Impact of Environmental Changes on Economic Performance of Broadacre Farms in Australian Wheat Belt Regions

A Thesis submitted by

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ABSTRACT

Nearly all grain production in Australia takes place in the Wheat Belt regions. However, adverse environmental conditions in these areas pose a major challenge to the management of broadacre farm businesses. The aim of this study was to determine the main drivers of profitability and productivity changes, and the determinants of inefficiency for wheat and non-wheat crops (e.g. canola, sorghum, oats, rice, barley, field peas, lupines and grain legumes) in 12 farm regions from 1990 to 2016 in the Australian Wheat Belt regions. The 12 farm regions were grouped based on rainfall and temperature levels into low, medium and high average annual rainfall farm regions (AARFRs) and average annual temperature farm regions (AATFRs), respectively.

The standard data envelopment analysis (DEA) technique was utilised to estimate the production frontier and to compute and decompose the total factor productivity (TFP) index (Lowe index method) into measures of technical, environmental and several efficiency changes. An aggregate quantity-price framework was adopted to decompose profitability change into measures of TFP and terms of trade changes. Efficiency measures were estimated using an output-oriented DEA model under the variable returns to scale (VRS) assumption. Technical efficiency was estimated under the constant returns to scale (CRS) assumption. Tobit regression was used to examine the effects of socioeconomic variables on eight efficiency indicators (scores) and the robustness of the results was checked using double bootstrap with truncated regression analysis, random effect Tobit model and lag model. These analyses were performed using the R software program.

Assessment of the effect of rainfall variation on productivity and profitability change revealed that the main drivers of TFP change were output-oriented rainfall efficiency change and technical change in high and medium AARFRs. TFP change and terms of trade change were the main drivers of profitability in the high and medium AARFRs, respectively. Results from the effect of temperature variation on productivity and profitability change also revealed that output-oriented temperature efficiency change, and technical change were the main drivers of TFP change in high AATFRs. The main driver of profitability change was change in terms of trade for the high, medium and low AATFRs.

The Tobit and double bootstrap models produced similar estimations, which confirmed the robustness of the Tobit model under both rainfall and temperature variation analysis. The

capital-labour ratio had a positive and significant influence on six efficiency indicators (technical and scale-mix efficiency and output-oriented technical efficiency (CRS and VRS), scale efficiency, scale and mix efficiency, and residual scale efficiency) under rainfall variation analysis, and five efficiency indicators (except scale efficiency) under temperature variation analysis. For both rainfall and temperature variation analyses, capital-labour ratio had a significantly negative influence on environmental efficiency. The land-labour ratio had a negative and significant influence on five efficiency indicators (technical and scale-mix efficiency and output-oriented of technical efficiency (CRS and VRS), scale and mix efficiency, and residual scale efficiency) under rainfall variation analysis, and six efficiency indicators (including mix efficiency) under temperature variation analysis. There was a positive and significant relationship between environmental efficiency and the land-labour ratio under both rainfall and temperature variation analyses. Age of farm manager had a negative and significant impact on four out of eight efficiency indicators (mix efficiency, scale and mix efficiency, residual scale efficiency, and technical and scale-mix efficiency) in only the temperature variation analysis. Significantly negative relationships were observed between some efficiency indicators (e.g. scale and mix efficiency, residual scale efficiency, and technical and scale-mix efficiency) and off-farm work of farm manager under both rainfall and temperature variation analysis.

These findings imply that farmers should be encouraged to continue adopting new technologies and management practices to overcome challenges due to environmental changes. Additionally, to improve the efficiency of farm regions in the face of both rainfall and temperature changes, policies that ensure the availability of capital and land should be developed that are aimed at encouraging younger people to join the farming workforce.

CERTIFICATION OF THESIS

This thesis is entirely the work of Ahmed Al-Nasih except where otherwise acknowledged. The work is original and has not previously been submitted for any other award, except where acknowledged.

A/Prof Guangnan Chen

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Principal Supervisor

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Student and supervisors' signatures of endorsement are held at USQ.

Dedicated
to

my parents and family

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LIST OF ABBREVIATIONS

AARFRs	Average Annual Rainfall Farm Regions
AATFRs	Average Annual Temperature Farm Regions
ABARES	Australian Bureau of Agricultural and Resource Economics and Sciences
ABS	Australian Bureau of Statistics
CSIRO	Commonwealth Science and Industrial Research Organization
DAFF	Department of Agriculture, Fisheries and Forestry
DEA	Data Envelopment Analysis
EE	Environmental Efficiency
EEr	Rainfall Efficiency
EEt	Temperature Efficiency
EFFI	Overall Efficiency Index
GDP	Gross Domestic Product
NSWC	New South Wales Central West
NSWN	New South Wales North West Slopes and Plains
NSWR	New South Wales Riverina
OECD	Organization for Economic Cooperation and Development
OEE	Output-oriented of Environmental Efficiency
OEEI	Output-oriented of Environmental Efficiency Index
OEEr	Output-oriented of Rainfall Efficiency
OEErI	Output-oriented of Rainfall Efficiency Index
OEEt	Output-oriented of Temperature Efficiency
OEEtI	Output-oriented of Temperature Efficiency Index
OTME	Output-oriented Technical and Mix Efficiency
OME	Output-oriented Mix Efficiency
OMEI	Output-oriented Mix Efficiency Index
OSE	Output-oriented Scale Efficiency
OSEI	Output-oriented Scale Efficiency Index
OSME	Output-oriented Scale-Mix Efficiency
OSMEI	Output-oriented Scale-Mix Efficiency Index
OTE	Output-oriented Technical Efficiency
OTE_{CRS}	Output-oriented Technical Efficiency under Constant Returns to Scale

OTEI	Output-oriented Technical Efficiency Index
OTE_{VRS}	Output-oriented Technical Efficiency under Variable Returns to Scale
QLDD	Queensland Darling Downs and Central Highlands of Queensland
QLDE	Queensland Eastern Darling Downs
ROSE	Residual Output-oriented Scale Efficiency
ROSEI	Residual Output-oriented Scale Efficiency Index
SAEP	South Australia Eyre Peninsula
SAMY	South Australia Murray Lands and Yorke Peninsula
SFA	Stochastic Frontier Analysis
TI	Technology Index
TFP	Total Factor Productivity
TFPI	Total Factor Productivity Index
TSME	Technical and Scale-Mix Efficiency
TT	Terms of trade
TTI	Terms of trade Index
VICC	Victoria Central North
VICM	Victoria Mallee
VICW	Victoria Wimmera
WACS	Western Australia Central and South Wheat Belt
WANE	Western Australia North and East Wheat Belt
PROFI	Profitability Index

CHAPTER 1: INTRODUCTION

This chapter is structured as follows: Section 1.1 highlights the background of the research. Sections 1.2 presents the motivation of this study. Sections 1.3 and 1.4 present the research questions and the aims and objectives, respectively, of the study. Section 1.5 is a summary of the methodology used in this study. Section 1.6 present the contributions of this study, while Section 1.7 shows the structure of the study.

1.1 Background

Nearly all grain production in Australia occurs under broadacre farming in the Wheat Belt (or Grain Belt) regions, which are located in the east, southeast and southwest of the country where rainfall, temperature, and soil (fertility) conditions are conducive for wheat production. These regions cover nearly 6 percent of Australia's total land area (7.7 million square kilometres or 46 million hectares) (Land Commodities 2012). Furthermore, wheat production covered 58 percent in 2011-2012 of the Wheat Belt regions (Land Commodities 2012). Other crops besides wheat such as barley, oats, lupin, canola, rice, sorghum, field peas, grain legumes and oilseeds are also grown in these regions, and livestock is also produced. These grain crops are often grown in rotation with wheat to optimise long-term farm output, to assist with pest and disease management and to enhance soil health and nutrition (PwC 2011a).

In Australia, wheat makes up approximately 56 percent of the total grain tonnes produced, followed by barley (18 percent), canola (8 percent), sorghum (4 percent), oats (3 percent) and a range of pulses collectively making up 5 percent (Grain Growers 2016). Wheat produced in Australia meets almost 100 percent of Australia's wheat needs and has generated approximately $6 billion per year as an export commodity since the mid-2000s until 2016 (Grain Growers 2016). Therefore, it is very important to improve the productivity, efficiency and profitability of crop production in these regions. A review of the existing literature provides evidence that increasing uncertainties due to drought (low rainfall) and temperature changes in the Wheat Belt farm regions of Australia since the 1990s has led to instability in crop price and challenges in the management of complex broadacre farm businesses (Gordon 2016; Kimura & Antón 2011; Kingwell 2011; Nicholls et al. 2003; Quiggin et al. 2010; Sheng, Jackson & Gooday 2017; Yang, Y. et al. 2016).

Generally, productivity, efficiency and profitability of farm regions are heavily dependent on environmental (climatic) change. According to the Food and Agriculture Organization of the United Nations FAO (2016), agriculture sustainability relies on the amount of interaction between agriculture and climate change. In addition, a shortage of major resources such as irrigation water and arable land can hinder productivity growth (Nossal & Sheng 2010; Sheng, Jackson & Gooday 2017; Zhao et al. 2008). Changes in climatic variables such as temperature, humidity, wind, and rainfall may lead to a decrease in the average water availability or may produce negative changes in the flow systems of rivers in producing negative changes in rivers' flow systems (Alcamo, FlÖRke & MÄRker 2007). However, the cost of the environment or the value of natural resources are not considered in the national accounts of many countries. "Drought plays a major role in the decline of the labour force in the agricultural sector and increases soil acidification and other issues". For example, the rural labour force in Australia decreased by 15 percent because of the drought in mid-2002 and 2003 (ABS 2012a; Hughes et al. 2016). Drought is expected to increase in all Australian farm regions including southern Australia and southwest Western Australia (WA) (Hughes et al. 2016). For instance, the Murray–Darling Basin has experienced its lowest water level because of the drought between 2007 and 2010 (Jiang & Grafton 2012). Hughes et al. (2016) also stated that irrigated land and profits are projected to decline towards 2030 due to droughts.

Total factor productivity (TFP) is a measure used in agricultural economics to determine long-term fluctuations and growth in farm production of farm regions. TFP measures how efficiently and intensively farm inputs are used to produce output (Comin 2006). According to Sheng et al. (2017), the TFP change of crop production in Australia was approximately 2.3 percent per annum from 1949 to 2012, and decreased by approximately 0.6 percent between 2000 and 2012. The inability of farmers to distribute their input or output mix more technically and efficiently, considering future changes such as environmental change, could lead to high variations in TFP from year-to-year. Typically, a positive change in farm TFP could lead to a positive change in farm profitability, where profitability refers to the ratio of revenue to cost (O'Donnell 2010). Profitability change is therefore a measure of value change (O'Donnell 2012c).

Another important measure of the performance and profitability of a farm business is efficiency, which compares the actual ratio of outputs to inputs with the optimal ratio of outputs

to inputs. In other words, the efficiency of a firm represents the actual productivity of that firm relative to the maximum possible productivity (Farrell 1957). It measures how efficiently a farm uses its inputs to achieve profit. The efficiency ratio is important for the estimation of the profitability ratio because an improvement in the efficiency ratio usually translates to improved profitability. O'Donnell (2012c), and Mugera, Langemeier and Ojede (2016) stated that there was a strong link between efficiency and profitability in agriculture.

When studying the sources of TFP, efficiency and profitability changes (indices) of a farm business, it is necessary to decompose these indices into several components attributable to technical change and efficiency change with environmental changes. The total factor productivity index (TFPI) is the ratio of aggregate output to aggregate input and can be decomposed into several components using a number of multiplicatively-complete indices (such as the Färe-Primont and Lowe indices). Several multiplicatively- complete indices have been defined by O'Donnell (2010, 2012a, 2012c). These include the Lowe, Färe-Primont, Laspeyres, Paasche, Fisher, Törnqvist, and Hicks-Moorsteen indices. The Lowe index is ideal for measuring quantity change and TFP change because it satisfies all seven axioms outlined by O'Donnell (2012c), and it provides assurance of a greater accuracy of results. However, it is less than ideal for measuring the changes in prices and terms of trade (TT).

In Australia, previous studies have concentrated on the determination of agricultural productivity without much attention to profitability (Hughes & Lawson 2017; Hughes et al. 2011; Hughes, Lawson & Valle 2017; Knopke, O'Donnell & Shepherd 2000; Kokic, Davidson & Boero Rodriguez 2006; Mullen 2007; Nossal et al. 2009; Salim & Islam 2010; Zhao et al. 2008) with the exception of Che *et al.* (2012) who presented an analysis based on the Törnqvist index and Islam, Xayavong and Kingwell (2014), and Kingwell et al. (2013a) on Färe-Primont index. This was due to poor availability of financial data in Australian farming sector. Several studies (Battese, Malik & Broca 1993; Battese, Malik & Gill 1996; Che et al. 2012; Hochman, Gobbett & Horan 2017; Hossain et al. 2013; Hughes & Lawson 2017; Hughes et al. 2011; Hughes, Lawson & Valle 2017; Kingwell et al. 2013a; Kokic, Davidson & Boero Rodriguez 2006; Kokic et al. 2005; Salim & Islam 2010; Sheng, Mullen & Zhao 2011; Skold & Popov 1990) have revealed that environmental variables (such as temperature and rainfall) actually play a significant role in determining efficiency and productivity.

Previous studies have focused on specific regions within specific states and cropping regions in Australia (Islam, Xayavong & Kingwell 2014). Others have considered environmental factors, but not as uncontrolled input (Islam et al. 2014; Islam, Xayavong & Kingwell 2014). Those that have considered rainfall as an uncontrolled input used either regional or state rainfall data in their analyses; however, they did not use the Lowe index method (Henderson & Kingwell 2005; Hughes et al. 2011; Khan, Salim & Bloch 2014). Others (Islam et al. 2014; Islam, Xayavong & Kingwell 2014) did not consider environmental factors as uncontrolled inputs and did not use the Lowe index method. Although Khan, Salim and Bloch (2014) used seasonal rainfall conditions as important input, it was not clear how rainfall was incorporated in the model. Additionally, other environmental variables such as temperature were not included in this study. Considering rainfall and temperature separately is necessary to examine the effect on productivity and efficiency from different perspectives using specific region-level rather than state-level average farm data. However, from the literature, it appears that no studies have investigated the dynamics of productivity and profitability changes, considering the effect of environmental (rainfall and temperature analysis) changes as an uncontrolled variable with the Lowe index model throughout the Wheat Belt regions of Australia by each farm region over the long term. It is important to recognise that environmental variables are not strongly disposable (O'Donnell 2018). Thus, it is necessary to consider these variables as a special input, not as market inputs because these inputs are beyond the control of the farmers (O'Donnell 2016).

