34	0.001	34	82,361	45	N.A.		8.61	6	0.999	DRS
55	Ratchaburi	0.001	33	0.001	33	0.000	33	66,299	17	88.27	18	41.57	21	0.999	DRS
56	Ratchaburi	0.000	1	0.000	1	0.000	1	80,904	39	N.A.		N.A.		1.000	CRS
57	Ratchaburi	0.000	1	0.000	1	0.000	1	71,668	25	N.A.		0.08	2	1.000	CRS
58	Ratchaburi	0.000	1	0.000	1	0.000	1	84,061	46	5.70	7	N.A.		1.000	CRS

Note that DDF1 – DDF3 models are estimated under the assumption of CRS; DDF4, NSMM and PSMM are estimated under the assumption of VRS. N.A. denotes the farm had negative NS or negative PS. O denotes the farm is an outlier for NSMM or PSMM.

Table D.4 Ranking by different efficiency measures, returns to scale, technical, environmental, and scale efficiency estimates of non-jasmine rice farms in the Northern region

Farm no.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
1	Chiangrai	0.000	1	0.000	1	0.000	1	196,448	59	N.A.		N.A.		1.000	CRS
2	Chiangrai	0.000	1	0.000	1	0.000	1	211,607	80	7.24	7	N.A.		1.000	CRS
3	Chiangrai	0.000	1	0.000	1	0.000	1	196,007	57	O		N.A.		1.000	CRS
4	Chiangrai	0.000	1	0.000	1	0.000	1	236,839	143	228.03	73	N.A.		1.000	CRS
5	Chiangrai	0.000	1	0.000	1	0.000	1	123,320	10	O		O		1.000	CRS
6	Chiangrai	0.011	89	0.011	89	0.005	89	204,236	69	87.26	38	39.38	31	0.999	DRS
7	Chiangrai	0.080	115	0.086	115	0.041	115	245,305	149	9.85	8	77.35	51	0.972	DRS
8	Chiangrai	0.007	87	0.007	87	0.003	87	162,329	29	N.A.		N.A.		0.993	DRS
9	Chiangrai	0.000	1	0.000	1	0.000	1	194,570	54	O		O		1.000	CRS
10	Chiangrai	0.000	1	0.000	1	0.000	1	222,822	108	15.53	11	N.A.		1.000	CRS
11	Phayao	0.000	1	0.000	1	0.000	1	216,268	90	20.45	12	N.A.		1.000	CRS
12	Phayao	0.000	1	0.000	1	0.000	1	221,463	102	N.A.		N.A.		1.000	CRS
13	Phayao	0.000	1	0.000	1	0.000	1	178,468	37	N.A.		49.84	37	1.000	CRS
14	Phayao	0.000	1	0.000	1	0.000	1	142,113	18	N.A.		68.05	45	1.000	CRS
15	Phayao	0.141	133	0.164	133	0.076	133	206,976	72	N.A.		47.21	36	0.999	DRS
16	Phayao	0.000	1	0.000	1	0.000	1	178,860	38	N.A.		18.40	14	1.000	CRS
17	Phayao	0.082	116	0.089	116	0.043	116	231,895	133	0.96	2	41.15	33	0.918	IRS
18	Lampang	0.000	1	0.000	1	0.000	1	222,291	105	N.A.		N.A.		1.000	CRS
19	Lampang	0.000	1	0.000	1	0.000	1	231,607	131	N.A.		N.A.		1.000	CRS
20	Lampang	0.000	1	0.000	1	0.000	1	232,179	135	N.A.		N.A.		1.000	CRS
21	Lampang	0.000	1	0.000	1	0.000	1	221,608	103	N.A.		N.A.		1.000	CRS
22	Lampang	0.000	1	0.000	1	0.000	1	225,784	112	N.A.		N.A.		1.000	CRS
23	Lamphun	0.079	113	0.085	113	0.041	113	227,333	115	N.A.		72.01	48	0.921	DRS
24	Chiangmai	0.000	1	0.000	1	0.000	1	178,418	36	N.A.		N.A.		1.000	CRS
25	*Chiangmai*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*233,456*	*138*	*N.A.*		*0.00*	*1*	*1.000*	*CRS*
26	Chiangmai	0.000	1	0.000	1	0.000	1	209,772	77	45.08	18	21.78	17	1.000	CRS
27	Chiangmai	0.000	1	0.000	1	0.000	1	221,360	100	61.42	27	35.30	27	1.000	CRS
28	Chiangmai	0.000	1	0.000	1	0.000	1	249,071	150	N.A.		12.82	12	1.000	CRS
29	Maehongson	0.000	1	0.000	1	0.000	1	235,508	141	N.A.		N.A.		1.000	CRS
30	Maehongson	0.000	1	0.000	1	0.000	1	232,146	134	N.A.		N.A.		1.000	CRS
31	Maehongson	0.000	1	0.000	1	0.000	1	229,034	124	N.A.		N.A.		1.000	CRS
32	Maehongson	0.000	1	0.000	1	0.000	1	232,900	137	N.A.		N.A.		1.000	CRS
33	Maehongson	0.000	1	0.000	1	0.000	1	239,431	146	N.A.		7.22	5	1.000	CRS
34	Maehongson	0.000	1	0.000	1	0.000	1	238,776	145	N.A.		7.22	4	1.000	CRS
35	Tak	0.098	120	0.109	120	0.052	120	228,326	121	87.03	37	N.A.		0.997	IRS
36	Tak	0.000	1	0.000	1	0.000	1	213,910	85	46.17	19	N.A.		1.000	CRS
37	Tak	0.034	96	0.035	96	0.017	96	231,442	130	66.80	28	N.A.		0.966	IRS
38	Tak	0.114	126	0.128	126	0.060	126	234,513	139	80.54	36	28.67	20	0.886	IRS
39	Tak	0.006	86	0.006	86	0.003	86	231,416	129	5.15	5	N.A.		0.994	DRS
40	Tak	0.090	117	0.098	117	0.047	117	227,087	114	33.91	15	N.A.		0.910	IRS
41	Tak	0.000	1	0.000	1	0.000	1	228,368	122	N.A.		N.A.		1.000	CRS
42	Kamphaengphet	0.140	132	0.163	132	0.075	132	227,488	116	O		159.86	72	0.938	DRS
43	Kamphaengphet	0.173	144	0.209	144	0.095	144	249,757	151	190.81	64	100.91	55	0.995	DRS
44	Kamphaengphet	0.201	151	0.251	151	0.112	151	211,661	81	401.78	94	104.04	58	1.000	IRS
45	Kamphaengphet	0.190	148	0.234	148	0.105	148	188,201	47	352.11	89	127.50	67	0.990	DRS
46	Kamphaengphet	0.000	1	0.000	1	0.000	1	163,461	30	O		101.10	56	1.000	CRS
47	Kamphaengphet	0.129	130	0.148	130	0.069	130	221,825	104	317.84	84	N.A.		0.871	DRS
48	Kamphaengphet	0.099	121	0.110	121	0.052	121	227,946	118	195.53	66	N.A.		0.921	IRS
49	Kamphaengphet	0.152	138	0.180	138	0.083	138	196,127	58	79.62	35	O		0.942	DRS
50	Kamphaengphet	0.000	1	0.000	1	0.000	1	224,645	111	N.A.		N.A.		1.000	CRS
51	Kamphaengphet	0.153	140	0.181	140	0.083	140	231,674	132	54.60	22	N.A.		0.847	IRS
52	Kamphaengphet	0.127	128	0.145	128	0.068	128	199,056	64	180.29	60	7.47	6	0.895	DRS
53	Kamphaengphet	0.191	149	0.236	149	0.105	149	213,705	84	358.90	92	68.73	46	0.997	DRS
54	Kamphaengphet	0.201	152	0.251	152	0.112	152	210,879	78	447.09	97	119.93	65	0.988	DRS
55	Kamphaengphet	0.155	141	0.184	141	0.084	141	182,172	41	177.73	59	157.47	70	0.869	DRS
56	Kamphaengphet	0.170	143	0.205	143	0.093	143	191,315	50	377.29	93	104.91	59	1.000	DRS
57	Sukhothai	0.143	135	0.167	135	0.077	135	126,961	12	298.89	82	169.84	73	0.981	DRS
58	Sukhothai	0.188	147	0.232	147	0.104	147	228,062	119	306.89	83	56.24	41	1.000	IRS
59	Sukhothai	0.137	131	0.159	131	0.074	131	208,622	75	181.66	61	N.A.		1.000	CRS
60	Sukhothai	0.000	1	0.000	1	0.000	1	209,585	76	N.A.		N.A.		1.000	CRS
61	*Sukhothai*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*208,518*	*74*	*0.00*	*1*	*N.A.*		*1.000*	*CRS*
62	Sukhothai	0.185	146	0.226	146	0.102	146	214,702	86	145.03	52	68.87	47	0.997	DRS
63	Sukhothai	0.153	139	0.180	139	0.083	139	215,221	88	413.63	95	158.96	71	0.999	DRS
64	Sukhothai	0.142	134	0.166	134	0.077	134	211,035	79	75.95	33	26.63	19	1.000	CRS
65	Sukhothai	0.193	150	0.239	150	0.107	150	230,586	126	189.64	63	74.87	49	1.000	IRS
66	Sukhothai	0.144	136	0.168	136	0.078	136	245,206	148	150.23	54	O		1.000	DRS
67	Sukhothai	0.108	123	0.121	123	0.057	123	156,160	24	467.91	99	O		0.995	DRS
68	Sukhothai	0.108	124	0.121	124	0.057	124	239,940	147	128.84	47	N.A.		0.964	DRS
69	Sukhothai	0.027	94	0.028	94	0.014	94	136,406	13	236.54	74	N.A.		0.983	DRS
70	Phrae	0.049	104	0.051	104	0.025	104	214,704	87	10.81	10	N.A.		0.984	IRS
71	Phrae	0.063	112	0.067	112	0.033	112	211,823	82	43.29	17	34.19	24	0.980	IRS
72	Nan	0.039	102	0.041	102	0.020	102	228,739	123	N.A.		12.57	11	0.961	IRS
73	Nan	0.000	1	0.000	1	0.000	1	236,971	144	5.04	4	N.A.		1.000	CRS
74	Uttaradit	0.000	84	0.000	84	0.000	84	49,835	5	O		N.A.		1.000	DRS
75	Uttaradit	0.016	91	0.016	91	0.008	91	142,260	19	257.51	77	N.A.		0.995	DRS
76	Uttaradit	0.020	93	0.020	93	0.010	93	221,445	101	61.15	24	108.79	62	1.000	CRS
77	Uttaradit	0.000	1	0.000	1	0.000	1	180,619	39	N.A.		N.A.		1.000	CRS