Crop production is affected by the socioeconomic conditions of farm owners and farm workers (Anigbogu, Agbasi & Okoli 2015). From the literature, several researchers such as Thiam, Bravo-Ureta and Rivas (2001), Binam et al. (2004), Latruffe et al. (2004), Paul et al. (2004), Grazhdaninova and Lerman (2005), Masterson (2007), Odeck (2007), , Abatania, Hailu and Mugera (2012), Wassie (2014) and Nguyen (2017) studied relationships between socioeconomic factors (independent variables) and efficiency factors (dependent variables). They found that factors such as age and gender of farmers and hired labour, level of education, farming experience, years of employment, geographical location of farms, capital-labour ratio, land-labour ratio, household size and credit availability had significant influences on efficiency measures such as technical efficiency. In addition, particularly in Australia, Kingwell et al. (2013a) showed that productivity and profitability change can be driven by socioeconomic variables. However, despite the significant contribution of agricultural households to

agricultural work, there is a paucity of literature on the social issues of these families and what they need in rural and remote areas (Alston 2012). Thus, this study seeks to remedy this situation by examining the impact of environmental changes on the economic performance of broadacre farms in Australian Wheat Belt regions.

1.2 Motivation of the Study

There is concern about the inadequacy of global agricultural resources to feed the world's population. These resources are becoming scarcer due to increased demand for them caused by the high and increasing global population (Lal 2008). In particular, the literature of the actual situation of agricultural economics reveal that Australian crop farmers are under increased pressure to produce more food to satisfy local and international demand (Eadie, Stone & Burton 2012; PMSEIC 2010). For example, Australia was the fifth largest exporter of wheat by five years average 2005–2006 to 2009–2010, behind the United States (US) (23%), Canada (15%), European Union (14%) and Russia (11%) (PwC 2011b). In addition, Australian wheat is rated high in the global market because of its superior quality (AEGIC 2018). Despite the growing global demand for grain, especially the Asia Pacific region, there are many challenges that face the Australian grain production industry, e.g. there has been a volatility in production volumes resulting from harsh and changing climates in some farm regions. The development of novel farming practices is necessary to improve the productivity and profitability of farmers.

The existing literature analysis has shown that environmental variables such as rainfall and temperature (although outside the control of farmers) play a significant role in determining the efficiency and productivity of Australian agriculture. Productivity decreased from 2005 to 2007 owing to prolonged drought and recovered by over 30 percent up to 2012 (Gordon 2016). Thus, adaptation to climate change by farmers is important because it helps farmers improve their resource-use efficiency by best practice, reduce the total cost of production and improve productivity (OECD 2015). Over a period of 20 years until 2014–2015, environmental change has had a significant effect on productivity levels. This is because of the deterioration in climatic conditions in the grain-farming regions. Therefore, this study provides a separate estimation of the impacts of rainfall and temperature conditions on productivity and efficiency across different farm regions to present different insight for farm managers and policy makers in future investment in Australian farm regions. This study seeks to determine the main sources of profitability and TFP changes, and to examine any inefficiencies for wheat and non-wheat

groups during the production process under different rainfall and temperature levels in 12 Australian farm regions.

1.3 Research Question for the Study

The main research question for this study is 'What are the main drivers of profitability and productivity changes and the determinants of inefficiency for annual wheat and non-wheat cropping on broadacre farms in the Wheat Belt regions of Australia?'

This also leads to the following sub research questions:

1. Do the components of profitability and TFP changes of crop production exist?
2. What are the main sources of profitability and TFP changes?
3. How do environmental variations affect profitability and TFP changes?
4. How do environmental variations affect efficiency scores?
5. How do socioeconomic variables affect efficiency indicators under environmental conditions?

1.4 Aim and Objectives of the Study

The aim of this study was to measure and explore profitability and productivity changes, and examine the scores of efficiency indicators (considering the impact of environmental variations) and determinants of inefficiency for the production of wheat and non-wheat crops (e.g. canola, sorghum, oats, rice, barley, field peas, lupines and grain legumes) in 12 farm regions in the Wheat Belt regions of Australia from 1990 to 2016. This was achieved by analysis of the productivity and performing efficiency of inputs such as fertiliser, chemicals and fuel, and the technologies employed in their use. The efficiency analysis was undertaken to explore the extent of efficiency and productivity variations across regions, to determine the sources of productivity and profitability changes of the wheat and non-wheat crops, and to explain the causes of variations considering environmental variations as uncontrolled inputs. Accordingly, the objectives of this study were:

1. To estimate technical efficiency, and the components of TFP change, profitability and productivity change decomposition in agriculture.
2. To investigate the main sources of profitability and TFP changes.
3. To examine the impact of environmental variations on profitability and TFP changes.

4. To examine the impact of environmental variations on the estimated scores of efficiency indicators.
5. To investigate the effect of socioeconomic variables on the efficiency indicators in environmental conditions.

1.5 Summary of Methodology Used in this Study

Average annual farm region-level panel dataset obtained from surveys conducted by AgSurf of the Australian Bureau of Agricultural Resource Economics and Sciences (ABARES 2017) was used in this study. ABARES is the official research arm of the Australian Government Department (Ministry) of Agriculture and Water Resources in Canberra. This dataset comprised 324 observations on the prices and quantities of agricultural outputs and inputs in 12 farm regions over the 27 years from 1990 to 2016. Rainfall and temperature data were obtained from the Scientific Information for Land Owners (SILO). Standard data envelopment analysis (DEA) technique was employed to estimate the production frontier and to compute and decompose the TFPI (Lowe index method) into measures of technical, environmental and several efficiency changes. Efficiency measures were estimated using the output-oriented DEA model under the variable returns to scale (VRS) assumption. Tobit regression was used to examine the effects of socioeconomic variables on eight efficiency indicators (scores) and the results were checked for robustness using the truncated regression and double bootstrap model introduced by Simar and Wilson (2007).

1.6 Contributions of the Research

This study attempted to help decision makers gain a better understanding of the behaviour of farms for annual crops in specific farm regions under different rainfall and temperature levels in the Australian Wheat Belt region. From this research, the following novel empirical contributions were obtained.

First, this research considered more components of productivity change and efficiency indicators than exist in the current literature both in Australian agriculture and worldwide. This will provide policy makers and farm managers with a bigger and clearer picture of farm performance by providing them with information on the main drivers of productivity and profitability changes and their relationships to rainfall and temperature variation over almost

three decades (1990–2016). This will, in turn, present them with more options to choose from during decision making towards the improvement of productivity and profitability of wheat and non-wheat production in the Wheat Belt regions of Australia. It will also encourage policy makers to develop new strategies aimed at promoting economic growth in farm regions.

Second, the majority of previous studies on environmental efficiency considered environmental variables such as rainfall and temperature as market inputs; however, very few studies considered them as uncontrolled (special) inputs. Unlike conventional inputs such as labour and fertiliser, which farmers can decide on different doses for their crops, rainfall and temperature are beyond the control of the farmers. Failure to study environmental variables as uncontrolled inputs may lead to inaccurate results.

Third, this study introduces the Lowe index. This study is the first in Australian agriculture that considers a new TFPI for the assessment of the productivity of wheat and non-wheat crop production in the Wheat Belt regions of Australia. The Lowe index gives assurance of a greater accuracy of results and is ideal for measuring quantity and TFP changes. This is because the Lowe index satisfies all seven axioms from the index number theory proposed by O'Donnell (2012b, 2016). A review of the existing literature showed that most of the studies of the Lowe index method were developed and performed by O'Donnell, with these studies undertaken only in the US. This contribution is consistent with the concept that each country is different in its environmental, economic and social conditions.

Finally, this research is the first in Australian agriculture to consider six explanatory variables during the assessment of the determinants of efficiency indicators in the Australian Wheat Belt regions. These include age of farm manager, the age of spouse of farm manager, off-farm work of farm manager, off-farm work of spouse of farm manager, capital-labour ratio and land-labour ratio. The eight efficiency indicators are outputs-oriented of technical efficiency, scale efficiency, mix efficiency, residual scale efficiency, scale-mix efficiency, technical and scale-mix efficiency, and overall environmental efficiency. One of the most important steps that may contribute to improving productivity is the identification of determinants that may affect efficiency indicators because inefficiency in the production process can lead to increased production costs in farm regions. Therefore, this contribution will assist policy makers to better understand the obstacles of various efficiency indicators to enable them to select the best and

most appropriate one to achieve efficiency in their crop production based on regional environmental conditions.

1.7 Structure of the Thesis

This thesis is organised into eight chapters. The chapters, specific objectives and outcomes of this study are connected as shown in the schematic diagram of the conceptual framework shown in Figure 1.1.

Chapter 1 provides the background, the research question and objectives, summary of methodology and findings, motivation and the significance of this research. A brief discussion of each chapter is presented below:

Chapter 2. This chapter presents background information that reviews the current situation of crop production in the Wheat Belt regions of Australia. In several sections, more information to support the justification for this study is provided.

Chapter 3. This chapter reviews past empirical studies from Australia and other parts of the world related to productivity and efficiency estimates and their relationship with environmental and socioeconomic changes of grain farming. The research areas were identified, and research questions established based on the literature in Chapters 2 and 3.

Chapter 4. This chapter outlines and justifies the methodology used to answer the research question and discusses the related econometric issues.

Chapter 5. This chapter presents two results of empirical index outcomes. First, the measurement of an analysis of rainfall variation on productivity and profitability change. Second, the measurement of an analysis of temperature variation on productivity and profitability change.

Chapter 6. This chapter presents empirical results of the effect of rainfall variation on efficiency and its determinants.

Chapter 7. This chapter presents empirical results of an analysis of temperature variation on efficiency and its determinants.

Chapter 8. This chapter presents the conclusion, policy implications, limitations and challenges, and recommendations for further research.

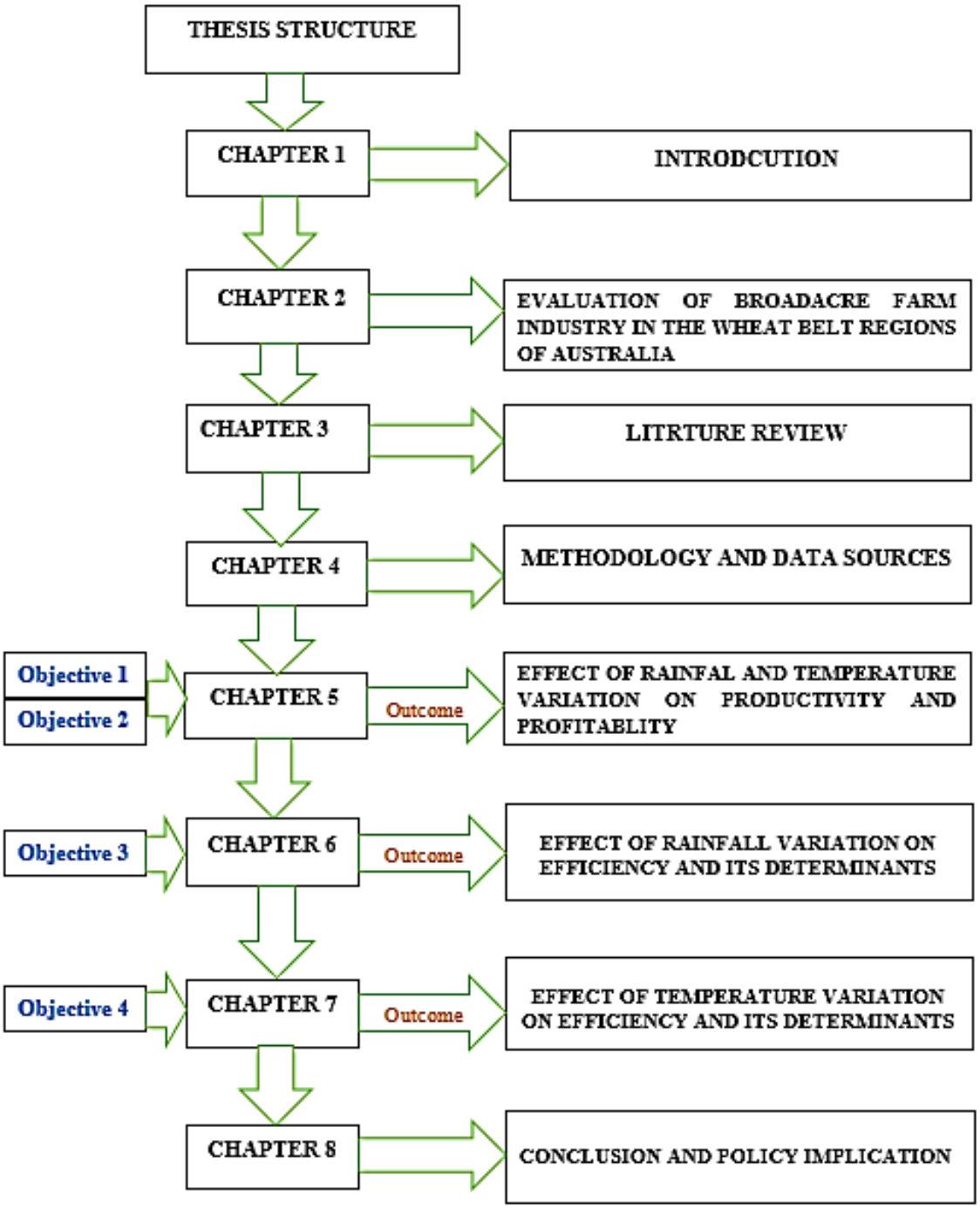

Figure 1.1: Research design and conceptual framework for the study

CHAPTER 2: EVALUATION OF BROADACRE FARM INDUSTRY IN THE WHEAT BELT REGIONS OF AUSTRALIA

2.1 Introduction

Globally, Australia is the driest inhabited continent. More than two-thirds of the continent is classified as arid or semi-arid and a third of the continent is desert (ABS 2012b). Only 10 percent of its land is suitable for cropping and pastures. Furthermore, this small percentage of land also requires the addition of different types of fertilisers to be suitable for agricultural production.