Table D.4 Continued

Farm No.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
78	Uttaradit	0.000	1	0.000	1	0.000	1	136,668	14	N.A.		N.A.		1.000	CRS
79	Uttaradit	0.000	1	0.000	1	0.000	1	111,662	8	O		O		1.000	CRS
80	Uttaradit	0.000	1	0.000	1	0.000	1	94,964	7	O		N.A.		1.000	CRS
81	Uttaradit	0.000	1	0.000	1	0.000	1	216,324	91	213.06	71	N.A.		1.000	CRS
82	Phitsanulok	0.000	1	0.000	1	0.000	1	200,726	67	132.30	48	55.59	40	1.000	CRS
83	Phitsanulok	0.000	1	0.000	1	0.000	1	235,744	142	145.84	53	N.A.		1.000	CRS
84	Phitsanulok	0.000	1	0.000	1	0.000	1	197,586	63	165.90	58	N.A.		1.000	CRS
85	Phitsanulok	0.000	1	0.000	1	0.000	1	228,277	120	289.36	81	40.87	32	1.000	CRS
86	Phitsanulok	0.051	107	0.054	107	0.026	107	220,473	96	70.55	30	29.17	21	0.986	IRS
87	Phitsanulok	0.016	92	0.017	92	0.008	92	222,341	106	93.00	41	38.43	30	0.995	IRS
88	Phitsanulok	0.000	1	0.000	1	0.000	1	220,542	98	70.93	31	N.A.		1.000	CRS
89	Phitsanulok	0.001	85	0.001	85	0.000	85	194,000	53	61.31	25	75.50	50	0.999	DRS
90	Phitsanulok	0.000	1	0.000	1	0.000	1	206,816	70	245.20	75	N.A.		1.000	CRS
91	Phitsanulok	0.000	1	0.000	1	0.000	1	157,286	27	188.85	62	N.A.		1.000	CRS
92	Phitsanulok	0.000	1	0.000	1	0.000	1	156,508	25	263.03	78	120.88	66	1.000	CRS
93	Phitsanulok	0.000	1	0.000	1	0.000	1	173,214	35	198.71	68	11.40	9	1.000	CRS
94	Phitsanulok	0.000	1	0.000	1	0.000	1	137,144	15	268.68	79	114.01	63	1.000	CRS
95	Phitsanulok	0.000	1	0.000	1	0.000	1	171,352	34	357.23	91	N.A.		1.000	CRS
96	Phichit	0.000	1	0.000	1	0.000	1	223,193	110	119.16	46	N.A.		1.000	CRS
97	Phichit	0.000	1	0.000	1	0.000	1	190,726	49	89.08	39	N.A.		1.000	CRS
98	Phichit	0.052	108	0.055	108	0.027	108	200,800	68	420.84	96	O		0.997	IRS
99	Phichit	0.049	105	0.052	105	0.025	105	182,596	42	111.19	44	45.36	35	1.000	CRS
100	Phichit	0.000	1	0.000	1	0.000	1	251,777	152	53.49	21	N.A.		1.000	CRS
101	Phichit	0.000	1	0.000	1	0.000	1	193,970	51	356.98	90	O		1.000	CRS
102	Phichit	0.063	111	0.067	111	0.032	111	170,672	33	349.00	88	O		0.960	DRS
103	Phichit	0.031	95	0.032	95	0.016	95	232,883	136	10.55	9	51.68	38	0.969	IRS
104	Phichit	0.000	1	0.000	1	0.000	1	196,904	61	N.A.		1.98	2	1.000	CRS
105	Phichit	0.000	1	0.000	1	0.000	1	122,969	9	N.A.		N.A.		1.000	CRS
106	Phichit	0.000	1	0.000	1	0.000	1	207,858	73	N.A.		N.A.		1.000	CRS
107	Phichit	0.037	99	0.039	99	0.019	99	144,380	20	207.58	70	95.77	54	0.963	DRS
108	Phichit	0.038	101	0.040	101	0.019	101	193,988	52	330.83	87	N.A.		0.987	DRS
109	Phichit	0.007	88	0.007	88	0.004	88	126,154	11	N.A.		O		0.993	DRS
110	Nakhonsawan	0.055	110	0.058	110	0.028	110	182,160	40	246.93	76	102.55	57	1.000	IRS
111	Nakhonsawan	0.079	114	0.086	114	0.041	114	222,648	107	110.12	43	35.97	28	0.998	IRS
112	Nakhonsawan	0.014	90	0.014	90	0.007	90	215,392	89	161.21	57	9.17	8	0.997	IRS
113	Nakhonsawan	0.000	1	0.000	1	0.000	1	230,634	127	55.35	23	N.A.		1.000	CRS
114	Nakhonsawan	0.000	1	0.000	1	0.000	1	10,455	3	O		O		1.000	CRS
115	Nakhonsawan	0.038	100	0.039	100	0.019	100	138,722	16	134.26	49	107.73	61	0.962	DRS
116	Nakhonsawan	0.045	103	0.047	103	0.023	103	146,197	22	269.50	80	29.95	23	1.000	DRS
117	Nakhonsawan	0.000	1	0.000	1	0.000	1	41,838	4	558.57	100	N.A.		1.000	CRS
118	Nakhonsawan	0.000	1	0.000	1	0.000	1	187,457	46	N.A.		N.A.		1.000	CRS
119	Nakhonsawan	0.000	1	0.000	1	0.000	1	216,603	92	53.13	20	N.A.		1.000	CRS
120	Nakhonsawan	0.000	1	0.000	1	0.000	1	183,310	43	61.38	26	N.A.		1.000	CRS
121	Nakhonsawan	0.000	1	0.000	1	0.000	1	151,312	23	N.A.		29.68	22	1.000	CRS
122	Nakhonsawan	0.000	1	0.000	1	0.000	1	194,799	55	N.A.		37.92	29	1.000	CRS
123	Nakhonsawan	0.000	1	0.000	1	0.000	1	235,090	140	5.44	6	N.A.		1.000	CRS
124	Nakhonsawan	0.051	106	0.054	106	0.026	106	158,378	28	198.41	67	21.32	16	0.997	IRS
125	Nakhonsawan	0.054	109	0.057	109	0.028	109	220,499	97	104.17	42	8.32	7	0.949	IRS
126	Nakhonsawan	0.036	98	0.037	98	0.018	98	188,467	48	N.A.		34.99	25	0.994	DRS
127	Nakhonsawan	0.000	1	0.000	1	0.000	1	145,379	21	151.05	55	80.23	52	1.000	CRS
128	*Nakhonsawan*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*0*	*1*	*O*		*N.A.*		*1.000*	*CRS*
129	Nakhonsawan	0.000	1	0.000	1	0.000	1	218,638	93	39.59	16	N.A.		1.000	CRS
130	Nakhonsawan	0.000	1	0.000	1	0.000	1	141,759	17	22.59	13	133.81	69	1.000	CRS
131	Nakhonsawan	0.036	97	0.037	97	0.018	97	230,949	128	23.85	14	35.29	26	0.993	DRS
132	Nakhonsawan	0.093	118	0.102	118	0.049	118	196,610	60	74.73	32	58.32	42	0.981	DRS
133	Nakhonsawan	0.000	1	0.000	1	0.000	1	229,814	125	N.A.		6.28	3	1.000	CRS
134	Nakhonsawan	0.000	1	0.000	1	0.000	1	227,870	117	N.A.		12.29	10	1.000	CRS
135	Nakhonsawan	0.094	119	0.103	119	0.049	119	226,919	113	77.74	34	41.45	34	0.999	IRS
136	Uthaithani	0.152	137	0.179	137	0.082	137	206,841	71	225.81	72	N.A.		0.964	DRS
137	Uthaithani	0.121	127	0.138	127	0.064	127	185,885	45	203.36	69	81.29	53	0.999	DRS
138	Uthaithani	0.167	142	0.200	142	0.091	142	200,193	66	194.90	65	54.06	39	0.991	IRS
139	Uthaithani	0.113	125	0.127	125	0.060	125	220,319	95	113.44	45	60.08	43	0.998	DRS
140	Uthaithani	0.000	1	0.000	1	0.000	1	222,853	109	N.A.		N.A.		1.000	CRS
141	Uthaithani	0.129	129	0.148	129	0.069	129	157,093	26	329.68	86	132.28	68	0.908	DRS
142	Uthaithani	0.179	145	0.217	145	0.098	145	212,629	83	155.18	56	107.36	60	0.975	IRS
143	Uthaithani	0.102	122	0.113	122	0.053	122	195,591	56	327.48	85	23.56	18	0.898	DRS
144	Phetchabun	0.000	1	0.000	1	0.000	1	169,192	31	N.A.		N.A.		1.000	CRS
145	Phetchabun	0.000	1	0.000	1	0.000	1	88,310	6	69.25	29	O		1.000	CRS
146	Phetchabun	0.000	1	0.000	1	0.000	1	220,756	99	3.54	3	20.68	15	1.000	CRS
147	Phetchabun	0.000	1	0.000	1	0.000	1	200,121	65	N.A.		15.65	13	1.000	CRS
148	Phetchabun	0.000	1	0.000	1	0.000	1	169,750	32	O		O		1.000	CRS
149	Phetchabun	0.000	1	0.000	1	0.000	1	220,282	94	144.58	51	N.A.		1.000	CRS
150	Phetchabun	0.000	1	0.000	1	0.000	1	5,234	2	454.65	98	O		1.000	CRS
151	Phetchabun	0.000	1	0.000	1	0.000	1	185,709	44	90.68	40	115.73	64	1.000	CRS
152	Phetchabun	0.000	1	0.000	1	0.000	1	197,450	62	134.44	50	66.96	44	1.000	CRS

Note that DDF1 – DDF3 models are estimated under the assumption of CRS; DDF4, NSMM and PSMM are estimated under the assumption of VRS. N.A. denotes the farm had negative NS or negative PS. O denotes the farm is an outlier for NSMM or PSMM.

Table D.5 Ranking by different efficiency measures, returns to scale, technical, environmental, and scale efficiency estimates of non-jasmine rice farms in the North-eastern region

Farm No.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
1	Nongbualamphu	0.000	1	0.000	1	0.000	1	42,687	30	N.A.		N.A.		0.893	DRS
2	Nongkhai	0.161	52	0.142	52	0.076	53	42,618	29	2.62	2	18.31	21	0.994	DRS
3	Nongkhai	0.032	45	0.097	49	0.028	45	48,303	57	52.81	32	27.74	23	0.723	IRS
4	Nongkhai	0.000	1	0.000	1	0.000	1	43,413	38	7.25	7	41.18	28	0.840	DRS
5	Nongkhai	0.248	62	0.251	60	0.133	61	47,384	55	32.00	23	58.83	30	1.000	IRS
6	Nongkhai	0.000	1	0.000	1	0.000	1	48,210	56	N.A.		N.A.		1.000	CRS
7	Nongkhai	0.030	44	0.265	61	0.030	48	44,356	39	9.12	9	17.34	20	0.769	IRS
8	Nongkhai	0.000	1	0.000	1	0.000	1	44,742	42	34.08	25	O		0.792	DRS
9	Sakonnakhon	0.000	1	0.000	1	0.000	1	43,216	36	N.A.		N.A.		0.992	DRS
10	Sakonnakhon	0.040	46	0.040	43	0.020	44	42,002	23	4.13	4	15.00	18	0.968	DRS
11	Sakonnakhon	0.094	51	0.119	51	0.052	51	43,008	34	22.51	18	7.50	13	0.974	IRS
12	Sakonnakhon	0.000	1	0.000	1	0.000	1	45,568	49	33.93	24	29.19	24	0.908	IRS
13	Sakonnakhon	0.222	60	0.161	53	0.098	57	45,413	48	23.12	19	1.50	5	0.986	DRS
14	Sakonnakhon	0.069	50	0.055	44	0.030	47	38,725	10	49.69	29	N.A.		0.912	DRS
15	Sakonnakhon	0.183	57	0.200	55	0.101	58	42,212	25	17.21	17	11.45	15	0.999	IRS
16	Nakhonphanom	0.265	63	0.446	63	0.166	63	44,688	41	50.77	31	N.A.		0.910	IRS
17	Mukdahan	0.194	58	0.234	58	0.106	59	43,254	37	9.40	10	3.66	11	0.997	DRS
18	Mukdahan	0.232	61	0.315	62	0.134	62	39,598	13	11.95	13	4.64	12	0.990	IRS
19	Mukdahan	0.175	56	0.081	47	0.061	52	31,170	5	O		O		0.875	DRS
20	Mukdahan	0.200	59	0.244	59	0.110	60	40,305	15	9.60	11	3.60	10	0.998	DRS
21	Mukdahan	0.000	1	0.000	1	0.000	1	43,196	35	4.76	5	1.15	4	0.745	IRS
22	Amnatcharoen	0.000	1	0.000	1	0.000	1	44,657	40	N.A.		N.A.		1.000	CRS
23	*Ubonratchathani*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*42,220*	*26*	*37.38*	*27*	*0.00*	*1*	*1.000*	*CRS*
24	Ubonratchathani	0.000	1	0.000	1	0.000	1	39,410	11	64.49	34	13.30	17	1.000	CRS
25	Ubonratchathani	0.020	42	0.108	50	0.020	43	42,353	27	7.70	8	10.37	14	0.874	IRS
26	Sisaket	0.066	49	0.086	48	0.038	50	44,897	43	6.24	6	12.68	16	0.897	IRS
27	Sisaket	0.172	55	0.186	54	0.093	55	49,838	59	28.48	22	N.A.		1.000	DRS
28	Sisaket	0.000	1	0.000	1	0.000	1	46,594	52	49.97	30	N.A.		1.000	CRS
29	Sisaket	0.168	53	0.201	56	0.092	54	60,672	63	60.47	33	52.39	29	0.999	DRS
30	Sisaket	0.171	54	0.206	57	0.093	56	46,217	50	40.25	28	O		0.999	DRS
31	Sisaket	0.000	1	0.000	1	0.000	1	40,895	17	10.81	12	0.18	2	1.000	CRS
32	Surin	0.000	1	0.000	1	0.000	1	26,270	3	O		O		1.000	CRS
33	Surin	0.000	1	0.000	1	0.000	1	58,044	61	O		O		1.000	CRS
34	Surin	0.000	1	0.000	1	0.000	1	41,142	18	N.A.		0.57	3	1.000	CRS
35	Surin	0.000	1	0.000	1	0.000	1	42,449	28	N.A.		N.A.		1.000	CRS
36	Buriram	0.000	1	0.000	1	0.000	1	46,517	51	O		O		0.923	DRS
37	Buriram	0.000	1	0.000	1	0.000	1	42,850	32	N.A.		1.60	7	1.000	CRS
38	Buriram	0.000	1	0.000	1	0.000	1	42,204	24	N.A.		N.A.		1.000	CRS
39	Buriram	0.000	1	0.000	1	0.000	1	41,511	21	N.A.		2.86	9	1.000	CRS
40	*Buriram*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*41,250*	*20*	*0.00*	*1*	*2.69*	*8*	*1.000*	*CRS*
41	Buriram	0.060	48	0.056	45	0.029	46	49,472	58	O		35.45	26	0.917	DRS
42	Mahasarakham	0.000	1	0.000	1	0.000	1	25,958	2	O		O		1.000	CRS
43	Mahasarakham	0.059	47	0.064	46	0.031	49	47,176	54	14.98	14	16.86	19	0.994	IRS
44	Kalasin	0.000	1	0.000	1	0.000	1	42,792	31	23.69	20	37.48	27	1.000	CRS
45	Khonkaen	0.000	1	0.000	1	0.000	1	59,201	62	N.A.		N.A.		1.000	CRS
46	Khonkaen	0.000	1	0.000	1	0.000	1	55,373	60	N.A.		N.A.		1.000	CRS
47	Chaiyaphum	0.030	43	0.025	42	0.014	42	42,922	33	O		N.A.		0.972	DRS
48	Chaiyaphum	0.000	1	0.000	1	0.000	1	40,736	16	N.A.		1.57	6	1.000	CRS
49	Chaiyaphum	0.000	1	0.000	1	0.000	1	45,068	45	N.A.		N.A.		1.000	CRS
50	Chaiyaphum	0.000	1	0.000	1	0.000	1	34,274	7	O		N.A.		1.000	CRS
51	Nakhonratchasima	0.000	1	0.000	1	0.000	1	39,963	14	36.83	26	N.A.		1.000	CRS
52	Nakhonratchasima	0.000	1	0.000	1	0.000	1	41,205	19	15.00	15	N.A.		1.000	CRS
53	Nakhonratchasima	0.000	1	0.000	1	0.000	1	33,714	6	O		N.A.		1.000	CRS
54	Nakhonratchasima	0.000	1	0.000	1	0.000	1	41,870	22	O		N.A.		1.000	CRS
55	Nakhonratchasima	0.000	1	0.000	1	0.000	1	46,760	53	24.03	21	N.A.		1.000	CRS
56	Nakhonratchasima	0.000	1	0.000	1	0.000	1	45,052	44	3.34	3	31.13	25	1.000	CRS
57	Nakhonratchasima	0.006	41	0.006	41	0.003	41	45,248	47	17.04	16	22.00	22	1.000	DRS
58	*Nakhonratchasima*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*0*	*1*	*N.A.*		*O*		*1.000*	*CRS*
59	Nakhonratchasima	0.000	1	0.000	1	0.000	1	36,458	8	O		O		1.000	CRS
60	Nakhonratchasima	0.000	1	0.000	1	0.000	1	39,595	12	N.A.		N.A.		1.000	CRS
61	Nakhonratchasima	0.000	1	0.000	1	0.000	1	45,095	46	N.A.		O		1.000	CRS
62	Nakhonratchasima	0.000	1	0.000	1	0.000	1	37,324	9	O		O		1.000	CRS
63	Nakhonratchasima	0.000	1	0.000	1	0.000	1	29,371	4	O		O		1.000	CRS