One of the main challenges faced globally is to meet the increasing demand for food derived from the increasing worldwide population (Ridoutt & Pfister 2010). Australian agricultural productivity (grain productivity) is under increasing pressure to produce more food to meet both local and international demand (Eadie, Stone & Burton 2012; PMSEIC 2010). Furthermore, Lê et al. (2014) stated that, from a study conducted in Tasmania, 6.6 percent of people have a low level of food security. This increasing demand increases the use of fertile land, irrigation water resources and other natural and production resources. Increasing productivity, profitability and agricultural efficiency are the main incentives for farmers to continue to increase supply and to fill the shortfall in the demand of local and international markets for crop products.

Climate change is also a major concern in Australia now and in the future. Many studies confirm the impact of environmental changes (e.g. rain and temperature) on the production and productivity of crops and therefore on profits and profitability. Thus, it is necessary to consider these changes when studying the agricultural economy. Successful adoption of efficient management practices in allocating production resources such as land and water to agriculture will play a significant role in this process (FAO 2011). The agricultural sector in Australia often suffers output volatility, which is exacerbated by fluctuating weather conditions. The highest volatility level in all sectors has been experienced over the last three decades. The drought of 2002-2003 caused a significant decline in agricultural production, leading to a 15 percent reduction in employment (Steffen 2015). The agriculture multifactor productivity (MFP) recorded a sharp decline of 17 percent over the same period (Productivity Commission 2005).

The Australian agricultural sector has adopted modern scientific agricultural practices since the early 20th century. The agricultural sector has used modern techniques to improve the productivity of cereals such as wheat, barley and others (Robertson et al. 2016). According to Lockie (2015), approximately 50 percent of the landmass in Australia is occupied by agricultural businesses. It contributes significantly to the Australian economic vitality. Agricultural activities also play a key role in the maintenance of environmental values and the ecosystem. This is achieved through proper management of farms in the Australian landscape. According to the Productivity Commission (2005), the agricultural sector has accounted for 2.2 percent of national gross domestic product (GDP) in recent years. In 2015–2016, agricultural employment (321,600 employees) increased by 1.3 from 2014–2015 (Chief Economist 2016). The Productivity Commission, an independent agency, is the Australian Government's principal review and advisory body on microeconomic policy and regulation.

The exports of agricultural products have also significantly increased in real terms from 1974-1975. It has been growing at an annual rate of approximately 3.5 percent, recording a tripling in growth since 1974-1975. According to National Farmers' Federation (2012), on average, Australia exports approximately 60 percent of its total agricultural produce. In 2010–2011, the export of agricultural products earned Australia $32.5 billion, which was an approximate 1.25 percent increase from what was earned in 2008–2009 (National Farmers' Federation 2012).

Lal (2008) defines sustainable agriculture as an approach of solving principal and applied issues associated with agriculture. By using a sustainable plan and management approach, and developing appropriate technologies, resources will be conserved, waste and environmental damage will be minimised, farm income will be improved, water and soil damage will be avoided and many other benefits will be achieved (Pretty 2008). The goals of sustainable agriculture are providing more farm profits; utilising more environmentally friendly activities such as soil and water protection; eliminating non-renewable materials such as fuels, fertilisers and pesticides; and some other social and environmental factors (Lichtfouse et al. 2009). As many researchers have mentioned, the heart of sustainable agriculture is the management and improvement of agricultural water consumption and energy usage. Australian broadacre farms have recently been facing more challenges in economic and environmental changes. This has been negatively reflected on the productivity and profitability of Australian agricultural farms.

Without sustainable agriculture, the gap between actual farm productivity and profitability and their potential will only increase (FAO 2014).

This chapter presents a review of the background in Australian agriculture and justification for the research in several sections. Section 2.2 presents cereal and wheat production in Australia. Section 2.3 presents natural economic resources. Section 2.4 highlights financial performance and grain markets of the broadacre farm industry. Section 2.5 describes the productivity and TT change. Section 2.6 shows the impact of climate change on broadacre cropping farm productivity. Section 2.7 discusses the impact of agricultural socioeconomic factors on productivity and profitability changes. Section 2.8 reviews the actual farm employment and environmental change. Finally, Section 2.9 provides the conclusion to the chapter.

2.2 Cereal and Wheat Production in Australia (Wheat Belt Regions)

Figures 2.1–2.5 show the variations in grain production and average area (per farm) in broadacre farm regions in the Wheat Belt of Australia. The figures also show the differences in production and average area between broadacre farm regions in the same states. The observed variations could be attributed to geographical location and differences in environmental conditions in these regions. Wheat and barley production are the most prominent in all broadacre farm regions, whereas rice production is almost non-existent. This may be because it is more economical to import than to produce rice.

Oilseeds have low average production; however, there is some missing data for the average area. Other crops such as canola, field peas, lupins, grain legumes, oats and sorghum have limited and varied average production and area dependent on farm region. It is clear that farm regions of WA have the largest production and land area.

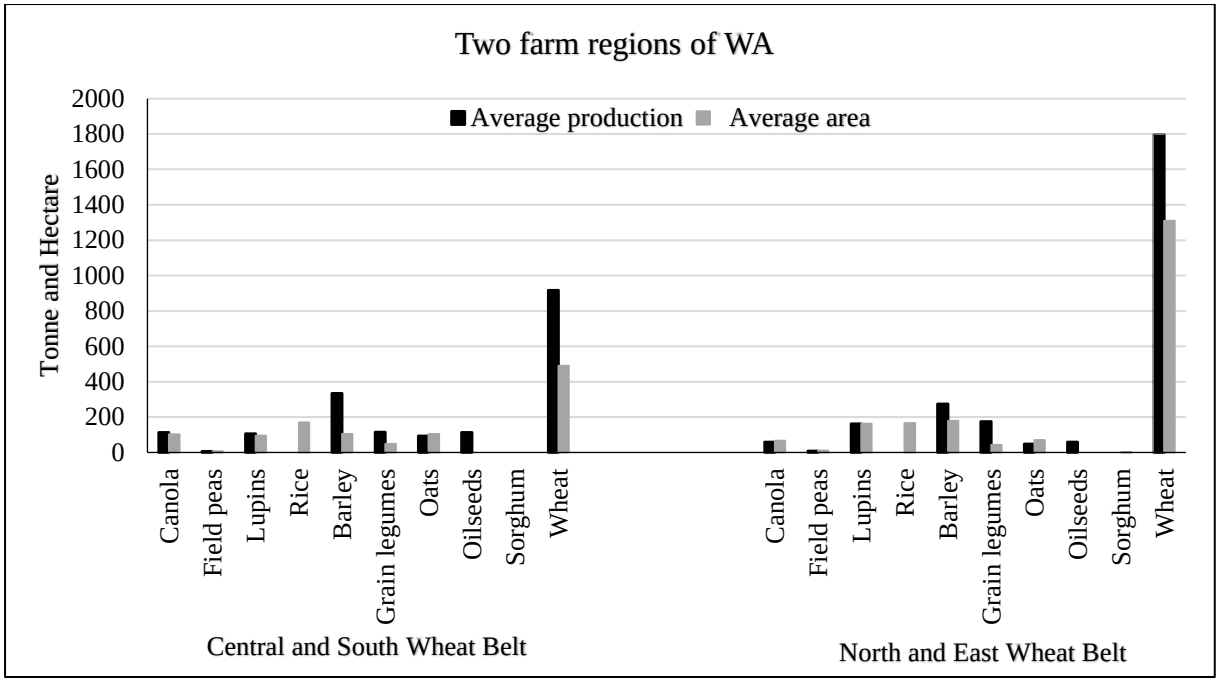

Figure 2.1 Grain production and average land area per farm in the broadacre farm regions of Western Australia (WA) over 1990-2016. Derived by the author from data of ABARES (2017).

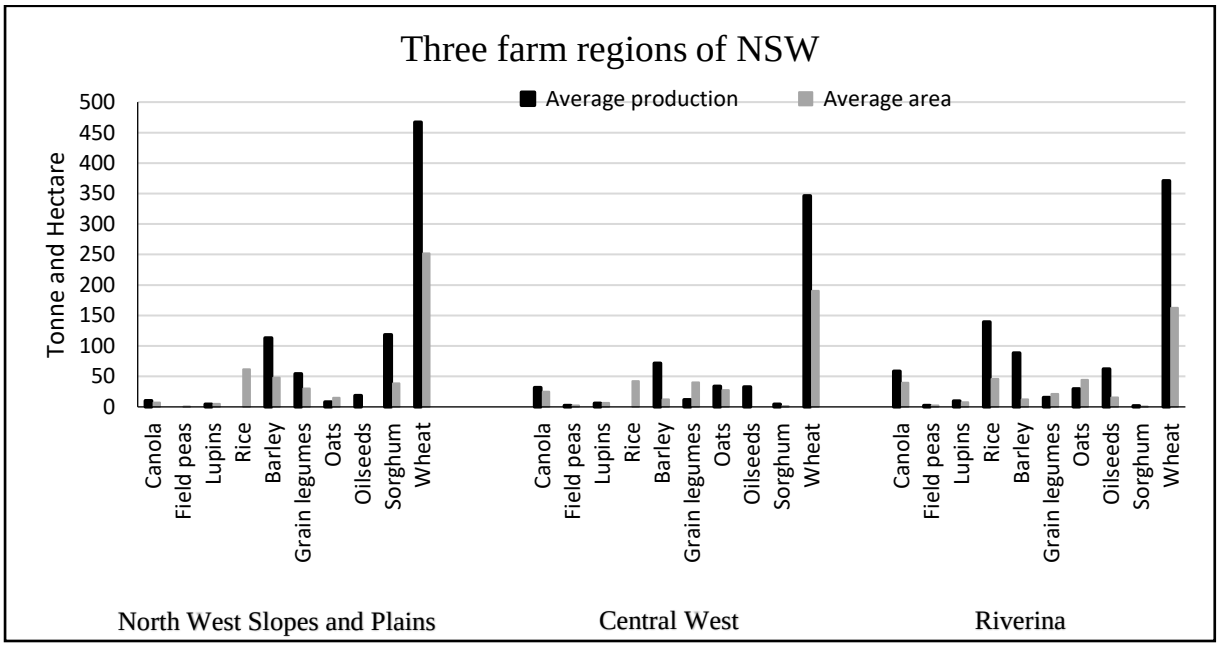

Figure 2.2 Grain production and average land area per farm in the broadacre farm regions of New South Wales (NSW) over 1990-2016. Derived by the author from data of ABARES (2017).

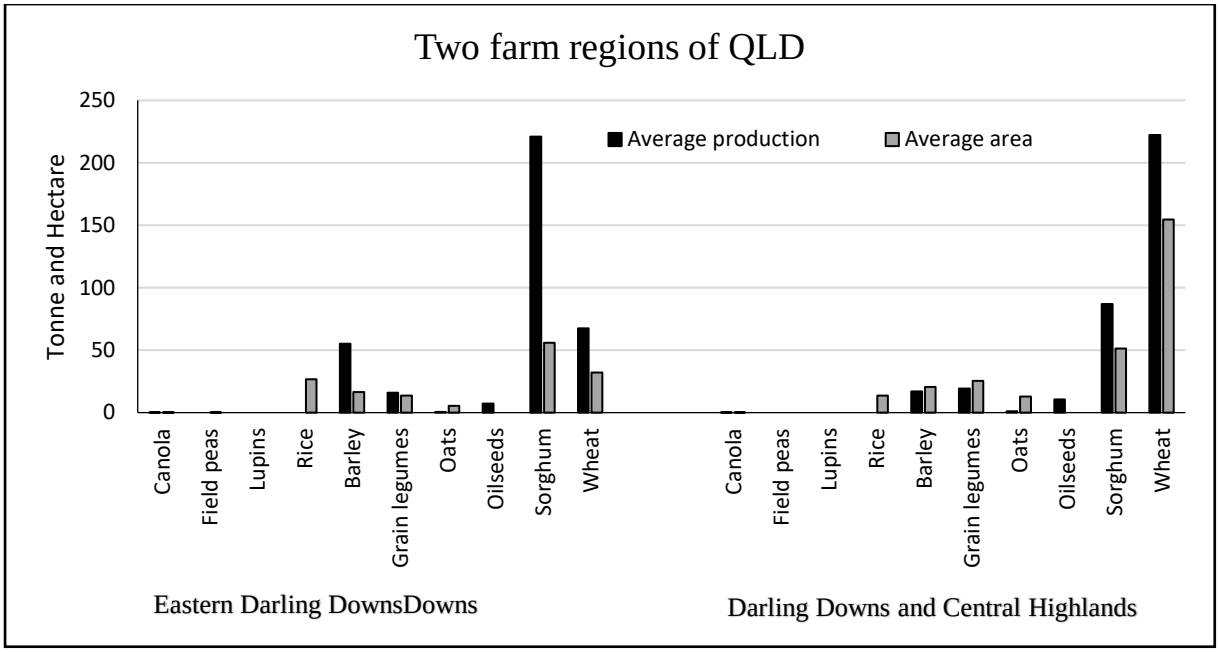

Figure 2.3 Grain production and average land area per farm in the broadacre farm regions of Queensland (QLD) over 1990-2016. Derived by the author from data of ABARES (2017).