Note that DDF1 – DDF4, NSMM, and PSMM models are estimated under the assumption of VRS. N.A. denotes the farm had negative NS or negative PS. O denotes the farm is an outlier for NSMM or PSMM.

Table D.6 Ranking by different efficiency measures, returns to scale, technical, environmental, and scale efficiency estimates of non-jasmine rice farms in the Central region

Farm No.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
1	Saraburi	0.082	133	0.089	133	0.043	133	339,360	136	559.25	157	72.01	66	0.925	DRS
2	Saraburi	0.252	189	0.336	189	0.144	189	366,744	199	138.90	77	56.20	52	1.000	IRS
3	Saraburi	0.000	1	0.000	1	0.000	1	334,208	128	28.41	18	N.A.		1.000	CRS
4	Saraburi	0.233	186	0.304	186	0.132	186	345,789	152	98.61	63	76.89	71	0.999	IRS
5	Saraburi	0.233	187	0.304	187	0.132	187	236,305	24	469.83	149	270.82	149	0.947	DRS
6	Saraburi	0.223	182	0.288	182	0.126	182	373,337	205	O		O		0.978	DRS
7	Saraburi	0.175	160	0.212	160	0.096	160	366,093	198	23.93	16	20.96	10	0.979	IRS
8	Saraburi	0.168	158	0.202	158	0.092	158	276,195	45	89.69	56	N.A.		0.832	DRS
9	Saraburi	0.090	137	0.099	137	0.047	137	344,807	149	63.02	36	23.12	11	1.000	CRS
10	Saraburi	0.227	185	0.294	185	0.128	185	346,208	153	87.61	53	179.84	119	1.000	IRS
11	Lopburi	0.168	159	0.203	159	0.092	159	344,477	147	99.53	64	55.80	49	1.000	IRS
12	Lopburi	0.181	163	0.222	163	0.100	163	321,590	97	177.32	92	74.55	68	1.000	IRS
13	Lopburi	0.074	128	0.080	128	0.038	128	327,839	113	44.60	30	N.A.		0.931	DRS
14	Lopburi	0.181	162	0.220	162	0.099	162	338,112	135	211.10	107	62.23	58	1.000	IRS
15	Lopburi	0.086	136	0.095	136	0.045	136	321,227	95	66.67	39	23.40	12	0.986	IRS
16	Lopburi	0.000	1	0.000	1	0.000	1	200,905	14	272.28	129	N.A.		1.000	CRS
17	Lopburi	0.124	143	0.141	143	0.066	143	350,426	168	55.47	32	35.07	30	0.950	IRS
18	Lopburi	0.049	122	0.052	122	0.025	122	327,529	112	37.61	23	N.A.		1.000	DRS
19	Lopburi	0.159	155	0.190	155	0.087	155	286,616	50	684.41	164	250.41	147	0.992	DRS
20	Lopburi	0.000	1	0.000	1	0.000	1	301,760	72	78.41	48	N.A.		1.000	CRS
21	Lopburi	0.000	1	0.000	1	0.000	1	269,848	39	56.61	34	N.A.		1.000	CRS
22	Singburi	0.006	90	0.006	90	0.003	90	333,569	124	271.61	128	N.A.		0.997	IRS
23	Singburi	0.029	113	0.029	113	0.014	113	239,718	25	254.93	117	247.93	146	0.999	DRS
24	Singburi	0.014	100	0.014	100	0.007	100	332,641	121	55.79	33	35.43	32	0.986	IRS
25	Singburi	0.040	120	0.042	120	0.021	120	325,521	110	124.74	72	112.53	93	0.995	IRS
26	Singburi	0.000	1	0.000	1	0.000	1	323,111	102	333.30	137	138.37	107	1.000	CRS
27	Singburi	0.016	102	0.017	102	0.008	102	288,721	52	268.82	127	108.81	91	0.999	IRS
28	Singburi	0.040	118	0.042	118	0.020	118	328,348	114	173.83	89	77.16	72	0.998	IRS
29	Singburi	0.012	97	0.012	97	0.006	97	328,679	116	139.26	79	100.76	88	0.999	IRS
30	Singburi	0.000	1	0.000	1	0.000	1	302,563	74	8.03	6	201.78	132	1.000	CRS
31	Singburi	0.011	95	0.011	95	0.005	95	332,855	123	186.99	97	108.65	90	1.000	DRS
32	Chainat	0.000	1	0.000	1	0.000	1	359,056	182	87.13	51	89.18	80	1.000	CRS
33	Chainat	0.031	114	0.032	114	0.016	114	340,333	138	125.56	74	202.38	134	0.999	IRS
34	Chainat	0.000	1	0.000	1	0.000	1	343,197	143	N.A.		N.A.		1.000	CRS
35	Chainat	0.009	94	0.009	94	0.005	94	265,308	35	161.89	84	191.94	128	0.997	DRS
36	Chainat	0.006	91	0.006	91	0.003	91	309,483	82	163.67	85	45.49	40	0.999	DRS
37	Chainat	0.003	89	0.003	89	0.001	89	190,869	12	260.95	123	132.93	105	0.997	DRS
38	Chainat	0.000	1	0.000	1	0.000	1	209,587	16	416.67	143	64.91	63	1.000	CRS
39	Chainat	0.000	1	0.000	1	0.000	1	300,631	70	195.98	102	N.A.		1.000	CRS
40	Chainat	0.000	1	0.000	1	0.000	1	343,249	144	253.29	116	N.A.		1.000	CRS
41	Chainat	0.000	1	0.000	1	0.000	1	321,965	98	323.72	135	278.05	150	1.000	CRS
42	Chainat	0.017	103	0.018	103	0.009	103	223,758	20	155.80	83	29.23	22	0.997	DRS
43	Chainat	0.000	1	0.000	1	0.000	1	301,848	73	N.A.		N.A.		1.000	CRS
44	Suphanburi	0.000	1	0.000	1	0.000	1	336,100	131	92.52	61	27.80	18	1.000	CRS
45	Suphanburi	0.000	1	0.000	1	0.000	1	296,830	63	123.11	71	N.A.		1.000	CRS
46	Suphanburi	0.000	1	0.000	1	0.000	1	324,467	104	6.49	4	167.75	115	1.000	CRS
47	Suphanburi	0.000	1	0.000	1	0.000	1	267,314	37	195.49	101	N.A.		1.000	CRS
48	Suphanburi	0.000	1	0.000	1	0.000	1	294,256	58	92.11	60	N.A.		1.000	CRS
49	Suphanburi	0.000	1	0.000	1	0.000	1	296,754	62	185.53	96	200.93	131	1.000	CRS
50	Suphanburi	0.000	1	0.000	1	0.000	1	221,524	19	O		220.18	138	1.000	CRS
51	Suphanburi	0.000	1	0.000	1	0.000	1	368,529	200	228.38	111	63.62	59	1.000	CRS
52	Suphanburi	0.000	1	0.000	1	0.000	1	349,246	160	173.32	88	99.95	87	1.000	CRS
53	Suphanburi	0.001	87	0.001	87	0.000	87	336,494	133	117.54	69	153.64	110	1.000	IRS
54	Suphanburi	0.000	1	0.000	1	0.000	1	336,668	134	87.56	52	32.99	27	1.000	CRS
55	Suphanburi	0.000	1	0.000	1	0.000	1	324,888	107	82.73	49	31.13	24	1.000	CRS
56	Suphanburi	0.000	1	0.000	1	0.000	1	293,547	57	N.A.		N.A.		1.000	CRS
57	Suphanburi	0.000	1	0.000	1	0.000	1	341,616	140	319.02	134	N.A.		1.000	CRS
58	*Suphanburi*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*330,371*	*120*	*N.A.*		*0.00*	*1*	*1.000*	*CRS*
59	Angthong	0.000	1	0.000	1	0.000	1	250,688	28	N.A.		N.A.		1.000	CRS
60	Angthong	0.119	142	0.135	142	0.063	142	334,131	127	11.77	10	40.08	36	0.998	IRS
61	Angthong	0.040	117	0.042	117	0.020	117	318,902	91	146.18	81	74.96	69	1.000	IRS
62	Angthong	0.000	1	0.000	1	0.000	1	292,726	56	N.A.		3.29	3	1.000	CRS
63	Angthong	0.000	1	0.000	1	0.000	1	349,970	165	74.14	45	32.53	26	1.000	CRS
64	Angthong	0.135	146	0.156	146	0.072	146	347,174	156	7.42	5	N.A.		0.960	IRS
65	Angthong	0.000	1	0.000	1	0.000	1	256,350	33	O		N.A.		1.000	CRS
66	Angthong	0.081	132	0.088	132	0.042	132	324,609	106	201.23	103	87.04	78	0.995	IRS
67	Angthong	0.064	125	0.069	125	0.033	125	339,936	137	N.A.		N.A.		0.999	IRS
68	Angthong	0.000	1	0.000	1	0.000	1	371,043	203	43.73	28	28.77	21	1.000	CRS
69	Ayutthaya	0.146	148	0.171	148	0.079	148	324,528	105	404.70	141	155.29	111	0.983	DRS
70	Ayutthaya	0.000	1	0.000	1	0.000	1	273,672	42	113.05	67	64.16	61	1.000	CRS
71	Ayutthaya	0.000	1	0.000	1	0.000	1	350,334	167	N.A.		N.A.		1.000	CRS
72	Ayutthaya	0.000	1	0.000	1	0.000	1	346,340	154	N.A.		N.A.		1.000	CRS
73	Ayutthaya	0.154	149	0.181	149	0.083	149	298,172	65	47.92	31	N.A.		0.865	DRS
74	Ayutthaya	0.157	152	0.187	152	0.085	152	350,068	166	41.18	27	26.38	17	0.982	IRS
75	Ayutthaya	0.000	1	0.000	1	0.000	1	361,875	189	N.A.		N.A.		1.000	CRS