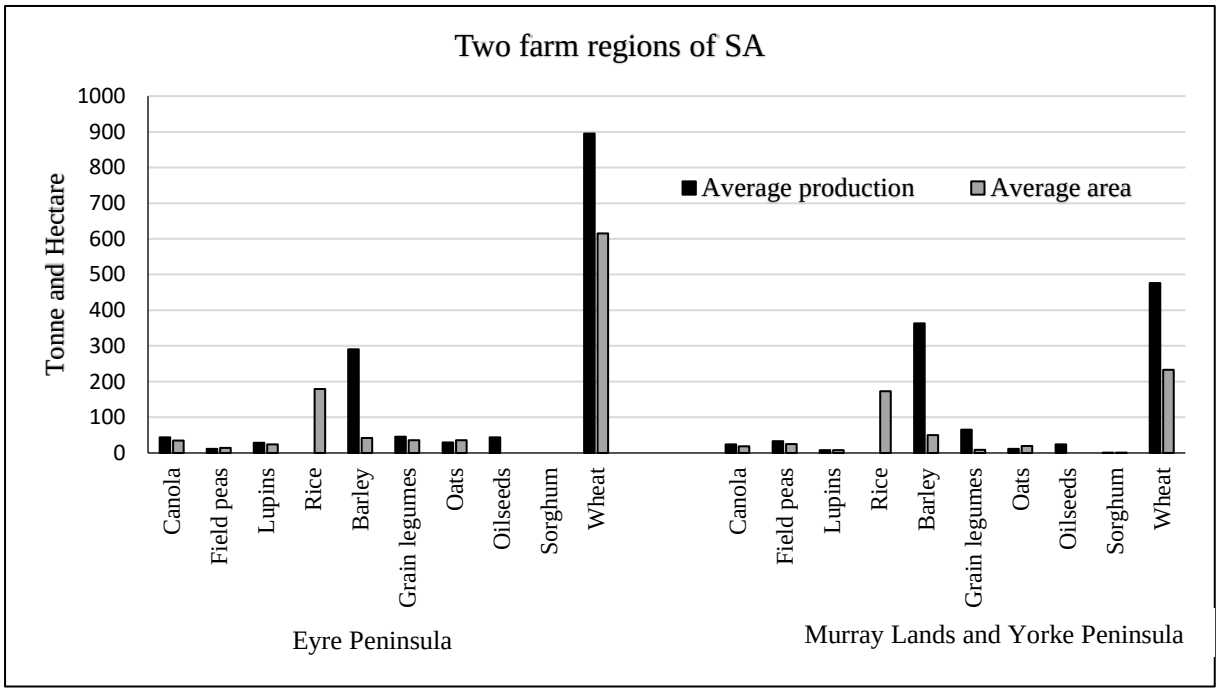

Figure 2.4 Grain production and average land area per farm in the broadacre farm regions of South Australia (SA) over 1990-2016. Derived by the author from data of ABARES (2017).

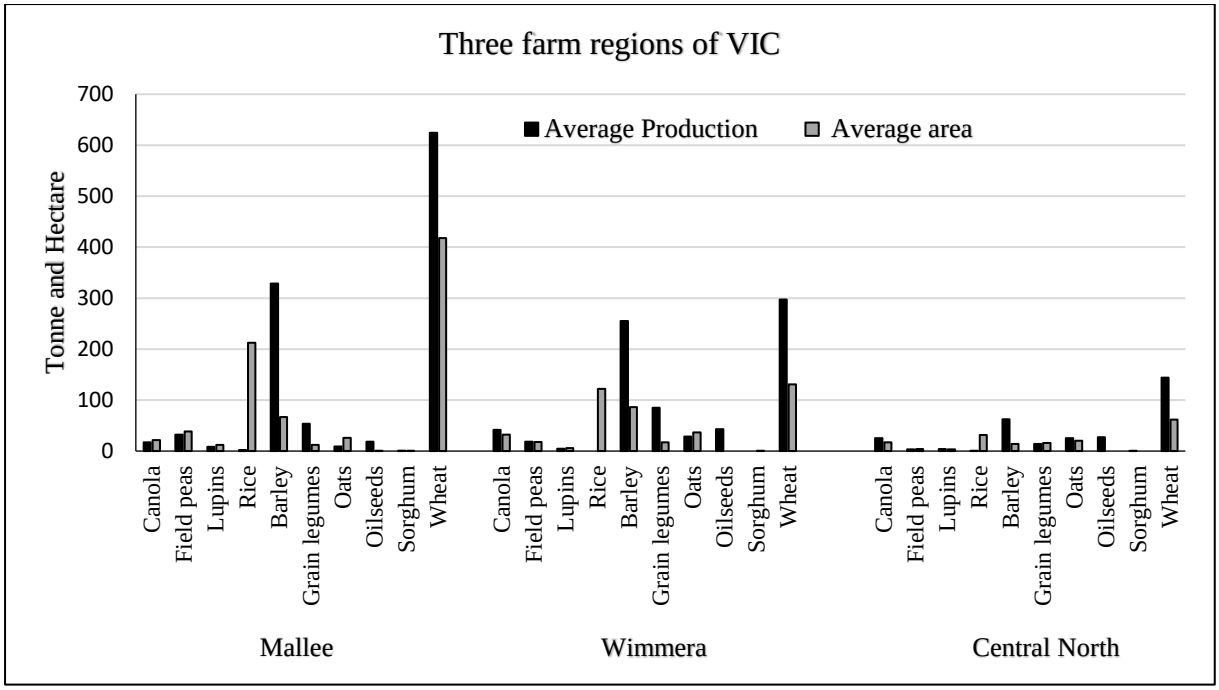

Figure 2.5 Grain production and average land area per farm in the broadacre farm regions of Victoria (VIC) over 1990–2016. Derived by the author from data of ABARES (2017).

In addition to the variations observed in average farm area and crop production between the farm regions, decline in total arable land area and number of broadacre farms between 1977–1978 and 2009–2010 were observed (Figure 2.6). Despite these decreases, agricultural revenues were steady but at low levels. Wheat Belt regions have been facing the challenge of drought situations, which lead to salinisation of the soil and decline of arable land. For example, the southern regions and the centre of the state of Queensland (DAFF 2014) have suffered from increasing salinisation of the soil and then increasing use of inputs (e.g. fertilisers, chemicals, fuels and labour) and water use. The supply of arable land has been decreasing rapidly over the last decades. For instance, the decrease in arable land area (percentage change) was approximately 42 percent between 1977–1978 and 2009–2010.

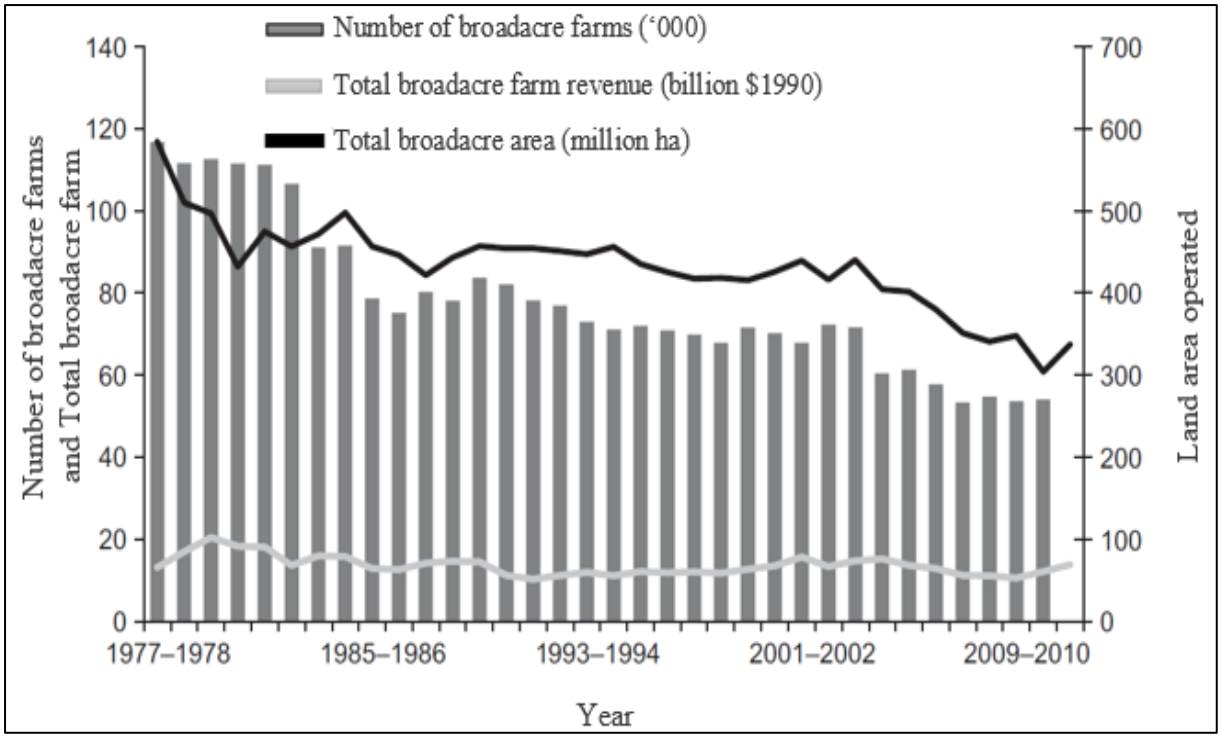

Figure 2.6 Number of farms, total farm revenue and area. Modified by author from Sheng et al. (2015).

2.3 Natural Economic Resources

Globally, land and water resources play a significant role in agricultural production. In Australia, arable lands for food production are limited and there is an increasing pressure on them (PMSEIC 2010). Australia could become an importer of wheat in the future owing to a reduction in rainfall in cereal growing regions.

Decreased rainfall and soil moisture with higher temperatures and increased evaporation are the most serious challenges in the Wheat Belt regions (Hughes et al. 2016). Irrigation water is also limited in Australian agriculture. Australia is one of the main countries that has suffered from water shortages (FAO 2011). In some areas, farmers only rely on rainfall for dryland production such as wheat and barley, and they might use underground water or river water for irrigation. Even in regions with high amounts of rainfall, farmers might still use irrigation to increase productivity and reliability. In addition, water scarcity is becoming a major issue not only in irrigated areas but also in the abundant rainfall areas because of the quantity and quality problems expected in the future (Pereria, Oweis & Zairi 2002). According to FAO (2016), the sustainability of agriculture relies on the size of the interaction of agriculture with climate change. Agricultural economics has a complicated relationship with the environment. In

general, the cost of an environmental resource or the value of natural resources are not considered in the national accounts in the economies in many countries. In Australia, many farmers utilise seasonal rainfall for irrigation purposes, even though Australia has a highly variable climate. The variations in these resources have negative effects on the productivity, efficiency and profitability of both winter and summer crops. Therefore, agricultural crop production can decline gradually (Gray, Oss-Emer & Sheng 2014).

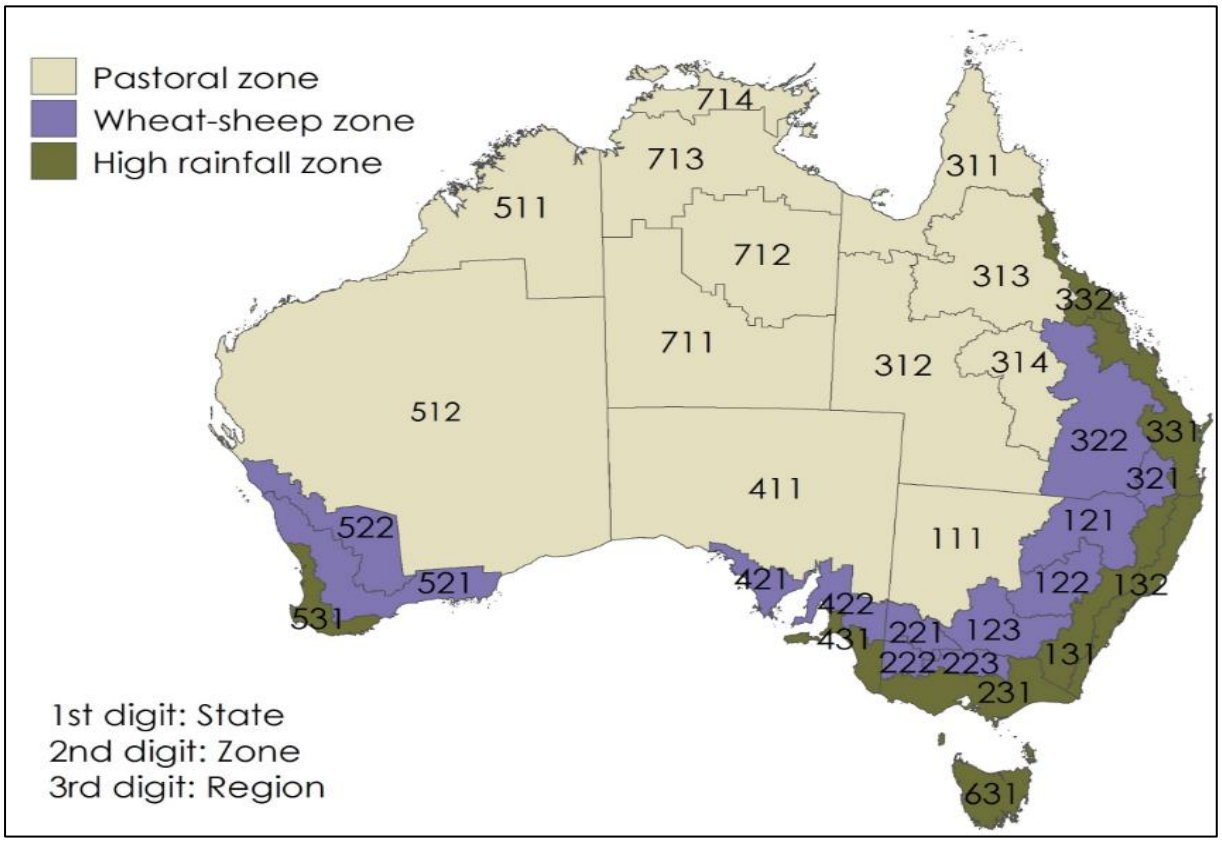

Figure 2.7 Australian broadacre zones and regions. Adopted from ABARES (2017).

2.3.1 Australian broadacre zones

According to ABARES, the three Australian national zones are the high rainfall zone, the Wheat Belt regions (wheat-sheep) zone and the pastoral zone (Figure 2.7). The Wheat Belt regions of Australia are made up of 12 farm regions namely New South Wales North West Slopes and Plains (NSWN), New South Wales Central West (NSWC), Victoria Central North (VICC), Queensland Eastern Darling Downs (QLDE), New South Wales Riverina (NSWR), Queensland Darling Downs and Central Highlands (QLDD), Western Australia Central and

South Wheat Belt (WACS), Western Australia North and East Wheat Belt (WANE), Victoria Mallee (VICM), Victoria Wimmera (VICW), South Australia Eyre Peninsula (SAEP) and South Australia Murray Lands and Yorke Peninsula (SAMY).

2.3.2 Relationship between environmental change and farm regions in Australia

2.3.2.1 Rainfall change

The average annual rainfall in the Wheat Belt regions ranges between 300 and 600 mm. Farms in the Wheat Belt regions and closer to the coast receive more annual rainfall than others. Land prices and grain productivity are mostly determined by the amount of rainfall in each mean farm region (Land Commodities 2012). Figure 2.8 shows that Australia's annual rainfall rate varies widely from year-to-year. This suggests once again that overall agricultural performance of productivity and profitability fluctuate from one broadacre farming region to another.