Table D.6 Continued

Farm No.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
76	Ayutthaya	0.000	1	0.000	1	0.000	1	357,034	177	N.A.		N.A.		1.000	CRS
77	Ayutthaya	0.158	153	0.187	153	0.086	153	319,823	92	110.39	66	59.24	54	0.999	IRS
78	Ayutthaya	0.158	154	0.188	154	0.086	154	358,191	179	12.40	11	N.A.		0.842	IRS
79	Ayutthaya	0.143	147	0.166	147	0.077	147	322,409	100	326.87	136	84.39	75	0.996	IRS
80	Ayutthaya	0.127	145	0.145	145	0.068	145	358,964	181	293.76	132	240.68	144	0.965	DRS
81	Nonthaburi	0.028	112	0.029	112	0.014	112	277,413	47	255.14	118	90.32	82	0.998	DRS
82	Nonthaburi	0.023	107	0.024	107	0.012	107	323,087	101	203.53	104	93.54	84	0.999	DRS
83	Nonthaburi	0.000	1	0.000	1	0.000	1	314,295	87	91.39	58	N.A.		1.000	CRS
84	Nonthaburi	0.025	109	0.025	109	0.013	109	267,983	38	226.41	110	112.47	92	0.999	DRS
85	Nonthaburi	0.026	110	0.027	110	0.013	110	307,871	79	210.57	106	153.06	109	0.999	IRS
86	Nonthaburi	0.035	116	0.037	116	0.018	116	298,813	68	261.20	124	126.40	101	1.000	IRS
87	Nonthaburi	0.021	105	0.021	105	0.010	105	202,525	15	248.87	113	186.83	126	0.997	DRS
88	Bangkok	0.000	1	0.000	1	0.000	1	325,031	108	98.01	62	129.89	103	1.000	CRS
89	Bangkok	0.000	1	0.000	1	0.000	1	298,744	67	91.88	59	N.A.		1.000	CRS
90	Bangkok	0.000	1	0.000	1	0.000	1	256,059	32	259.45	121	188.79	127	1.000	CRS
91	Bangkok	0.024	108	0.024	108	0.012	108	275,918	44	O		325.30	152	0.976	DRS
92	Bangkok	0.019	104	0.020	104	0.010	104	346,629	155	74.33	46	31.14	25	0.995	IRS
93	Bangkok	0.000	1	0.000	1	0.000	1	314,784	88	71.65	43	236.79	142	1.000	CRS
94	Pathumthani	0.001	88	0.001	88	0.001	88	255,639	31	456.67	147	85.09	76	0.999	DRS
95	Pathumthani	0.000	1	0.000	1	0.000	1	148,264	8	70.57	41	O		1.000	CRS
96	Pathumthani	0.000	1	0.000	1	0.000	1	334,044	126	64.72	38	46.83	41	1.000	CRS
97	Pathumthani	0.000	1	0.000	1	0.000	1	253,212	30	192.78	99	120.83	99	1.000	CRS
98	Pathumthani	0.000	1	0.000	1	0.000	1	329,215	118	70.91	42	48.04	42	1.000	CRS
99	Pathumthani	0.000	1	0.000	1	0.000	1	312,451	86	191.74	98	63.63	60	1.000	CRS
100	Pathumthani	0.000	1	0.000	1	0.000	1	143,648	7	535.46	155	233.00	141	1.000	CRS
101	Pathumthani	0.021	106	0.021	106	0.011	106	320,227	93	261.26	125	117.46	97	0.999	IRS
102	Pathumthani	0.008	93	0.008	93	0.004	93	209,877	17	372.88	140	171.93	118	0.992	DRS
103	Pathumthani	0.000	1	0.000	1	0.000	1	226,014	21	184.26	94	199.67	130	1.000	CRS
104	Nakhonnayok	0.000	1	0.000	1	0.000	1	334,577	130	63.80	37	26.24	15	1.000	CRS
105	Nakhonnayok	0.000	1	0.000	1	0.000	1	317,001	90	N.A.		95.04	85	1.000	CRS
106	Nakhonnayok	0.000	1	0.000	1	0.000	1	292,073	55	N.A.		28.58	19	1.000	CRS
107	Nakhonnayok	0.000	1	0.000	1	0.000	1	321,379	96	38.80	25	59.77	55	1.000	CRS
108	Nakhonnayok	0.000	1	0.000	1	0.000	1	328,606	115	N.A.		66.19	64	1.000	CRS
109	Nakhonnayok	0.000	1	0.000	1	0.000	1	342,304	141	N.A.		40.94	38	1.000	CRS
110	Nakhonnayok	0.001	86	0.001	86	0.000	86	296,175	61	N.A.		142.22	108	0.999	DRS
111	Nakhonnayok	0.208	172	0.262	172	0.116	172	320,315	94	249.15	114	113.82	95	0.997	DRS
112	Nakhonnayok	0.210	173	0.266	173	0.117	173	315,942	89	632.49	161	396.30	154	0.994	DRS
113	Nakhonnayok	0.212	175	0.270	175	0.119	175	349,341	161	145.32	80	59.77	56	0.998	DRS
114	Nakhonnayok	0.211	174	0.267	174	0.118	174	322,275	99	176.61	90	73.88	67	0.987	DRS
115	Nakhonnayok	0.154	150	0.182	150	0.083	150	323,184	103	290.69	130	N.A.		0.846	DRS
116	Prachinburi	0.000	1	0.000	1	0.000	1	334,417	129	176.68	91	N.A.		1.000	CRS
117	Prachinburi	0.040	119	0.042	119	0.020	119	352,389	171	25.91	17	9.02	7	0.960	IRS
118	Prachinburi	0.000	1	0.000	1	0.000	1	348,895	159	N.A.		34.56	29	1.000	CRS
119	Prachinburi	0.370	198	0.587	198	0.227	198	438,730	214	O		O		0.983	DRS
120	Prachinburi	0.155	151	0.183	151	0.084	151	359,934	185	138.89	76	41.94	39	0.999	IRS
121	Prachinburi	0.377	199	0.606	199	0.233	199	373,447	207	466.11	148	220.08	137	0.985	DRS
122	Prachinburi	0.348	194	0.533	194	0.211	194	352,640	173	479.91	151	239.24	143	0.997	IRS
123	Prachinburi	0.365	197	0.575	197	0.223	197	360,607	188	408.20	142	157.44	113	0.999	DRS
124	Prachinburi	0.194	167	0.241	167	0.107	167	310,240	84	216.97	108	210.29	135	0.806	DRS
125	Prachinburi	0.000	1	0.000	1	0.000	1	345,110	150	N.A.		7.80	6	1.000	CRS
126	Prachinburi	0.189	164	0.232	164	0.104	164	325,400	109	347.18	138	245.90	145	0.972	DRS
127	Prachinburi	0.365	196	0.575	196	0.223	196	353,977	174	292.29	131	163.06	114	1.000	DRS
128	Chachoengsao	0.218	180	0.279	180	0.123	180	306,695	76	O		O		1.000	IRS
129	Chachoengsao	0.243	188	0.321	188	0.138	188	307,009	77	650.72	163	222.87	139	0.974	DRS
130	Chachoengsao	0.177	161	0.216	161	0.097	161	369,521	202	O		N.A.		0.911	DRS
131	Chachoengsao	0.190	166	0.235	166	0.105	166	349,347	162	219.47	109	119.83	98	0.994	IRS
132	Chachoengsao	0.226	184	0.291	184	0.127	184	265,548	36	O		O		0.965	DRS
133	Chachoengsao	0.220	181	0.282	181	0.124	181	273,065	41	510.85	153	184.50	125	0.999	DRS
134	Chachoengsao	0.224	183	0.288	183	0.126	183	356,530	176	62.48	35	28.63	20	1.000	DRS
135	Chachoengsao	0.000	1	0.000	1	0.000	1	355,588	175	N.A.		N.A.		1.000	CRS
136	Chachoengsao	0.000	1	0.000	1	0.000	1	360,225	187	N.A.		N.A.		1.000	CRS
137	Chachoengsao	0.046	121	0.048	121	0.023	121	362,009	190	N.A.		29.80	23	0.954	IRS
138	Sakaeo	0.498	208	0.991	208	0.331	208	375,795	208	22.66	15	N.A.		0.977	DRS
139	Sakaeo	0.000	1	0.000	1	0.000	1	349,895	164	N.A.		N.A.		1.000	CRS
140	Sakaeo	0.338	193	0.512	193	0.204	193	362,866	191	N.A.		N.A.		0.998	DRS
141	Sakaeo	0.442	206	0.792	206	0.284	206	364,152	193	33.59	21	183.25	124	0.982	DRS
142	Sakaeo	0.513	211	1.053	211	0.345	211	368,697	201	9.35	8	50.93	47	1.000	CRS
143	Sakaeo	0.301	191	0.430	191	0.177	191	342,483	142	164.06	86	89.93	81	0.993	IRS
144	Sakaeo	0.522	214	1.091	214	0.353	214	392,101	211	44.35	29	55.83	50	0.790	DRS
145	Sakaeo	0.379	200	0.609	200	0.233	200	358,618	180	33.48	20	34.28	28	0.981	DRS
146	Sakaeo	0.350	195	0.539	195	0.212	195	343,950	145	N.A.		N.A.		0.795	DRS
147	Chanthaburi	0.514	212	1.058	212	0.346	212	379,977	209	72.52	44	48.18	43	0.976	IRS
148	Chanthaburi	0.520	213	1.082	213	0.351	213	382,913	210	118.99	70	117.09	96	0.985	IRS
149	Chanthaburi	0.472	207	0.895	207	0.309	207	363,522	192	89.92	57	87.38	79	0.987	DRS
150	Chanthaburi	0.512	210	1.050	210	0.344	210	365,500	195	40.41	26	25.56	14	0.700	IRS
151	Chanthaburi	0.506	209	1.023	209	0.338	209	365,315	194	104.82	65	79.53	73	0.989	IRS

Table D.6 Continued

Farm No.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
152	Trat	0.194	168	0.241	168	0.108	168	227,496	23	450.23	145	306.06	151	0.806	DRS
153	Trat	0.016	101	0.016	101	0.008	101	276,663	46	310.21	133	39.66	35	0.984	DRS
154	Trat	0.072	127	0.077	127	0.037	127	330,249	119	139.21	78	4.22	5	0.944	DRS
155	Trat	0.160	156	0.190	156	0.087	156	241,243	26	180.10	93	130.80	104	0.904	DRS
156	Rayong	0.394	201	0.650	201	0.245	201	365,779	196	2.00	2	35.07	31	0.923	IRS
157	Rayong	0.419	205	0.722	205	0.265	205	433,263	213	570.03	159	O		1.000	DRS
158	Rayong	0.406	203	0.685	203	0.255	203	371,420	204	451.02	146	171.13	117	0.999	DRS
159	Rayong	0.411	204	0.697	204	0.258	204	395,275	212	O		O		0.999	DRS
160	Rayong	0.401	202	0.670	202	0.251	202	373,370	206	N.A.		123.09	100	0.996	IRS
161	Chonburi	0.075	130	0.081	130	0.039	130	275,831	43	N.A.		98.86	86	0.926	DRS
162	Chonburi	0.126	144	0.145	144	0.067	144	251,386	29	11.09	9	129.58	102	0.979	DRS
163	Chonburi	0.013	99	0.013	99	0.007	99	310,760	85	N.A.		23.55	13	0.987	DRS
164	Chonburi	0.074	129	0.080	129	0.038	129	246,127	27	N.A.		91.89	83	0.926	DRS
165	*Chonburi*	*0.080*	*131*	*0.086*	*131*	*0.041*	*131*	*351,849*	*170*	*0.00*	*1*	*39.34*	*34*	*0.975*	*IRS*
166	Chonburi	0.000	1	0.000	1	0.000	1	336,320	132	N.A.		N.A.		1.000	CRS
167	Chonburi	0.000	1	0.000	1	0.000	1	281,744	48	N.A.		N.A.		1.000	CRS
168	Samutprakan	0.000	1	0.000	1	0.000	1	163,919	9	255.50	120	181.64	121	1.000	CRS
169	Samutprakan	0.000	1	0.000	1	0.000	1	166,631	10	N.A.		261.98	148	1.000	CRS
170	Samutprakan	0.000	1	0.000	1	0.000	1	286,737	51	76.54	47	56.61	53	1.000	CRS
171	Samutprakan	0.000	1	0.000	1	0.000	1	105,431	3	N.A.		O		1.000	CRS
172	Samutsakhon	0.104	140	0.116	140	0.055	140	333,993	125	259.65	122	112.99	94	0.996	DRS
173	Samutsakhon	0.013	98	0.013	98	0.007	98	347,744	158	204.79	105	83.57	74	0.987	DRS
174	Samutsakhon	0.067	126	0.072	126	0.035	126	347,410	157	69.95	40	68.46	65	0.970	DRS
175	Samutsakhon	0.109	141	0.122	141	0.057	141	365,964	197	84.68	50	26.24	16	0.997	DRS
176	Samutsakhon	0.102	139	0.114	139	0.054	139	256,780	34	477.63	150	210.96	136	0.977	DRS
177	Nakhonpathom	0.000	1	0.000	1	0.000	1	349,717	163	18.23	13	3.19	2	1.000	CRS
178	Nakhonpathom	0.000	1	0.000	1	0.000	1	220,290	18	267.25	126	49.99	45	1.000	CRS
179	Nakhonpathom	0.007	92	0.007	92	0.003	92	291,061	53	444.25	144	168.95	116	0.998	DRS
180	Nakhonpathom	0.000	1	0.000	1	0.000	1	351,066	169	N.A.		13.75	8	1.000	CRS
181	Nakhonpathom	0.026	111	0.027	111	0.013	111	103,156	2	O		O		0.974	DRS
182	Nakhonpathom	0.000	1	0.000	1	0.000	1	308,443	80	13.19	12	14.12	9	1.000	CRS
183	Nakhonpathom	0.000	1	0.000	1	0.000	1	291,991	54	9.24	7	55.97	51	1.000	CRS
184	Nakhonpathom	0.000	1	0.000	1	0.000	1	110,131	4	N.A.		N.A.		1.000	CRS
185	Nakhonpathom	0.000	1	0.000	1	0.000	1	126,049	5	251.25	115	137.59	106	1.000	CRS
186	Kanchanaburi	0.011	96	0.011	96	0.005	96	359,746	184	116.12	68	76.22	70	0.993	IRS
187	Kanchanaburi	0.000	1	0.000	1	0.000	1	191,228	13	O		O		1.000	CRS
188	Kanchanaburi	0.051	123	0.053	123	0.026	123	270,752	40	192.92	100	182.71	122	0.956	DRS
189	Kanchanaburi	0.063	124	0.067	124	0.032	124	307,769	78	569.82	158	328.50	153	0.937	DRS
190	Kanchanaburi	0.086	135	0.094	135	0.045	135	168,447	11	O		O		0.931	DRS
191	Kanchanaburi	0.000	1	0.000	1	0.000	1	328,839	117	20.91	14	102.53	89	1.000	CRS
192	*Kanchanaburi*	*0.031*	*115*	*0.032*	*115*	*0.016*	*115*	*0*	*1*	*O*		*O*		*0.969*	*DRS*
193	Kanchanaburi	0.083	134	0.091	134	0.043	134	344,523	148	37.05	22	49.36	44	1.000	CRS
194	Kanchanaburi	0.000	1	0.000	1	0.000	1	226,892	22	229.45	112	N.A.		1.000	CRS
195	Kanchanaburi	0.093	138	0.103	138	0.049	138	294,422	59	638.04	162	O		0.998	DRS
196	Ratchaburi	0.000	1	0.000	1	0.000	1	139,553	6	O		182.72	123	1.000	CRS
197	Ratchaburi	0.000	1	0.000	1	0.000	1	326,886	111	129.25	75	85.43	77	1.000	CRS
198	Ratchaburi	0.000	1	0.000	1	0.000	1	300,135	69	184.71	95	64.70	62	1.000	CRS
199	Ratchaburi	0.000	1	0.000	1	0.000	1	298,458	66	89.36	55	50.93	46	1.000	CRS
200	Ratchaburi	0.000	1	0.000	1	0.000	1	357,960	178	3.18	3	3.67	4	1.000	CRS
201	Phetchaburi	0.217	178	0.276	178	0.121	178	297,157	64	506.03	152	198.84	129	1.000	CRS
202	Phetchaburi	0.217	179	0.277	179	0.121	179	301,570	71	517.64	154	201.86	133	1.000	CRS
203	Phetchaburi	0.216	177	0.276	177	0.121	177	294,874	60	575.71	160	226.83	140	0.889	DRS
204	Phetchaburi	0.214	176	0.273	176	0.120	176	359,146	183	155.42	82	60.07	57	1.000	CRS
205	Phetchaburi	0.000	1	0.000	1	0.000	1	345,526	151	87.91	54	N.A.		1.000	CRS
206	Phetchaburi	0.000	1	0.000	1	0.000	1	332,722	122	538.69	156	N.A.		1.000	CRS
207	Phetchaburi	0.000	1	0.000	1	0.000	1	303,076	75	33.19	19	155.62	112	1.000	CRS
208	Phetchaburi	0.160	157	0.191	157	0.087	157	284,571	49	255.16	119	181.63	120	0.969	DRS
209	Phetchaburi	0.205	170	0.258	170	0.114	170	352,438	172	125.01	73	51.10	48	0.995	IRS
210	Prachuapkhirikhan	0.189	165	0.233	165	0.104	165	360,207	186	N.A.		N.A.		0.990	DRS
211	Prachuapkhirikhan	0.195	169	0.242	169	0.108	169	309,683	83	N.A.		N.A.		0.805	DRS
212	Prachuapkhirikhan	0.313	192	0.455	192	0.185	192	341,265	139	37.70	24	40.78	37	0.970	DRS
213	Prachuapkhirikhan	0.289	190	0.407	190	0.169	190	343,981	146	168.18	87	36.79	33	0.999	DRS
214	Prachuapkhirikhan	0.205	171	0.259	171	0.114	171	308,527	81	358.35	139	N.A.		0.795	DRS

Note that DDF1 – DDF3 models are estimated under the assumption of CRS; DDF4, NSMM and PSMM are estimated under the assumption of VRS. N.A. denotes the farm had negative NS or negative PS. O denotes the farm is an outlier for NSMM or PSMM.

Table D.7 Ranking by different efficiency measures, returns to scale, technical, environmental, and scale efficiency estimates of non-jasmine rice farms in the Southern region

Farm No.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
1	Chumphon	0.260	83	0.352	83	0.150	83	155,795	84	128.27	46	84.41	57	0.978	DRS
2	Chumphon	0.255	80	0.342	80	0.146	80	140,021	35	O		O		0.992	DRS
3	Chumphon	0.231	77	0.300	77	0.130	77	148,941	56	91.89	40	25.52	39	0.995	DRS
4	Chumphon	0.252	79	0.337	79	0.144	79	170,163	99	O		O		0.971	DRS
5	Chumphon	0.217	76	0.277	76	0.121	76	182,986	100	214.47	50	31.42	44	0.834	DRS
6	Chumphon	0.207	73	0.261	73	0.116	73	146,920	51	72.65	38	34.34	47	0.930	DRS
7	Chumphon	0.243	78	0.322	78	0.139	78	152,400	68	63.04	37	48.45	51	0.973	DRS
8	Chumphon	0.264	84	0.358	84	0.152	84	159,092	96	16.43	21	3.60	6	0.874	IRS
9	Suratthani	0.000	1	0.000	1	0.000	1	142,694	41	N.A.		10.61	17	1.000	CRS
10	Suratthani	0.000	1	0.000	1	0.000	1	146,943	52	3.59	7	16.61	30	1.000	CRS
11	Suratthani	0.000	1	0.000	1	0.000	1	142,243	40	21.10	23	11.59	18	1.000	CRS
12	Suratthani	0.004	47	0.004	47	0.002	47	128,319	22	55.22	35	55.71	52	0.996	DRS
13	Suratthani	0.004	48	0.004	48	0.002	48	123,755	17	15.22	20	71.58	56	0.996	DRS
14	Suratthani	0.000	1	0.000	1	0.000	1	123,962	18	104.32	41	N.A.		1.000	CRS
15	Krabi	0.375	96	0.600	96	0.231	96	156,771	89	O		O		0.684	IRS
16	Krabi	0.000	1	0.000	1	0.000	1	157,417	93	N.A.		N.A.		1.000	CRS
17	Krabi	0.000	1	0.000	1	0.000	1	157,272	92	N.A.		N.A.		1.000	CRS
18	Krabi	0.000	1	0.000	1	0.000	1	159,458	98	N.A.		N.A.		1.000	CRS
19	Krabi	0.348	93	0.535	93	0.211	93	156,132	86	N.A.		1.41	3	0.719	IRS
20	Krabi	0.000	1	0.000	1	0.000	1	155,724	82	N.A.		N.A.		1.000	CRS
21	Trang	0.256	81	0.344	81	0.147	81	155,791	83	0.68	3	10.55	16	0.789	IRS
22	Trang	0.000	1	0.000	1	0.000	1	155,329	80	N.A.		5.60	7	1.000	CRS
23	Trang	0.392	99	0.646	99	0.244	99	156,433	88	11.75	17	29.22	43	0.947	IRS
24	Trang	0.380	97	0.612	97	0.234	97	154,322	76	N.A.		O		0.722	DRS
25	Trang	0.383	98	0.620	98	0.237	98	159,350	97	O		O		0.924	DRS
26	Trang	0.000	1	0.000	1	0.000	1	156,816	91	N.A.		N.A.		1.000	CRS
27	Trang	0.000	1	0.000	1	0.000	1	156,176	87	N.A.		N.A.		1.000	CRS
28	Trang	0.286	86	0.400	86	0.167	86	158,176	95	27.34	26	56.31	53	0.714	DRS
29	Trang	0.397	100	0.657	100	0.247	100	157,655	94	9.13	15	17.17	31	0.756	IRS
30	Nakhonsithammarat	0.213	75	0.270	75	0.119	75	96,136	12	O		O		0.787	DRS
31	Nakhonsithammarat	0.209	74	0.263	74	0.116	74	139,943	33	O		O		0.987	DRS
32	Nakhonsithammarat	0.000	1	0.000	1	0.000	1	156,778	90	N.A.		N.A.		1.000	CRS
33	Nakhonsithammarat	0.023	54	0.023	54	0.011	54	146,772	49	N.A.		6.39	9	0.977	DRS
34	Nakhonsithammarat	0.000	1	0.000	1	0.000	1	131,391	25	N.A.		N.A.		1.000	CRS
35	Nakhonsithammarat	0.188	69	0.232	69	0.104	69	152,624	70	16.80	22	N.A.		0.997	IRS
36	Nakhonsithammarat	0.207	72	0.261	72	0.115	72	125,794	20	O		O		0.959	DRS
37	Nakhonsithammarat	0.188	70	0.232	70	0.104	70	146,756	47	123.72	45	O		0.993	IRS
38	Phatthalung	0.117	64	0.133	64	0.062	64	149,308	59	N.A.		8.16	11	0.883	IRS
39	Phatthalung	0.125	66	0.143	66	0.067	66	151,177	65	43.67	30	8.17	12	0.919	IRS
40	Phatthalung	0.066	58	0.071	58	0.034	58	144,174	42	N.A.		26.91	40	0.979	DRS
41	Phatthalung	0.068	59	0.073	59	0.035	59	145,548	46	40.04	29	7.89	10	0.996	DRS
42	Phatthalung	0.092	61	0.101	61	0.048	61	112,996	14	12.52	18	31.52	45	0.908	DRS
43	Phatthalung	0.085	60	0.093	60	0.044	60	76,369	6	3.46	6	103.00	59	0.915	DRS
44	Phatthalung	0.009	50	0.009	50	0.004	50	140,898	37	N.A.		11.85	19	0.991	IRS
45	Phatthalung	0.118	65	0.134	65	0.063	65	139,985	34	N.A.		14.37	22	0.995	IRS
46	Phatthalung	0.000	1	0.000	1	0.000	1	120,554	16	N.A.		44.39	48	1.000	CRS
47	Phatthalung	0.000	1	0.000	1	0.000	1	146,766	48	N.A.		0.98	2	1.000	CRS
48	Phatthalung	0.000	1	0.000	1	0.000	1	134,186	27	105.19	42	16.51	29	1.000	CRS
49	Phatthalung	0.000	1	0.000	1	0.000	1	150,202	62	14.66	19	10.16	15	1.000	CRS
50	Phatthalung	0.000	1	0.000	1	0.000	1	131,019	23	N.A.		20.89	36	1.000	CRS
51	Phatthalung	0.014	53	0.014	53	0.007	53	135,270	28	54.96	34	28.54	42	0.986	DRS
52	Phatthalung	0.000	1	0.000	1	0.000	1	149,146	58	23.68	24	16.14	27	1.000	CRS
53	Phatthalung	0.010	51	0.010	51	0.005	51	65,624	5	91.27	39	O		0.990	DRS
54	Phatthalung	0.107	63	0.119	63	0.056	63	78,323	7	O		O		0.893	DRS
55	*Phatthalung*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*146,807*	*50*	*0.00*	*1*	*27.64*	*41*	*1.000*	*CRS*
56	Phatthalung	0.000	1	0.000	1	0.000	1	125,913	21	49.96	32	O		1.000	CRS
57	Phatthalung	0.054	56	0.057	56	0.028	56	137,632	31	26.62	25	18.95	35	0.946	DRS
58	Songkhla	0.000	1	0.000	1	0.000	1	115,940	15	O		N.A.		1.000	CRS
59	Songkhla	0.000	1	0.000	1	0.000	1	131,076	24	62.39	36	14.67	24	1.000	CRS
60	*Songkhla*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*0*	*1*	*O*		*N.A.*		*1.000*	*CRS*
61	Songkhla	0.000	1	0.000	1	0.000	1	140,552	36	50.61	33	18.83	34	1.000	CRS
62	Songkhla	0.000	1	0.000	1	0.000	1	57,508	4	O		O		1.000	CRS
63	Songkhla	0.000	1	0.000	1	0.000	1	48,837	3	O		N.A.		1.000	CRS
64	Songkhla	0.000	1	0.000	1	0.000	1	91,869	10	134.22	48	N.A.		1.000	CRS
65	Songkhla	0.000	1	0.000	1	0.000	1	108,794	13	129.85	47	112.64	61	1.000	CRS
66	Songkhla	0.000	1	0.000	1	0.000	1	78,874	8	138.38	49	105.14	60	1.000	CRS
67	Songkhla	0.000	1	0.000	1	0.000	1	141,292	38	N.A.		8.25	13	1.000	CRS
68	Songkhla	0.000	1	0.000	1	0.000	1	144,838	45	N.A.		2.53	5	1.000	CRS
69	*Songkhla*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*141,307*	*39*	*N.A.*		*0.00*	*1*	*1.000*	*CRS*