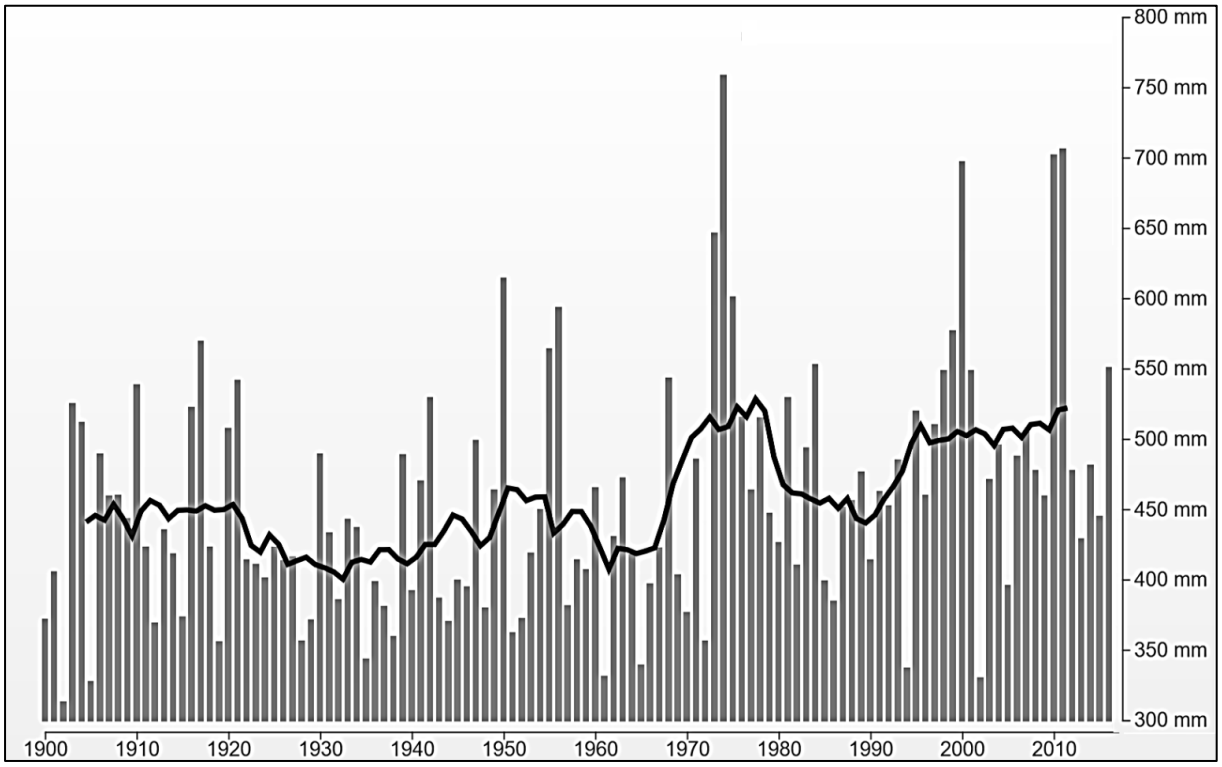

Figure 2.8 Australian annual average rainfall over more 100 years. Adopted from the Buraeu of Meteorology (BoM 2017a).

Australian agriculture in the Wheat Belt regions depends on several climatic factors including soil moisture, annual rainfall rate and temperature. The annual rate of rainfall varies from region to region. For example, the Central North region of VIC represented the highest annual rainfall rate during 1990–2016, whereas the Mallee region had the lowest (Figure 2.9) (SILO 2017).

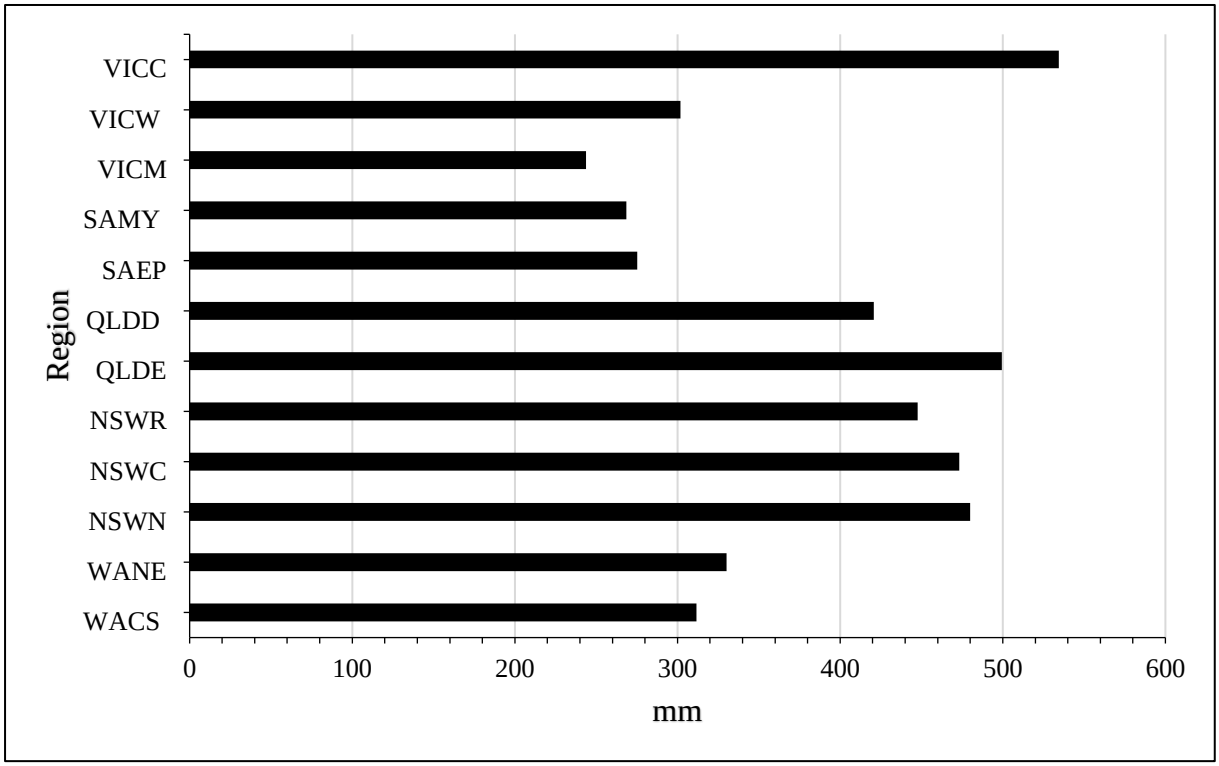

Figure 2.9 The variation of annual average rainfalls (mm) between broadacre farm regions during 1990-2016. Derived by the author from data of SILO (2017).

For the annual rainfall change, Figure 2.10 provides an example of a gradual decrease in rainfall in the Central and South Wheat Belt farm regions between 1990 and 2016, which shows the growing drought problem in Wheat Belt regions. This variation could lead to variability in productivity and profitability of broadacre farms. Hughes, Lawson and Valle (2017) confirmed that a decrease in rainfall had a negative impact on grain productivity from 1977–1978 to 2014–2015.

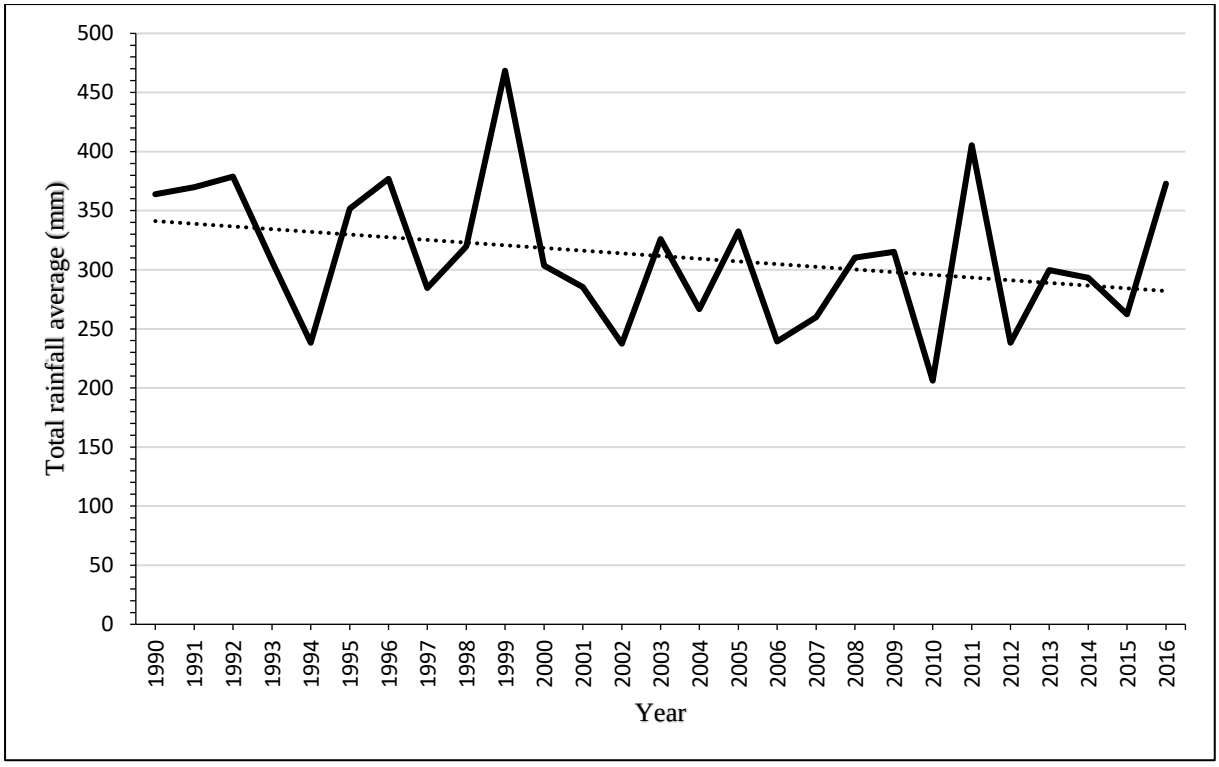

Figure 2.10 Total average annual rainfall in the Central and South Wheat Belt farm region. Derived by the author from data of BoM (2017b) and SILO (2017)

2.3.2.2 Temperature change

Australia has experienced gradually increasing higher temperatures since 1980 (Figure 2.11). According to CSIRO and BoM (2016), Australia's mean temperature has continued to increase and 2013, 2014, and 2015 were the hottest years on record. Temperature change also plays an important role in the direction of drought severity. Soil moisture change is directly related to temperature change (Steffen, Hughes & Perkins 2014). The average temperature anomalies over the past 100 years range from -1.20 °C to +1.20 °C.

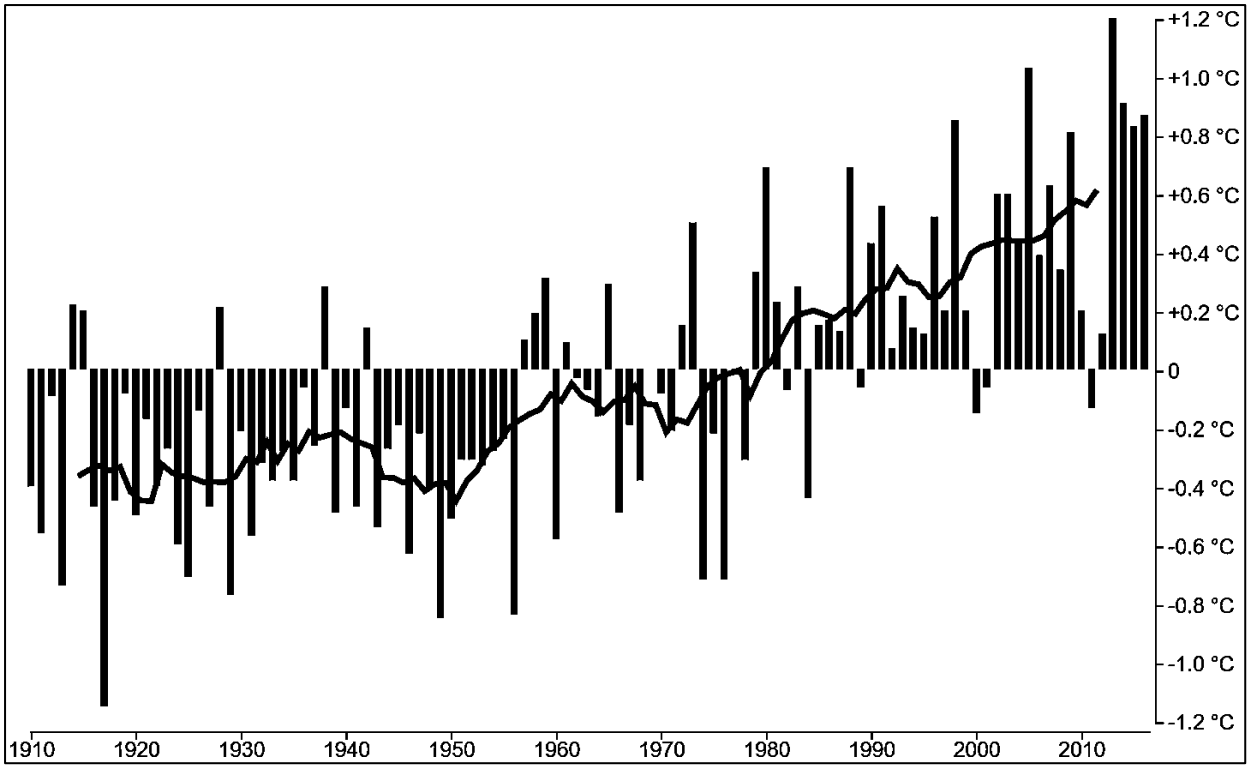

Figure 2.11 Annual average temperature anomaly – Australia (1910–2016). Modified by author from BoM (2017a).