Table D.7 Continued

Farm No.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
70	Songkhla	0.000	1	0.000	1	0.000	1	90,845	9	O		N.A.		1.000	CRS
71	Songkhla	0.007	49	0.007	49	0.004	49	19,727	2	O		O		0.994	DRS
72	Songkhla	0.000	1	0.000	1	0.000	1	147,189	53	N.A.		N.A.		1.000	CRS
73	Songkhla	0.000	1	0.000	1	0.000	1	132,618	26	116.53	44	N.A.		1.000	CRS
74	Songkhla	0.000	1	0.000	1	0.000	1	135,391	29	111.65	43	N.A.		1.000	CRS
75	Satun	0.162	67	0.194	67	0.088	67	154,156	75	5.04	9	24.01	37	0.991	DRS
76	Satun	0.306	88	0.441	88	0.181	88	154,771	78	9.01	14	18.18	33	0.694	IRS
77	Satun	0.185	68	0.227	68	0.102	68	92,194	11	49.68	31	O		0.815	DRS
78	Satun	0.256	82	0.345	82	0.147	82	152,744	71	8.33	13	17.40	32	0.744	IRS
79	Satun	0.197	71	0.245	71	0.109	71	125,769	19	36.58	28	95.96	58	0.991	DRS
80	Satun	0.302	87	0.432	87	0.178	87	151,504	66	7.88	11	31.96	46	0.977	DRS
81	Satun	0.315	90	0.459	90	0.187	90	150,796	64	N.A.		13.36	21	0.969	IRS
82	Satun	0.313	89	0.456	89	0.186	89	152,573	69	3.43	5	15.27	26	0.931	IRS
83	Pattani	0.283	85	0.395	85	0.165	85	135,569	30	N.A.		61.43	55	0.717	DRS
84	Pattani	0.057	57	0.061	57	0.029	57	149,137	57	8.07	12	45.21	49	0.943	DRS
85	Pattani	0.000	1	0.000	1	0.000	1	147,212	54	N.A.		1.60	4	1.000	CRS
86	Pattani	0.000	1	0.000	1	0.000	1	155,447	81	N.A.		N.A.		1.000	CRS
87	Pattani	0.000	1	0.000	1	0.000	1	144,386	43	11.37	16	46.28	50	1.000	CRS
88	Pattani	0.012	52	0.012	52	0.006	52	138,735	32	N.A.		N.A.		0.988	DRS
89	Pattani	0.344	91	0.524	91	0.208	91	150,753	63	0.54	2	16.49	28	0.996	IRS
90	Pattani	0.098	62	0.109	62	0.052	62	150,179	61	N.A.		11.99	20	0.902	DRS
91	Pattani	0.000	1	0.000	1	0.000	1	144,702	44	N.A.		N.A.		1.000	CRS
92	Pattani	0.000	1	0.000	1	0.000	1	153,024	72	N.A.		N.A.		1.000	CRS
93	Pattani	0.347	92	0.530	92	0.210	92	149,495	60	N.A.		14.46	23	0.995	IRS
94	Pattani	0.044	55	0.046	55	0.023	55	147,559	55	N.A.		8.28	14	0.956	DRS
95	Pattani	0.352	94	0.543	94	0.213	94	153,766	73	6.87	10	25.14	38	0.992	DRS
96	Pattani	0.000	1	0.000	1	0.000	1	155,086	79	1.89	4	6.29	8	1.000	CRS
97	Pattani	0.373	95	0.595	95	0.229	95	154,591	77	4.42	8	15.03	25	0.738	IRS
98	Pattani	0.000	1	0.000	1	0.000	1	154,130	74	N.A.		N.A.		1.000	CRS
99	Pattani	0.000	1	0.000	1	0.000	1	155,987	85	N.A.		N.A.		1.000	CRS
100	Pattani	0.000	1	0.000	1	0.000	1	152,225	67	30.85	27	58.73	54	1.000	CRS

Note that DDF1 – DDF3 models are estimated under the assumption of CRS; DDF4, NSMM and PSMM are estimated under the assumption of VRS. N.A. denotes the farm had negative NS or negative PS. O denotes the farm is an outlier for NSMM and PSMM.

Table D.8 Ranking by different efficiency measures, returns to scale, technical, environmental, and scale efficiency estimates of glutinous rice farms in the Northern region

Farm No.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
1	Chiangrai	0.000	1	0.000	1	0.000	1	23,126	64	N.A.		N.A.		0.980	DRS
2	Chiangrai	0.000	1	0.000	1	0.000	1	12,961	7	N.A.		13.23	23	1.000	CRS
3	Chiangrai	0.000	1	0.000	1	0.000	1	12,088	5	O		N.A.		0.994	DRS
4	Chiangrai	0.000	1	0.000	1	0.000	1	17,146	23	N.A.		N.A.		1.000	CRS
5	Chiangrai	0.000	1	0.000	1	0.000	1	13,606	8	O		O		0.966	DRS
6	Chiangrai	0.000	1	0.000	1	0.000	1	16,252	18	N.A.		8.99	16	1.000	CRS
7	Chiangrai	0.000	1	0.000	1	0.000	1	16,917	21	O		O		1.000	CRS
8	Chiangrai	0.000	1	0.000	1	0.000	1	18,585	29	N.A.		N.A.		0.954	DRS
9	Chiangrai	0.000	1	0.000	1	0.000	1	17,025	22	22.66	11	13.40	24	1.000	CRS
10	Chiangrai	0.000	1	0.000	1	0.000	1	14,367	11	N.A.		16.70	26	1.000	DRS
11	Phayao	0.000	1	0.000	1	0.000	1	21,722	53	38.23	15	0.54	2	1.000	CRS
12	Phayao	0.000	1	0.000	1	0.000	1	21,068	47	N.A.		4.02	7	1.000	CRS
13	Phayao	0.000	1	0.000	1	0.000	1	14,512	12	4.29	5	O		1.000	CRS
14	Phayao	0.000	1	0.000	1	0.000	1	14,078	10	N.A.		34.65	34	0.838	DRS
15	Phayao	0.000	1	0.000	1	0.000	1	18,468	27	12.20	9	4.97	9	1.000	CRS
16	Phayao	0.055	85	0.055	84	0.028	83	21,964	55	14.60	10	14.01	25	1.000	CRS
17	Phayao	0.000	1	0.000	1	0.000	1	15,539	15	9.04	7	N.A.		1.000	CRS
18	Phayao	0.000	1	0.000	1	0.000	1	19,428	37	N.A.		N.A.		1.000	CRS
19	Phayao	0.000	1	0.000	1	0.000	1	16,314	19	N.A.		0.78	3	1.000	CRS
20	Phayao	0.000	1	0.000	1	0.000	1	18,860	31	3.25	3	5.46	11	1.000	CRS
21	Phayao	0.000	1	0.000	1	0.000	1	19,285	35	N.A.		1.72	5	1.000	CRS
22	Lampang	0.000	1	0.000	1	0.000	1	25,400	78	N.A.		N.A.		0.979	IRS
23	Lampang	0.000	1	0.000	1	0.000	1	21,301	48	N.A.		N.A.		1.000	CRS
24	Lampang	0.000	1	0.000	1	0.000	1	25,790	80	N.A.		20.74	28	1.000	CRS
25	Lampang	0.000	1	0.000	1	0.000	1	20,733	45	N.A.		N.A.		0.893	DRS
26	Lampang	0.000	1	0.000	1	0.000	1	21,423	49	N.A.		6.35	12	0.953	DRS
27	Lampang	0.000	1	0.000	1	0.000	1	26,574	82	N.A.		N.A.		0.861	DRS
28	Lampang	0.000	1	0.000	1	0.000	1	16,183	17	N.A.		O		1.000	CRS
29	Lampang	0.048	83	0.078	86	0.030	85	24,764	75	N.A.		3.03	6	0.959	IRS
30	Lampang	0.072	86	0.053	83	0.031	86	21,484	50	N.A.		4.67	8	0.927	DRS
31	Lampang	0.000	1	0.000	1	0.000	1	19,683	39	N.A.		N.A.		1.000	CRS
32	Lamphun	0.000	1	0.000	1	0.000	1	20,983	46	N.A.		O		0.974	DRS

Table D.8 Continued

Farm No.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
33	*Lamphun*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*14,680*	*14*	*0.00*	*1*	*N.A.*		*1.000*	*CRS*
34	Lamphun	0.000	1	0.000	1	0.000	1	22,920	62	27.01	13	N.A.		0.965	IRS
35	Lamphun	0.025	76	0.026	76	0.013	76	23,151	65	N.A.		N.A.		1.000	IRS
36	Lamphun	0.000	1	0.000	1	0.000	1	23,732	69	N.A.		22.55	30	1.000	CRS
37	Lamphun	0.000	1	0.000	1	0.000	1	20,485	44	6.61	6	24.10	31	0.993	IRS
38	Lamphun	0.000	1	0.000	1	0.000	1	13,648	9	N.A.		N.A.		1.000	CRS
39	Lamphun	0.000	1	0.000	1	0.000	1	5,492	2	N.A.		O		1.000	CRS
40	Lamphun	0.000	1	0.000	1	0.000	1	19,389	36	N.A.		O		1.000	CRS
41	*Lamphun*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*0*	*1*	*N.A.*		*O*		*1.000*	*CRS*
42	Lamphun	0.023	75	0.024	75	0.012	75	19,660	38	N.A.		7.40	14	0.999	IRS
43	Chiangmai	0.000	1	0.000	1	0.000	1	18,278	26	N.A.		12.18	22	1.000	CRS
44	Chiangmai	0.000	1	0.000	1	0.000	1	7,493	3	N.A.		11.84	20	1.000	CRS
45	Chiangmai	0.000	1	0.000	1	0.000	1	22,433	56	N.A.		N.A.		1.000	CRS
46	Chiangmai	0.000	1	0.000	1	0.000	1	12,562	6	0.14	2	20.74	29	1.000	CRS
47	Chiangmai	0.000	1	0.000	1	0.000	1	14,571	13	O		O		1.000	CRS
48	Chiangmai	0.000	1	0.000	1	0.000	1	19,872	40	N.A.		N.A.		1.000	CRS
49	Chiangmai	0.004	73	0.004	73	0.002	73	20,410	43	3.57	4	25.44	33	0.998	IRS
50	Chiangmai	0.005	74	0.005	74	0.003	74	21,571	51	N.A.		7.70	15	0.998	IRS
51	Chiangmai	0.000	1	0.000	1	0.000	1	19,979	41	N.A.		N.A.		1.000	CRS
52	Chiangmai	0.000	1	0.000	1	0.000	1	22,554	59	N.A.		N.A.		1.000	CRS
53	Maehongson	0.000	1	0.000	1	0.000	1	23,507	68	N.A.		9.49	17	1.000	CRS
54	*Maehongson*	*0.000*	*1*	*0.000*	*1*	*0.000*	*1*	*24,793*	*76*	*N.A.*		*0.00*	*1*	*0.944*	*IRS*
55	Maehongson	0.000	1	0.000	1	0.000	1	23,058	63	N.A.		12.04	21	0.909	IRS
56	Maehongson	0.000	1	0.000	1	0.000	1	23,440	66	N.A.		N.A.		1.000	CRS
57	Maehongson	0.047	82	0.047	81	0.023	82	30,603	88	N.A.		6.40	13	0.974	DRS
58	Tak	0.294	92	0.426	92	0.176	92	31,373	90	N.A.		N.A.		0.993	IRS
59	Tak	0.260	91	0.318	90	0.148	91	23,453	67	N.A.		N.A.		0.993	DRS
60	Tak	0.000	1	0.000	1	0.000	1	30,405	87	N.A.		N.A.		0.935	DRS
61	Tak	0.089	87	0.338	91	0.089	90	24,342	72	N.A.		N.A.		0.818	IRS
62	Tak	0.000	1	0.000	1	0.000	1	22,499	57	N.A.		N.A.		0.918	IRS
63	Kamphaengphet	0.000	1	0.000	1	0.000	1	24,135	71	43.39	18	O		0.990	DRS
64	Kamphaengphet	0.000	1	0.000	1	0.000	1	22,631	60	11.27	8	N.A.		0.918	IRS
65	Kamphaengphet	0.040	79	0.035	78	0.020	79	24,452	74	41.03	16	O		0.974	DRS
66	Kamphaengphet	0.000	1	0.000	1	0.000	1	18,528	28	N.A.		N.A.		1.000	CRS
67	Sukhothai	0.000	1	0.000	1	0.000	1	30,850	89	N.A.		N.A.		0.939	DRS
68	Sukhothai	0.000	1	0.000	1	0.000	1	32,611	91	N.A.		N.A.		0.920	DRS
69	Sukhothai	0.171	90	0.090	88	0.068	88	26,555	81	N.A.		O		0.913	DRS
70	Sukhothai	0.000	1	0.000	1	0.000	1	24,356	73	N.A.		N.A.		1.000	CRS
71	Phrae	0.043	80	0.045	80	0.022	80	21,612	52	36.08	14	N.A.		1.000	IRS
72	Phrae	0.000	1	0.000	1	0.000	1	19,249	34	N.A.		N.A.		1.000	CRS
73	Phrae	0.000	1	0.000	1	0.000	1	15,811	16	N.A.		N.A.		1.000	CRS
74	Phrae	0.000	1	0.000	1	0.000	1	18,068	25	N.A.		N.A.		1.000	CRS
75	Phrae	0.000	1	0.000	1	0.000	1	25,229	77	N.A.		N.A.		0.960	DRS
76	Nan	0.000	1	0.000	1	0.000	1	20,178	42	N.A.		1.09	4	1.000	CRS
77	Nan	0.000	1	0.000	1	0.000	1	22,905	61	O		17.52	27	1.000	CRS
78	Nan	0.054	84	0.057	85	0.028	84	19,249	33	N.A.		5.23	10	0.997	DRS
79	Nan	0.000	1	0.000	1	0.000	1	17,880	24	N.A.		9.94	18	1.000	CRS
80	Nan	0.000	1	0.000	1	0.000	1	18,827	30	N.A.		10.50	19	1.000	CRS
81	Uttaradit	0.044	81	0.050	82	0.023	81	18,912	32	25.60	12	24.20	32	0.993	IRS
82	Uttaradit	0.000	1	0.000	1	0.000	1	22,511	58	O		N.A.		1.000	CRS
83	Uttaradit	0.036	77	0.035	77	0.018	77	21,786	54	O		N.A.		0.989	DRS
84	Uttaradit	0.000	1	0.000	1	0.000	1	26,674	83	O		N.A.		1.000	CRS
85	Uttaradit	0.000	1	0.000	1	0.000	1	28,052	84	O		N.A.		1.000	CRS
86	Uttaradit	0.000	1	0.000	1	0.000	1	9,255	4	O		N.A.		1.000	CRS
87	Phitsanulok	0.000	1	0.000	1	0.000	1	16,440	20	O		N.A.		0.937	DRS
88	Phetchabun	0.038	78	0.040	79	0.019	78	25,651	79	43.40	19	N.A.		0.999	IRS
89	Phetchabun	0.000	1	0.000	1	0.000	1	23,973	70	O		O		0.996	DRS
90	Phetchabun	0.000	1	0.000	1	0.000	1	30,326	86	O		O		1.000	CRS
91	Phetchabun	0.091	88	0.084	87	0.044	87	50,389	92	O		O		0.927	DRS
92	Phetchabun	0.153	89	0.091	89	0.069	89	29,772	85	42.06	17	N.A.		0.969	DRS

Note that DDF1 – DDF4, NSMM, and PSMM models are estimated under the assumption of VRS. N.A. denotes the farm had negative NS or negative PS. O denotes the farm is an outlier for NSMM and PSMM.

Table D.9 Ranking by different efficiency measures, returns to scale, technical, environmental, and scale efficiency estimates of glutinous rice farms in the North-eastern region

Farm No.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
1	Loei	0.000	1	0.000	1	0.000	1	19,932	108	N.A.		N.A.		1.000	CRS
2	Loei	0.000	1	0.000	1	0.000	1	17,988	95	N.A.		1.00	5	1.000	CRS
3	Loei	0.000	1	0.000	1	0.000	1	16,187	70	N.A.		14.69	60	1.000	CRS
4	*Loei*	*0.023*	*69*	*0.024*	*69*	*0.012*	*69*	*21,222*	*121*	*0.00*	*1*	*22.49*	*80*	*0.977*	*DRS*
5	Loei	0.045	81	0.047	81	0.023	81	20,343	112	43.40	74	15.97	65	0.955	DRS
6	Loei	0.000	1	0.000	1	0.000	1	11,898	18	N.A.		N.A.		1.000	CRS
7	Nongbualamphu	0.000	1	0.000	1	0.000	1	15,183	59	N.A.		N.A.		1.000	CRS
8	Nongbualamphu	0.000	1	0.000	1	0.000	1	10,490	7	N.A.		3.31	18	1.000	CRS
9	Nongbualamphu	0.185	173	0.226	173	0.102	173	18,071	96	N.A.		11.31	52	0.962	DRS
10	Nongbualamphu	0.000	1	0.000	1	0.000	1	16,430	76	N.A.		N.A.		1.000	CRS
11	Nongbualamphu	0.038	74	0.039	74	0.019	74	27,635	155	N.A.		18.93	70	0.962	DRS
12	Nongbualamphu	0.000	1	0.000	1	0.000	1	28,515	156	46.81	79	N.A.		1.000	CRS
13	Nongbualamphu	0.129	125	0.147	125	0.069	125	17,527	89	3.51	9	3.15	17	1.000	CRS
14	Nongbualamphu	0.000	1	0.000	1	0.000	1	14,869	53	N.A.		N.A.		1.000	CRS
15	Udonthani	0.153	147	0.180	147	0.083	147	55,238	180	50.07	83	37.72	100	0.923	DRS
16	Udonthani	0.000	1	0.000	1	0.000	1	11,236	11	2.96	6	N.A.		1.000	CRS
17	*Udonthani*	*0.003*	*62*	*0.003*	*62*	*0.001*	*62*	*0*	*1*	*65.12*	*93*	*12.02*	*54*	*0.997*	*DRS*
18	Udonthani	0.000	1	0.000	1	0.000	1	14,986	55	N.A.		33.75	93	1.000	CRS
19	Udonthani	0.047	82	0.049	82	0.024	82	13,789	39	16.08	39	22.88	81	0.953	DRS
20	Udonthani	0.134	131	0.155	131	0.072	131	26,063	147	3.18	7	20.26	73	0.992	DRS
21	Udonthani	0.003	64	0.003	64	0.002	64	17,075	84	N.A.		5.50	23	0.997	DRS
22	Udonthani	0.156	149	0.185	149	0.084	149	42,266	177	O		O		0.937	DRS
23	Udonthani	0.091	101	0.100	101	0.047	101	21,367	125	6.43	17	31.29	90	0.975	DRS
24	Udonthani	0.142	140	0.165	140	0.076	140	26,605	150	141.03	107	O		0.999	DRS
25	Udonthani	0.191	174	0.236	174	0.105	174	16,966	82	5.85	14	6.40	29	0.965	DRS
26	Udonthani	0.000	1	0.000	1	0.000	1	14,518	48	12.57	31	N.A.		1.000	CRS
27	Udonthani	0.115	116	0.131	116	0.061	116	17,745	91	N.A.		2.71	14	0.954	IRS
28	Udonthani	0.047	83	0.049	83	0.024	83	33,719	168	N.A.		N.A.		0.953	DRS
29	Udonthani	0.134	130	0.155	130	0.072	130	25,319	145	N.A.		N.A.		0.991	DRS
30	Nongkhai	0.169	165	0.204	165	0.092	165	40,122	175	O		40.73	103	0.990	DRS
31	Nongkhai	0.168	161	0.201	161	0.091	161	38,042	172	O		57.06	113	0.991	DRS
32	Nongkhai	0.168	163	0.202	163	0.092	163	23,322	134	36.05	71	34.94	97	0.998	DRS
33	Nongkhai	0.146	143	0.171	143	0.079	143	16,232	72	8.21	20	23.49	83	0.994	IRS
34	Nongkhai	0.041	79	0.042	79	0.021	79	17,824	92	N.A.		N.A.		0.959	DRS
35	Nongkhai	0.171	167	0.207	167	0.094	167	30,249	162	43.86	75	34.61	96	0.991	DRS
36	Nongkhai	0.132	129	0.153	129	0.071	129	25,182	143	N.A.		25.39	85	0.998	DRS
37	Nongkhai	0.169	164	0.203	164	0.092	164	20,379	113	10.58	25	37.18	98	1.000	CRS
38	Nongkhai	0.168	162	0.202	162	0.092	162	25,956	146	19.89	47	50.55	110	0.998	DRS
39	Nongkhai	0.167	160	0.200	160	0.091	160	29,612	160	30.03	64	71.49	118	0.994	DRS
40	Sakonnakhon	0.117	117	0.132	117	0.062	117	16,305	74	145.28	108	67.96	116	0.883	DRS
41	Sakonnakhon	0.076	91	0.082	91	0.039	91	25,061	142	N.A.		O		0.924	DRS
42	Sakonnakhon	0.149	145	0.175	145	0.080	145	18,535	99	9.33	22	6.27	28	0.967	DRS
43	Sakonnakhon	0.107	110	0.120	110	0.056	110	11,530	16	12.97	32	2.69	13	0.994	DRS
44	Sakonnakhon	0.135	133	0.156	133	0.073	133	43,579	178	N.A.		N.A.		0.865	DRS
45	Sakonnakhon	0.140	138	0.163	138	0.075	138	16,210	71	24.25	52	11.73	53	0.990	DRS
46	Sakonnakhon	0.000	1	0.000	1	0.000	1	21,134	119	34.89	68	O		1.000	CRS
47	Sakonnakhon	0.000	1	0.000	1	0.000	1	14,745	52	8.13	19	O		1.000	CRS
48	Sakonnakhon	0.135	132	0.156	132	0.072	132	19,470	105	26.67	58	27.68	87	0.967	DRS
49	Sakonnakhon	0.123	120	0.140	120	0.066	120	27,358	153	O		O		0.877	DRS
50	Sakonnakhon	0.083	93	0.090	93	0.043	93	12,210	23	N.A.		7.84	37	0.947	DRS
51	Sakonnakhon	0.095	103	0.104	103	0.050	103	19,092	102	15.90	38	N.A.		0.905	DRS
52	Nakhonphanom	0.159	154	0.190	154	0.087	154	23,492	136	N.A.		2.32	11	0.998	DRS
53	Nakhonphanom	0.204	178	0.256	178	0.113	178	20,947	117	N.A.		1.60	6	0.996	DRS
54	Nakhonphanom	0.000	1	0.000	1	0.000	1	25,194	144	N.A.		N.A.		1.000	CRS
55	Nakhonphanom	0.000	1	0.000	1	0.000	1	10,778	9	3.33	8	17.20	69	1.000	CRS
56	Nakhonphanom	0.181	170	0.221	170	0.100	170	14,568	50	16.58	40	2.25	9	0.996	DRS
57	Nakhonphanom	0.161	156	0.192	156	0.088	156	16,702	79	4.94	11	21.68	77	0.981	IRS
58	Nakhonphanom	0.199	177	0.249	177	0.111	177	27,259	152	O		O		0.965	DRS
59	Nakhonphanom	0.000	1	0.000	1	0.000	1	33,866	169	N.A.		N.A.		1.000	CRS
60	Nakhonphanom	0.194	176	0.241	176	0.108	176	22,495	130	60.86	89	9.35	45	1.000	DRS
61	Nakhonphanom	0.166	158	0.199	158	0.090	158	15,337	60	17.30	42	25.52	86	0.972	DRS
62	Nakhonphanom	0.096	106	0.106	106	0.051	106	12,183	22	6.14	15	7.09	34	0.946	IRS
63	Nakhonphanom	0.176	169	0.214	169	0.097	169	12,900	28	25.66	56	2.26	10	0.916	DRS
64	Mukdahan	0.016	67	0.016	67	0.008	67	27,457	154	N.A.		N.A.		0.984	DRS
65	Mukdahan	0.141	139	0.164	139	0.076	139	40,558	176	O		O		0.984	DRS
66	Mukdahan	0.000	1	0.000	1	0.000	1	17,026	83	O		O		1.000	CRS
67	Mukdahan	0.108	111	0.121	111	0.057	111	9,868	4	10.99	26	N.A.		0.950	DRS
68	Mukdahan	0.140	137	0.162	137	0.075	137	32,408	166	O		O		0.932	DRS
69	Mukdahan	0.124	121	0.141	121	0.066	121	14,549	49	32.13	66	N.A.		0.918	DRS