Figure 2.12 shows the temperature conditions in each region of the Wheat Belt over 27 years. Darling Downs and Central Highlands and Central and South Wheat Belt farm region have had the highest temperatures whereas the Wimmera and Murray land and Yorke Peninsula have had the lowest temperatures. This variation in temperature between one region and another may also lead to variation in the level of soil moisture in each agricultural region and then cause variation in productivity, profitability and efficiency. It is therefore necessary to determine the economic changes of agricultural areas as a result of the impact of temperature changes in each region. For example, the increasing drought between 2002 and 2003 led to a decline in agricultural productivity, which led to a decline in GDP of 1 percent (Steffen 2015).

Figure 2.13 displays the gradual increase in temperature in the Central and South Wheat Belt regions between 1990 and 2016. This provides further evidence on the rising temperature problem.

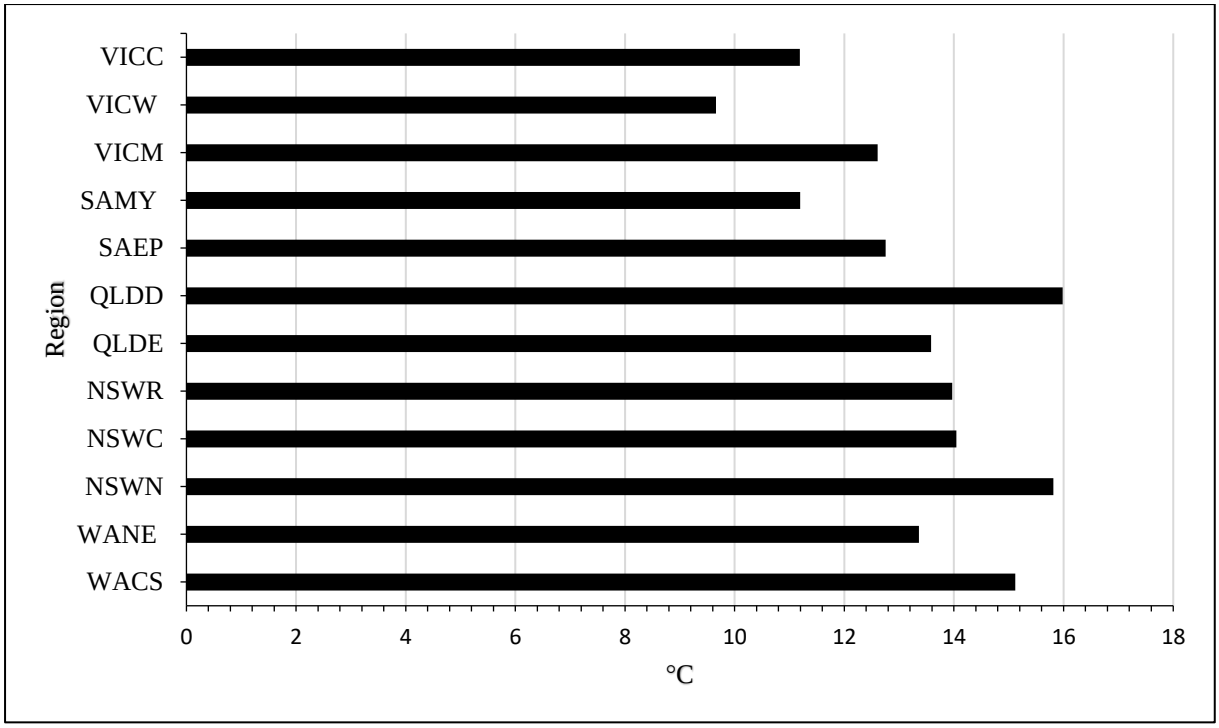

Figure 2.12 Total annual average temperature (°C) of broadacre farm regions in all Wheat Belt regions of Australia during 1990-2016. Derived by the author from data of SILO (2017).

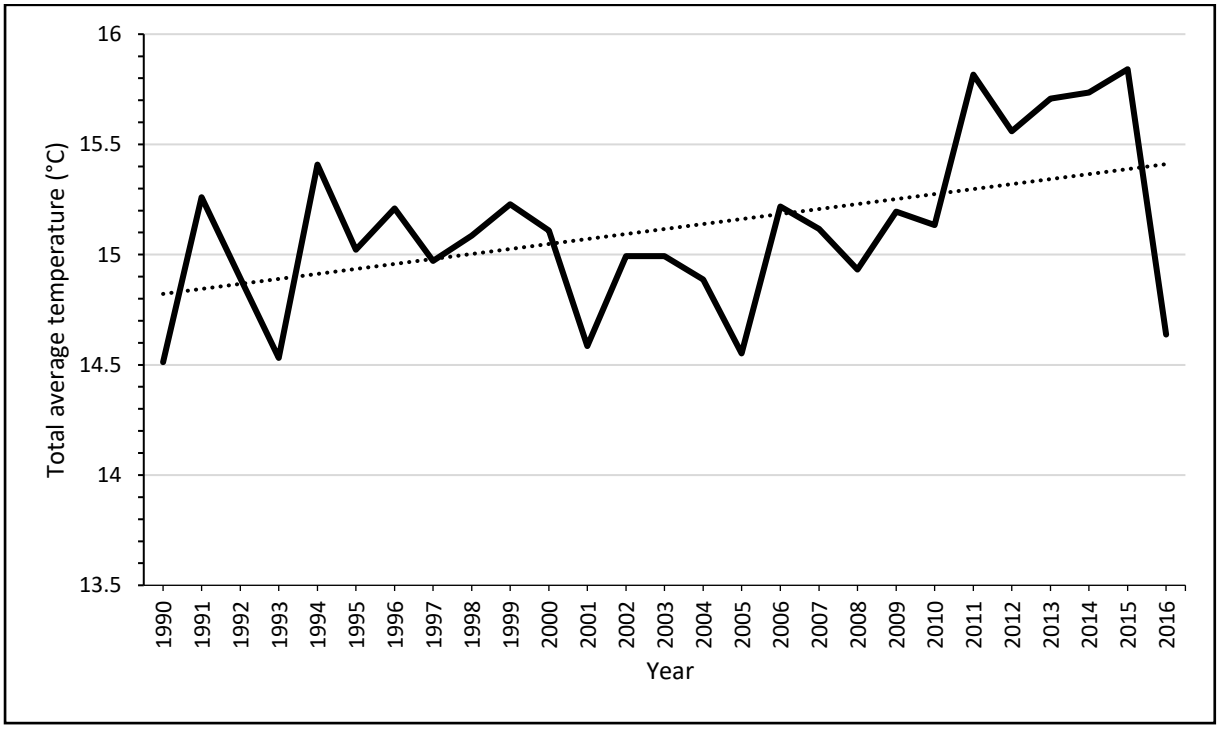

Figure 2.13 Total annual temperature average in the Central and South Wheat Belt farm regions. Derived by the author from data of SILO (2017).

2.3.2.3 Adaptation to environmental change

Climate change has a significant impact on the national and international agricultural commodity markets (Kingwell 2006). FAO (2007) presents two main types of adaptation. First, short-term measures can be adopted by farmers to climate change such as changing the time of seeding or harvest based on adaptation to rainfall change. Second, long-term adaptation that represents major strategies and structural changes such as application of new technologies and management of water and land use efficiency. For example, the use of adaptive practices and irrigation improvement had a significant and positive effect on productivity (Roco et al. 2017).

In Australia, the government has embraced the policy of climate change through programmes such as the CSIRO Climate Adaptation Flagship and the Garnaut Climate Change Review (Garnaut 2015). Furthermore, many institutions have provided a large number of studies and research aimed at adapting to climate change effectively and efficiently in the agricultural sector (Nelson et al. 2010). According to Peel, McMahon and Finlayson (2004), Australia's environmental conditions exhibit greater variability than those in other countries. Therefore, the productivity and profitability of Australian agriculture could fluctuate more than other nations (Kingwell 2006; Kingwell et al. 2013a). Environmental variables such as rainfall and temperature, although outside the control of farmers, have been observed to play a significant role in determining the efficiency and productivity of Australian agriculture (Battese, Malik & Broca 1993; Battese, Malik & Gill 1996; Che et al. 2012; Hochman, Gobbett & Horan 2017; Hossain et al. 2013; Hughes & Lawson 2017; Kingwell et al. 2013a; Kokic, Davidson & Boero Rodriguez 2006; Kokic et al. 2005; Salim & Islam 2010; Sheng, Mullen & Zhao 2011; Skold & Popov 1990). Over a period of 20 years until 2014–2015, environmental change has had a significant effect on productivity levels. This is because of the deterioration in climatic conditions in the grain-farming regions.

Adaptation to climate change by farmers is important as it helps farmers to improve resource-use efficiency by best practice, reduce the total cost of production and improve productivity (OECD 2015). Furthermore, to ensure the long-term sustainability of Australian agriculture, adaptation strategies should be adopted to meet the challenges of climate change. For instance, strategies that resulted in a strong increment in productivity from 2006 to 2007 contributed to supporting crop farmers to offset the decline in productivity due to the deterioration of the climate (Hughes, Lawson & Valle 2017). The sensitivity of farm productivity to environmental

change between wet and dry conditions has increased since the 1990s. Farmers achieved the highest performance during the 1990s in years with wet environmental conditions. The evidence suggests that farmers are implementing long-term adaptation strategies by focusing on new technologies and improved management practices in dry conditions (Hughes, Lawson & Valle 2017). For instance, environmental adaptation activities by farmers such as no-till cropping practices help obtain better soil moisture during summer (Hunt & Kirkegaard 2012).

2.4 Financial Performance and Grain Markets of the Broadacre Farm Industry

Australian agriculture consists of several sectors including livestock farms, vegetables, horticulture, and dairy. Industrial crops and dryland cropping farms are one of the vital and most significant sectors of agricultural production in particular, and of GDP in general. In the Wheat Belt regions, the local economy relies mainly on the income of grain farms (i.e. wheat group and non-wheat group such as canola, barley, rice, field peas, lupins, grain legumes, oats, sorghum and oilseed). Grain, pulse and oilseed revenues represent 27 percent of Australia's agricultural production income (Figure 2.14). The gross values of wheat, barley, canola, pulse, sorghum, oats, maize and rice were approximately AU$7.4 billion, AU$2.7 billion, AU$2.4 billion, AU$2.7 billion, AU$236 million, AU$547 million, AU$140 million and AU$252 million, respectively, in 2016–2017. The wheat crop group is the largest contributor by value in the grain broadacre farm industry (ABS 2017).

Table 2.1 presents the financial performance by percent farm business profit in each broadacre farm region for eight years. The financial performance estimates are expressed in 2016–2017 dollars. This agricultural sector consists of 12 farm regions in the Wheat Belt regions. With the exception of farm regions in VIC, all farm regions in other states achieved profits in 2016. However, farm regions in the North and East Wheat Belt of WA, Central West of NSW, and Central North of VIC experienced losses in 2013 while all others obtained profits. In 2010, only four (Eastern Darling Downs, QLD; Eyre Peninsula, Murray Lands and Yorke Peninsula, SA; and Wimmera, VIC) out of the 12 farm regions received profits. Farm business profits decreased in all farm regions in 1991 and 2007. Wimmera experienced the highest loss in 1991 and 2007. In 1995, 1999 and 2003, most of the farm regions experienced losses.

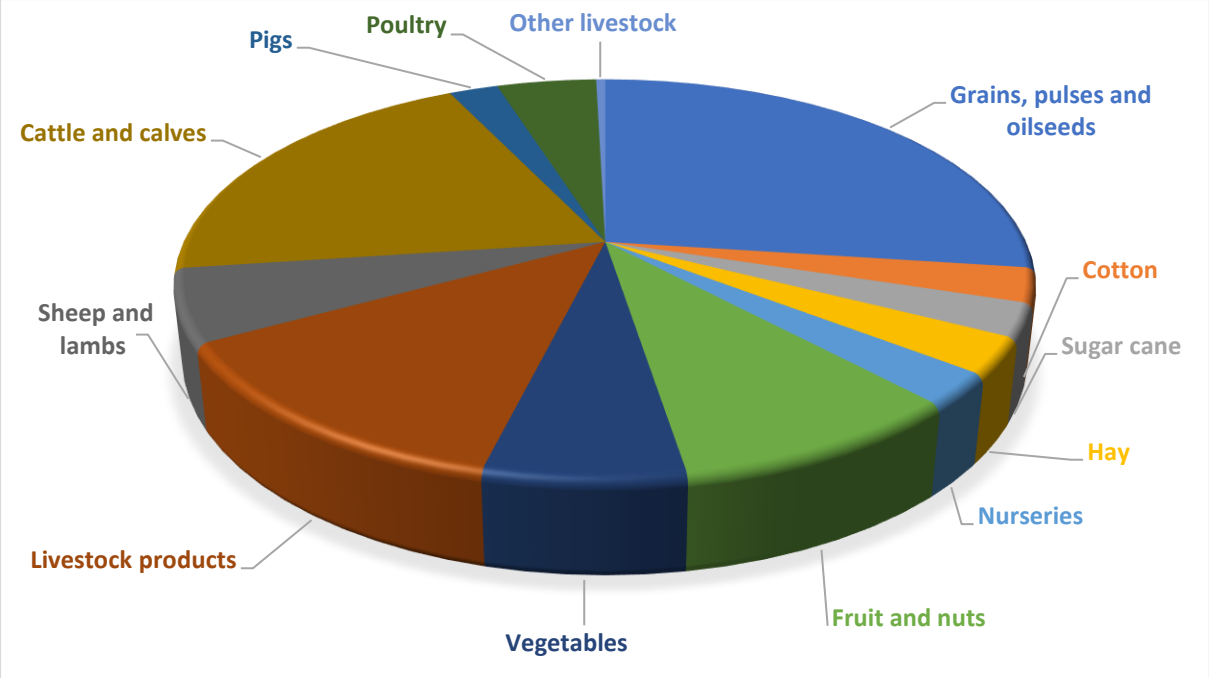

Figure 2.14 Australian grains production contribution value to Australian agriculture (2016-2017). Derived by the author from data of ABS (2017).

Table 2.1: Financial performance of broadacre grain farming, by region average per farm.

Region	Percent farm business Profit							
	1991	1995	1999	2003	2007	2010	2013	2016
WACS	-17. 23	11.62	-1.97	18.78	-13.42	-10.32	10.86	20.53
WANE	-17.13	25.69	- 1.23	- 20.95	- 29.94	- 3.71	- 6.18	40.45
NSWN	-18.64	- 54.63	4.86	- 56.75	- 29.44	- 9.02	10.96	48.11
NSWC	-40. 67	- 58.75	7.04	- 24.31	- 61.72	- 35.10	- 10.31	25.90
NSWR	-29.37	- 12.14	14.44	- 21.04	-55.13	-28.07	16.55	35.63
QLDE	-58.23	-35.11	-13.44	-43.22	-50.13	21.57	6.05	59.73
QLDD	-1.27	-10.83	3.57	-41.53	-27.55	-9.89	8.39	69.25
SAEP	-59.74	-28.89	-4.09	26.94	-55.22	47.01	35.72	17.05
SAMY	-66.14	10.22	-6.84	25.81	-37.27	11.47	23.34	35.53
VICM	-62.94	-68.97	-35.78	-7.44	-35.88	-8.11	24.93	-30.58
VICW	-74.02	-36.84	-24.77	-54.12	-77.76	24.07	28.07	-52.25
VICC	-70.65	-56.50	-47.50	-57.17	-65.11	-34.45	-2.76	-25.89

Source: Derived by the author from data of ABARES (2017).

Economic or environmental reasons are behind these decreases or increases in farm profits. They could be caused by the decrease in output price and/or increase in input price (cost). For example, the decrease in agricultural profits in 1991 was due to, in large part, the declining sale price of the crop (ABARES 2017). It could also be due to high or low rainfall/ temperature. For instance, although sale prices for crops rose, profits declined in 2003, 2007 and 2010 due

to deteriorating weather and drought, which was reflected in the decrease in production rate (ABS 2012a; Hughes et al. 2016; Jiang & Grafton 2012). However, rising uncertainties due to drought and hikes in temperature on for both winter and summer crops in the Wheat Belt farm regions of Australia since the 1990s has led to instability in crop price and challenges in the management of complex broadacre farm businesses (Gordon 2016; Kimura & Antón 2011; Kingwell 2011; Nicholls et al. 2003; Quiggin et al. 2010; Sheng, Jackson & Gooday 2017; Yang, Y. et al. 2016). According to Kingwell (2006), the expected study showed declining crop production was the main factor in the decline in farming profit due to climate degradation.

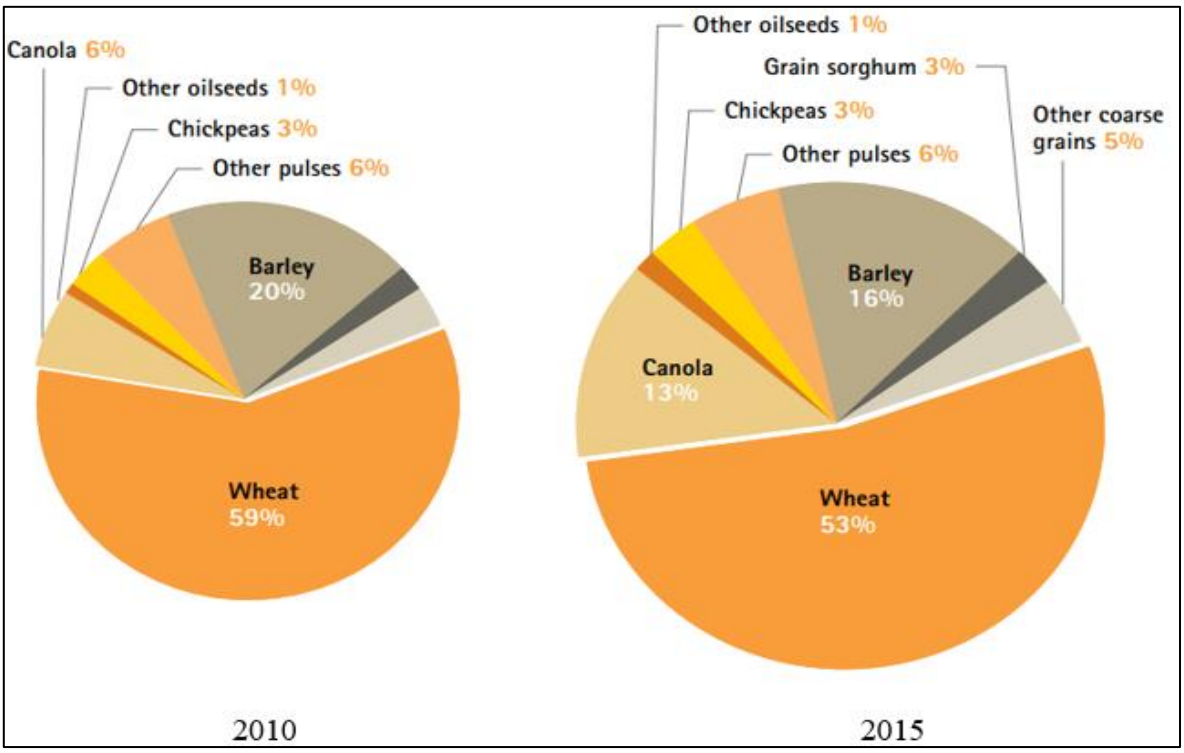

Figure 2.15 Comparison of Australian grain export between 2010 and 2015 (ABARES 2010, 2016b).

The grain market is the largest market in the world. Internationally, Australia cannot compete with some large grain crops such as maize, rice and oilseeds. Wheat, barley, and canola are the main Australian export products. Australian broadacre farming experiences more pressure due to the supply and demand of these crops. Figure 2.15 shows that wheat exports contributed approximately 53 percent, barley contributed 16 percent and canola contributed 13 percent to the total grain exports of Australia during 2010–2015. The relative contribution of wheat and barley export has decreased. This could be due to increased demand for wheat and barley product locally and internationally. On the other hand, the relative contribution of canola and

sorghum has increased. In terms of income, Australian grain broadacre cropping directly contributed $10 billion in 2010 and this increased to $11.5 billion in 2015 to the national economy (ABARES 2010, 2016b).

2.5 Productivity and Terms of Trade Change in Australian Agriculture

Productivity growth plays a significant role in economic growth, economic fluctuations and farmers maintaining profit (Comin 2006; Xia, Zhao & Valle 2017). Profitability growth over the long term plays a critical role in improving the livelihoods of farmers and increasing the investment of agricultural resources. This suggests that more attention is required to encourage farmers to increase agricultural productivity and improve efficiency to meet the increasing domestic and international food demand because of increasing population density. In addition, with productivity growth, it is possible to support farmers when profitability decreases owing to declining TT (output prices relative to input prices). Figure 2.16 shows the historical trend of TFP and TT from 1950–1951 to 2013–2014. TT declined over the period 1950–1951 to 2013–2014. It is clear that the relationship between TFP and TT is inverse. Overtime when the TFP is increased, the TT is decreased (Xia, Zhao & Valle 2017).

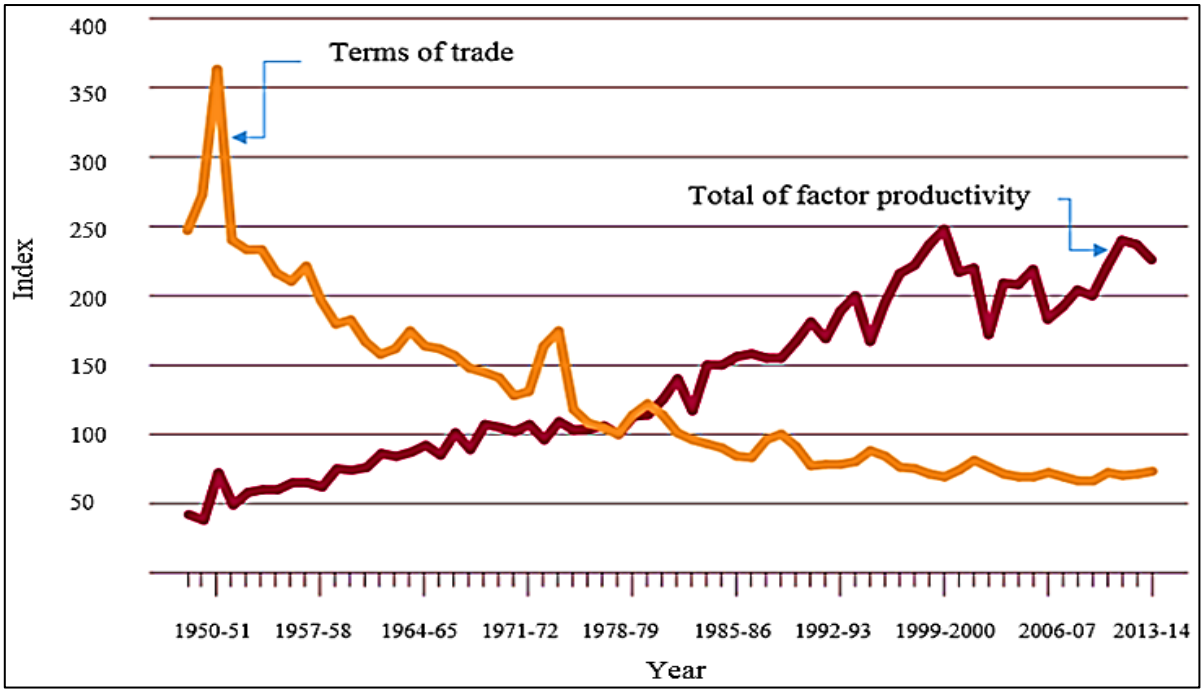

Figure 2.16 TFP and TT of Australian agriculture from 1948–1949 to 2013–2014. 1977-1978 =100. Modified by author from Sheng and Jackson (2015).

Table 2.2 demonstrates the variation in the rate of productivity growth in each broadacre industry from 1977–1978 to 2014–2015. Overall, over the long term, the cropping industry has had a higher average productivity growth than that of the livestock industries. This could be because of the reallocation of resources and the use of advanced technologies in crop production over the past three decades (Mullen 2007; Sheng et al. 2016). Although input declined by 0.6 percent per annum, broadacre cropping output strongly increased by 2.6 percent per annum between 2001–2002 and 2014–15. Generally, this variation in input, output and TFP are mainly due to changing environmental conditions. According to Valle (2016), the 1 percent per annum reduction in inputs was the main driver of productivity growth of an average of 1.1 percent per annum while effecting a 0.1 percent per annum growth of output between 1977–1978 and 2013–2014. However, it appears that most of the decline in farm profits was due to declining production and productivity because of the increasing years of drought and decreasing number of wet years, which have reduced the contribution to expected profits in mixed broadacre farms during wet years (Kingwell 2006).

Table 2.2 TFP, and output and input growth by Australian broadacre industries from 1977–1978 to 2014–2015

Industry	**Variables**	**Growth rate (percent)**	
		1977–1978 and 2014–2015	**2001–2002 and 2014–2015**
All broadacre	TFP	1.1	1.4
	Output	0.1	-0.4
	Input	-1.0	-1.8
Cropping	TFP	1.5	2.1
	Output	2.6	2.6
	Input	1.2	0.6
Mixed livestock–crops	TFP	0.9	1.2
	Output	-0.8	-1.6
	Input	-1.8	-2.8
Sheep	TFP	0.3	2.7
	Output	-2.6	-3.3
	Input	-2.9	-5.9
Beef	TFP	1.3	0.5
	Output	1.1	0.1
	Input	-0.2	-0.3

Source: Adopted from Xia, Zhao and Valle (2017).

2.6 Impact of Climate Change on Broadacre Cropping Farm Productivity

Decreased rainfall is one of the main causes of growing drought. In farming regions, wind, humidity, temperature, and sunlight can affect the evapotranspiration rate. High evapotranspiration rates can lead to a loss of soil moisture and increased drought in the field, which may affect the overall productivity and profitability of farms in various regions. For example, some parts of farm regions in southern NSW and in the northern parts of the western cropping zone have experienced decline in the average winter rainfall from 2000–2001 to 2014–2015 (Xia, Zhao & Valle 2017). This decline has led to lower TFP by an average of 6.5 percent after 2000–2001 in NSW and by an average of 7.7 percent in WA broadacre farm regions. In particular, the productivity of the grain farms was also significantly affected by the change in environmental conditions. For instance, wheat yields decreased by 14.8 percent in VIC and by 16.3 percent in WA under long-term climate conditions (Hughes, Lawson & Valle 2017). Areas in cropping regions with lower rainfall are more sensitive to a reduction in rainfall than areas with higher rainfall, and are therefore more impacted by climate change. However, since 2000–2001 some regions have experienced a slight improvement in grain productivity such as in northern NSW and QLD and southern Australia (Figure 2.17) (Hughes, Lawson & Valle 2017).

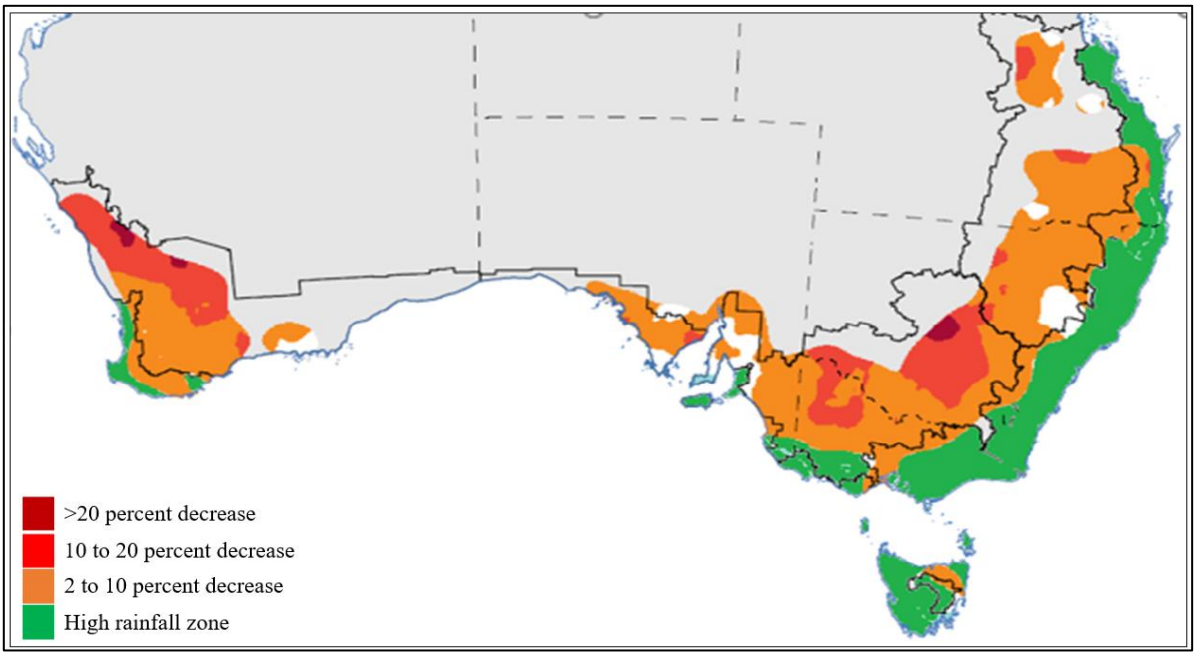

Figure 2.17 Average climate change impact on cropping productivity change from 2000–2001 to 2014–2015, relative to 1914–2015 to 2014–2015. Modified by author. Adopted from Hughes, Lawson and Valle (2017).