Table D.9 Continued

Farm No.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
70	Yasothon	0.146	141	0.171	141	0.079	141	17,106	85	8.41	21	N.A.		0.889	IRS
71	Yasothon	0.000	1	0.000	1	0.000	1	14,470	47	1.34	4	15.71	64	1.000	CRS
72	Yasothon	0.065	86	0.069	86	0.033	86	19,968	109	N.A.		10.60	49	0.991	IRS
73	Yasothon	0.000	1	0.000	1	0.000	1	15,066	56	N.A.		N.A.		1.000	CRS
74	Yasothon	0.096	105	0.106	105	0.050	105	24,001	139	5.17	12	14.48	59	0.998	DRS
75	Yasothon	0.000	1	0.000	1	0.000	1	37,450	171	N.A.		N.A.		1.000	CRS
76	Yasothon	0.000	1	0.000	1	0.000	1	33,609	167	N.A.		N.A.		1.000	CRS
77	Yasothon	0.000	1	0.000	1	0.000	1	14,308	45	N.A.		6.75	33	1.000	CRS
78	Yasothon	0.121	118	0.138	118	0.064	118	14,584	51	17.47	43	21.73	78	0.879	IRS
79	Amnatcharoen	0.149	146	0.175	146	0.081	146	15,174	58	14.12	35	15.48	63	0.993	DRS
80	Amnatcharoen	0.182	172	0.223	172	0.100	172	39,214	173	113.44	101	O		0.993	DRS
81	Amnatcharoen	0.156	150	0.185	150	0.085	150	40,001	174	N.A.		6.23	27	0.995	DRS
82	Amnatcharoen	0.181	171	0.221	171	0.100	171	44,449	179	O		66.26	115	0.993	DRS
83	Amnatcharoen	0.042	80	0.043	80	0.021	80	13,694	37	27.96	61	15.25	61	0.958	IRS
84	Ubonratchathani	0.138	135	0.160	135	0.074	135	24,567	140	N.A.		5.31	22	0.986	IRS
85	Ubonratchathani	0.159	153	0.189	153	0.086	153	15,779	65	34.73	67	2.49	12	0.999	DRS
86	Ubonratchathani	0.157	152	0.187	152	0.085	152	21,179	120	117.53	103	O		0.999	IRS
87	Ubonratchathani	0.166	159	0.199	159	0.091	159	23,621	137	63.32	91	19.51	71	0.999	IRS
88	Ubonratchathani	0.163	157	0.194	157	0.089	157	20,232	111	45.46	77	39.30	101	0.997	DRS
89	Ubonratchathani	0.000	1	0.000	1	0.000	1	10,972	10	N.A.		N.A.		1.000	CRS
90	Ubonratchathani	0.098	108	0.108	108	0.051	108	14,917	54	48.77	81	9.09	43	0.902	DRS
91	Ubonratchathani	0.022	68	0.022	68	0.011	68	18,795	101	18.58	44	31.98	91	0.991	DRS
92	Ubonratchathani	0.028	72	0.029	72	0.014	72	17,408	86	5.55	13	20.30	74	0.991	DRS
93	Ubonratchathani	0.157	151	0.186	151	0.085	151	16,478	77	52.85	86	5.19	21	0.952	IRS
94	Ubonratchathani	0.115	115	0.130	115	0.061	115	14,038	43	28.87	63	N.A.		0.885	IRS
95	Ubonratchathani	0.155	148	0.184	148	0.084	148	13,818	41	22.10	50	N.A.		0.845	IRS
96	Ubonratchathani	0.000	1	0.000	1	0.000	1	13,779	38	N.A.		8.79	41	1.000	CRS
97	Sisaket	0.000	1	0.000	1	0.000	1	13,457	36	36.04	70	0.77	4	1.000	CRS
98	Sisaket	0.000	1	0.000	1	0.000	1	12,675	26	9.44	23	15.40	62	1.000	CRS
99	Sisaket	0.000	1	0.000	1	0.000	1	12,103	19	15.64	37	3.89	19	1.000	CRS
100	Sisaket	0.000	1	0.000	1	0.000	1	11,780	17	13.02	33	8.15	38	1.000	CRS
101	Sisaket	0.000	1	0.000	1	0.000	1	15,422	61	9.96	24	20.53	76	1.000	CRS
102	Sisaket	0.000	1	0.000	1	0.000	1	11,505	15	4.88	10	7.80	36	1.000	CRS
103	Sisaket	0.000	1	0.000	1	0.000	1	10,299	6	N.A.		1.75	7	1.000	CRS
104	Surin	0.003	63	0.003	63	0.002	63	13,324	33	13.23	34	6.67	32	0.997	IRS
105	Surin	0.000	1	0.000	1	0.000	1	13,924	42	31.01	65	N.A.		1.000	CRS
106	Surin	0.000	1	0.000	1	0.000	1	16,392	75	104.91	98	37.69	99	1.000	CRS
107	Surin	0.000	1	0.000	1	0.000	1	12,461	24	47.88	80	N.A.		1.000	CRS
108	Surin	0.000	1	0.000	1	0.000	1	11,274	12	11.21	28	5.65	24	1.000	CRS
109	Surin	0.000	1	0.000	1	0.000	1	8,992	3	74.83	95	N.A.		1.000	CRS
110	Surin	0.000	1	0.000	1	0.000	1	9,872	5	11.24	29	N.A.		1.000	CRS
111	Buriram	0.000	1	0.000	1	0.000	1	16,777	81	0.64	2	9.32	44	1.000	CRS
112	Buriram	0.000	1	0.000	1	0.000	1	12,965	29	N.A.		N.A.		1.000	CRS
113	Buriram	0.111	113	0.125	113	0.059	113	12,539	25	N.A.		2.89	15	0.889	IRS
114	Buriram	0.085	95	0.093	95	0.044	95	14,052	44	6.25	16	6.48	30	0.962	IRS
115	Buriram	0.039	75	0.040	75	0.020	75	12,161	21	6.46	18	6.15	26	0.977	IRS
116	Buriram	0.100	109	0.111	109	0.052	109	13,071	31	11.12	27	9.66	46	0.996	IRS
117	Buriram	0.139	136	0.162	136	0.075	136	16,048	69	51.82	84	23.69	84	0.983	DRS
118	Mahasarakham	0.058	85	0.062	85	0.030	85	5,085	2	O		O		0.942	DRS
119	Mahasarakham	0.000	1	0.000	1	0.000	1	11,348	13	N.A.		N.A.		1.000	CRS
120	Mahasarakham	0.000	1	0.000	1	0.000	1	23,302	133	N.A.		2.01	8	1.000	CRS
121	Mahasarakham	0.052	84	0.055	84	0.027	84	16,234	73	N.A.		10.08	48	0.982	IRS
122	Mahasarakham	0.069	88	0.074	88	0.036	88	18,647	100	N.A.		13.07	58	0.994	DRS
123	Mahasarakham	0.089	100	0.098	100	0.047	100	19,231	103	75.24	96	28.35	89	0.982	IRS
124	Mahasarakham	0.095	104	0.105	104	0.050	104	29,477	158	108.42	99	47.55	107	0.994	DRS
125	Mahasarakham	0.088	98	0.097	98	0.046	98	31,237	163	168.34	109	20.52	75	0.993	DRS
126	Mahasarakham	0.089	99	0.097	99	0.046	99	24,732	141	111.38	100	52.17	112	0.999	DRS
127	Mahasarakham	0.114	114	0.129	114	0.060	114	23,159	132	50.03	82	20.04	72	0.900	DRS
128	Mahasarakham	0.086	96	0.094	96	0.045	96	21,784	127	70.30	94	N.A.		0.997	DRS
129	Mahasarakham	0.072	89	0.078	89	0.037	89	15,924	67	20.44	48	49.90	109	0.984	DRS
130	Mahasarakham	0.000	1	0.000	1	0.000	1	18,473	98	N.A.		N.A.		1.000	CRS
131	*Mahasarakham*	*0.088*	*97*	*0.096*	*97*	*0.046*	*97*	*17,510*	*88*	*O*		*0.00*	*1*	*0.996*	*DRS*
132	Mahasarakham	0.040	78	0.042	78	0.021	78	20,966	118	24.61	53	10.68	50	0.968	DRS
133	Roiet	0.000	1	0.000	1	0.000	1	11,439	14	N.A.		N.A.		1.000	CRS
134	Roiet	0.091	102	0.100	102	0.048	102	22,791	131	137.62	106	39.43	102	0.999	IRS
135	Roiet	0.000	1	0.000	1	0.000	1	13,810	40	41.91	73	N.A.		1.000	CRS
136	Roiet	0.075	90	0.081	90	0.039	90	15,724	64	27.37	59	8.52	40	0.931	IRS
137	Roiet	0.080	92	0.087	92	0.042	92	21,331	124	16.67	41	0.03	2	0.956	IRS
138	Kalasin	0.000	1	0.000	1	0.000	1	20,000	110	27.62	60	48.12	108	1.000	CRS
139	Kalasin	0.000	1	0.000	1	0.000	1	17,938	94	21.93	49	43.29	105	1.000	CRS
140	Kalasin	0.000	1	0.000	1	0.000	1	10,663	8	N.A.		7.11	35	1.000	CRS
141	Kalasin	0.000	1	0.000	1	0.000	1	16,583	78	25.07	54	57.80	114	1.000	CRS

Table D.9 Continued

Farm No.	Province	DDF1	Rank	DDF2	Rank	DDF3	Rank	DDF4	Rank	NSMM	Rank	PSMM	Rank	SE	RTS
142	Kalasin	0.024	70	0.024	70	0.012	70	26,354	149	120.94	104	46.93	106	0.979	DRS
143	Kalasin	0.000	1	0.000	1	0.000	1	18,345	97	N.A.		N.A.		1.000	CRS
144	Kalasin	0.000	1	0.000	1	0.000	1	13,418	34	N.A.		N.A.		1.000	CRS
145	Kalasin	0.000	1	0.000	1	0.000	1	19,371	104	N.A.		N.A.		1.000	CRS
146	Kalasin	0.000	1	0.000	1	0.000	1	15,126	57	N.A.		N.A.		1.000	CRS
147	Kalasin	0.000	1	0.000	1	0.000	1	23,441	135	N.A.		N.A.		1.000	CRS
148	Kalasin	0.000	1	0.000	1	0.000	1	20,804	116	97.98	97	N.A.		1.000	CRS
149	Kalasin	0.035	73	0.036	73	0.018	73	20,490	114	N.A.		6.06	25	0.971	DRS
150	Kalasin	0.040	77	0.042	76	0.020	77	15,950	68	19.25	45	4.00	20	0.980	DRS
151	Kalasin	0.040	76	0.042	77	0.020	76	21,309	122	N.A.		23.38	82	0.960	DRS
152	Khonkaen	0.146	142	0.171	142	0.079	142	37,064	170	127.94	105	69.50	117	0.992	DRS
153	Khonkaen	0.084	94	0.092	94	0.044	94	17,890	93	N.A.		12.75	57	0.935	DRS
154	Khonkaen	0.136	134	0.157	134	0.073	134	15,800	66	23.76	51	8.48	39	1.000	CRS
155	Khonkaen	0.000	1	0.000	1	0.000	1	13,446	35	11.48	30	N.A.		1.000	CRS
156	Khonkaen	0.148	144	0.174	144	0.080	144	17,436	87	57.18	87	34.17	94	0.982	DRS
157	Khonkaen	0.175	168	0.212	168	0.096	168	13,146	32	26.58	57	16.28	67	0.978	DRS
158	Khonkaen	0.160	155	0.190	155	0.087	155	15,458	62	28.51	62	16.09	66	0.964	DRS
159	Khonkaen	0.097	107	0.107	107	0.051	107	15,559	63	35.98	69	21.91	79	0.903	IRS
160	Khonkaen	0.000	1	0.000	1	0.000	1	22,017	128	0.81	3	16.78	68	1.000	CRS
161	Khonkaen	0.131	127	0.150	127	0.070	127	19,564	106	51.93	85	32.82	92	1.000	CRS
162	Khonkaen	0.110	112	0.124	112	0.058	112	27,021	151	64.67	92	43.10	104	0.890	DRS
163	Khonkaen	0.125	123	0.143	123	0.067	123	16,715	80	58.82	88	N.A.		0.983	IRS
164	Chaiyaphum	0.000	1	0.000	1	0.000	1	14,311	46	N.A.		12.52	55	1.000	CRS
165	Chaiyaphum	0.204	179	0.257	179	0.114	179	28,926	157	61.08	90	O		0.951	DRS
166	Chaiyaphum	0.026	71	0.026	71	0.013	71	29,510	159	45.92	78	3.06	16	0.980	DRS
167	Chaiyaphum	0.005	65	0.005	65	0.002	65	21,654	126	N.A.		10.98	51	0.995	DRS
168	Chaiyaphum	0.209	180	0.265	180	0.117	180	17,636	90	25.11	55	9.84	47	0.997	IRS
169	Chaiyaphum	0.193	175	0.239	175	0.107	175	22,363	129	19.47	46	34.39	95	0.997	DRS
170	Chaiyaphum	0.126	124	0.144	124	0.067	124	21,326	123	N.A.		N.A.		0.977	IRS
171	Nakhonratchasima	0.000	1	0.000	1	0.000	1	19,630	107	N.A.		N.A.		1.000	CRS
172	Nakhonratchasima	0.121	119	0.138	119	0.064	119	12,761	27	45.40	76	28.03	88	0.948	DRS
173	Nakhonratchasima	0.000	1	0.000	1	0.000	1	12,139	20	1.93	5	6.56	31	1.000	CRS
174	Nakhonratchasima	0.170	166	0.205	166	0.093	166	32,098	165	O		12.62	56	0.962	DRS
175	Nakhonratchasima	0.132	128	0.152	128	0.071	128	31,412	164	O		50.83	111	0.994	DRS
176	Nakhonratchasima	0.068	87	0.073	87	0.035	87	30,192	161	N.A.		0.26	3	0.992	DRS
177	Nakhonratchasima	0.130	126	0.149	126	0.069	126	13,059	30	36.73	72	8.96	42	0.998	IRS
178	Nakhonratchasima	0.014	66	0.015	66	0.007	66	26,235	148	N.A.		N.A.		0.986	DRS
179	Nakhonratchasima	0.124	122	0.142	122	0.066	122	23,925	138	113.61	102	N.A.		0.955	DRS
180	Nakhonratchasima	0.000	1	0.000	1	0.000	1	20,670	115	14.21	36	O		1.000	CRS

Note that DDF1 – DDF3 models are estimated under the assumption of CRS; DDF4, NSMM and PSMM are estimated under the assumption of VRS. N.A. denotes the farm had negative NS or negative PS. O denotes the farm is an outlier for NSMM and PSMM.