According to CSIRO and BoM (2014), southern Australia has experienced a decline in average winter rainfall and a rise in temperature over the last two decades to 2013. Figure 2.18 demonstrates how environmental change affects TFP change. This figure shows the sensitivity of TFP under long-term average conditions (climate-adjusted TFP) for wet and dry TFP. The most critical point is the clear gap in farm performance between dry-year TFP and wet-year TFP. This indicates that cropping farms varied in TFP owing to their sensitivity to environmental variability. In addition, the drought is a serious challenge to farm income and may negatively affect agricultural profitability (Nelson, Kokic & Meinke 2007).

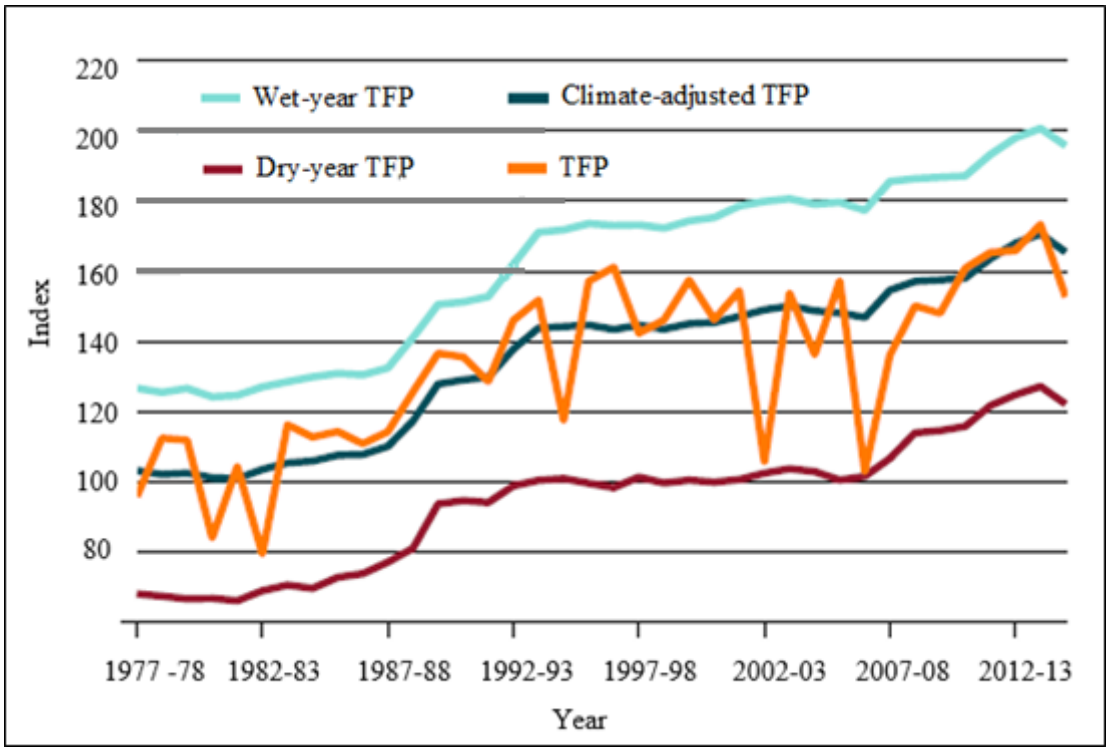

Figure 2.18 Relationships between environmental changes and TFP in cropping farms from 1977–78 to 2014–15. Adopted from Hughes, Lawson and Valle (2017).

Table 2.3 shows more details of TFP change at a regional level. Climate effects (except from 1977–1978 to 1993–1994) were the largest in the western regions. The TFP percent of cropping specialists, which include cereal grains, coarse grains, oilseeds, rice and/or pulses (Hughes et al. 2011), declined by 0.6 percent from the period covering 1977–1978 to 2014–2015 and by 5.7 percent from 2000–2001 to 2014–2015.

Table 2.3 Average annual climate effect on total factor productivity by industries and regions

Industry	Annual average TFP (percent)			
	1977–1978 to 1993–1994	1993–1994 to 2014–2015	2000–2001 to 2014–2015	1977–1978 to 2014–2015
All cropping farms	2.4	-3.2	-5.4	-0.9
Cropping specialists	2.9	-2.9	-5.7	-0.6
Mixed farms	2.1	-3.5	-5.7	-1.2
NSW	5.2	-2.8	-6.5	0.3
VIC	4.1	-3.6	-5.3	-0.6
QLD	1.6	-4.2	-5.1	-1.4
SA	0.5	-2.4	-1.9	-1.1
WA	-0.3	-3.7	-7.7	-2.5
Southern	2.9	-3.1	-5.1	-0.8
Northern	3.8	-3.0	-5.0	-0.2
Western	-0.3	-4.0	-8.2	-2.6

Source: Adopted from Hughes, Lawson and Valle (2017).

2.7 Impact of Agricultural Socioeconomic Factors on Productivity and Profitability Change

Socioeconomic variables such as age, gender, land size, farming experience, education, family size (population) and off-farm income have significant influence on productivity and profitability change of a farm business. Over 95 percent of Australian farm families are owners and employees of agricultural land and this situation is expected to continue for the next few decades (ABARES 2014). Therefore, that the study of socioeconomic components in rural and remote areas is very important in Australia. However, despite the significant contribution of agricultural households to agricultural work, there is a paucity of literature on the social issues of these families and what they need in rural and remote areas (Alston 2012). In Australia, very few studies have examined socioeconomic variables in the agricultural sector. Kingwell et al. (2013a) stated that productivity and profitability change can be driven by socioeconomic variables. Figure 2.19 shows the relationship between the relative population of farms and the classification of the general farm performance by the type of each farm. Kingwell et al. (2013a) found that most of the farms that were classified as growing or strong were crop farms or mixed

farms. Most livestock farms were classified as less secure. This evidence suggests that one of the socioeconomic factors (i.e. the percentage of farm population) can affect farm performance.

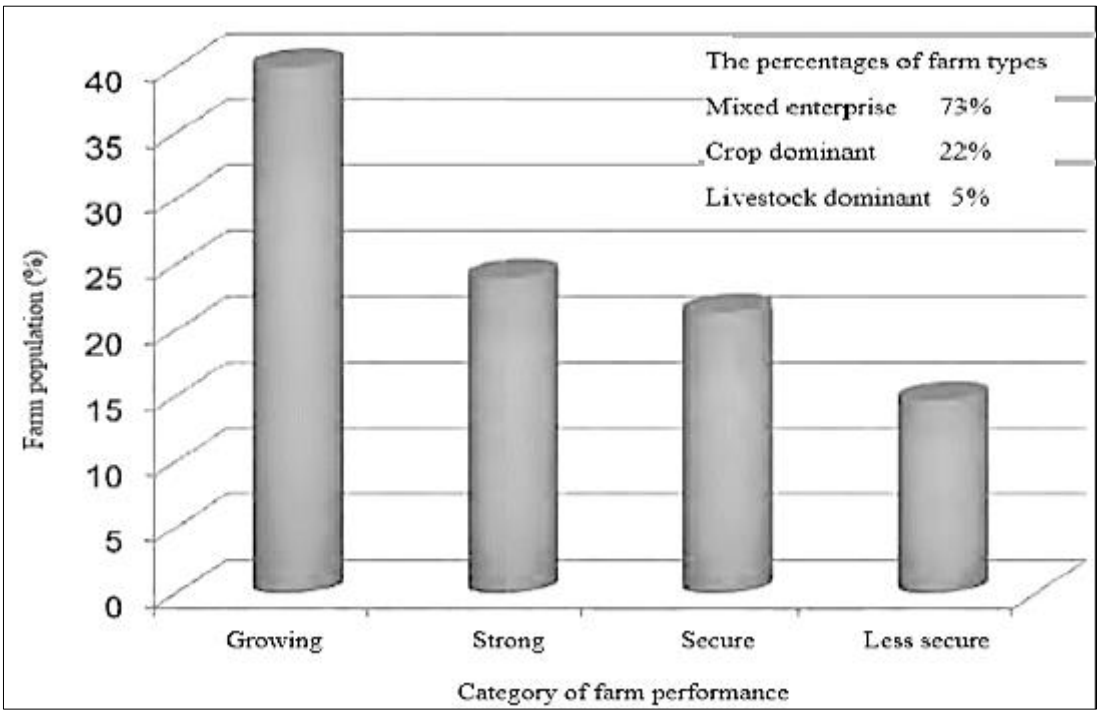

Figure 2.19 Farms ratios in the different performance categories. Modified by author from Kingwell et al. (2013a).

Kalirajan (1981) showed that the inefficiency of the production process of a farm can be affected by credit, education and experience of the farmers involved in the process and the general process of the farm. These factors were found to negatively affect the efficiency of the organisation. According to Hensher (2001), technical and economic inefficiencies may arise from failure to minimise the physical inputs, utilise the least cost combinations of inputs, and operate at the wrong point in the short-run and long-run average cost curves. The farms in each sector including wheat farming must be able to attain efficiency to be competitive locally, regionally and internationally. Attention to the sustainability of socioeconomic factors in Australia's agricultural and rural areas is instrumental in helping farmers and decision makers adapt to climate change over the long term (Alston 2012). Edwards, Gray and Hunter (2008, 2009) stated that the drought negatively affects the social and economic variables of the peasant. In addition, for the sake of the sustainability of Australian food security, a careful study of social and economic factors is required (Lê et al. 2014).

2.8 Actual Farm Employment and Environmental Change in Rural Australia

Globally, the labour force is one of the most significant factors in the agricultural sector. In Australia, farm workers represent an important social and economic component in rural areas ABARES (2016a) reported that the total number of farmers employed have decreased over time for 40 years (Figure 2.20).

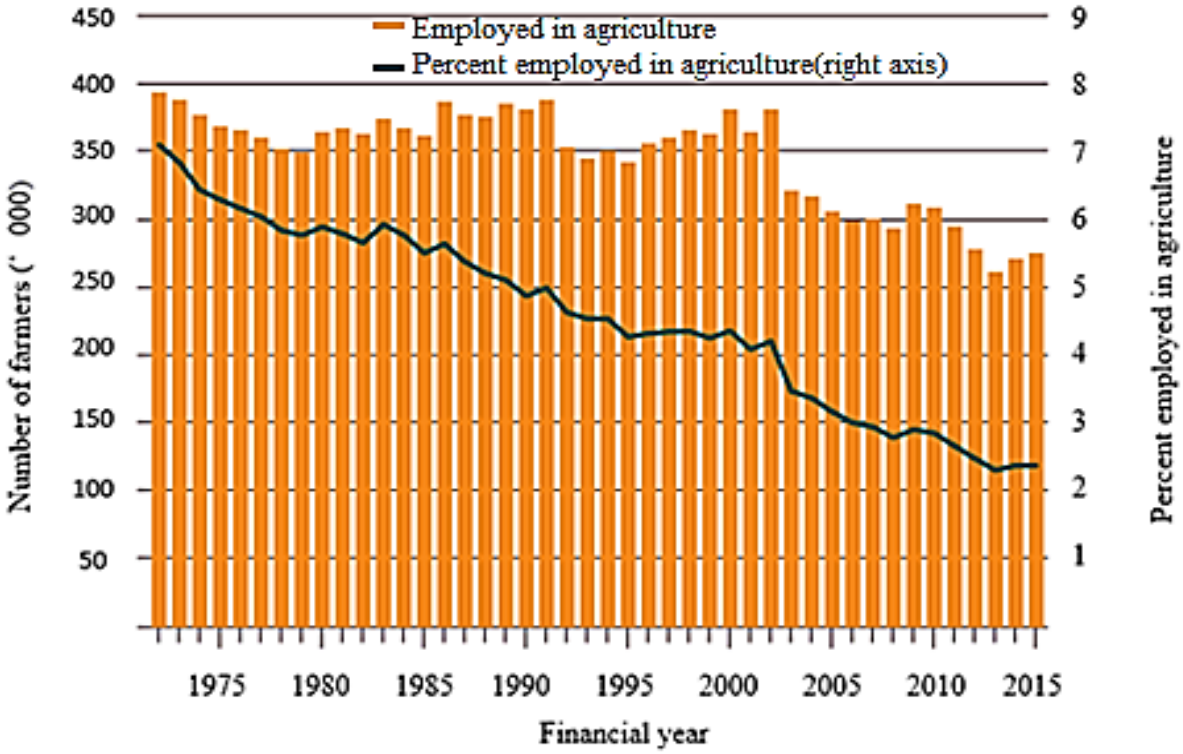

Figure 2.20 Australian farming labour force change during 1972–2015. Modified by author from ABARES (2016a).

It could be seen from Figure 2.20 that farming labour force has dropped between 1972 and 2015. For the period from 1990 to 2015 considered in this study, the number of farmers dropped from 375,000 in 1990 to 270,000 in 2015, representing about 28 percent drop. It has been suggested that this decline was due to the deterioration of the climate since the 1990s, forcing many farmers to leave their rural lands and migrate to urban cities due to financial losses because of the large changes in rainfall and temperature during the agricultural seasons (Gordon 2016; Kimura & Antón 2011; Kingwell 2011; Nicholls et al. 2003; Quiggin et al. 2010; Sheng, Jackson & Gooday 2017; Yang, Y. et al. 2016). For example, the Murray–Darling Basin regions lost about 6,000 workers and the GDP contribution declined to 5.7 percent in 2007–2008 due to drought (Wittwer 2010). Furthermore, found that in VIC, the number of

farmers who commit suicide has increased to at least one farmer every 3 weeks, with an average mortality rate of 11 to 19 per year in the drought years between 2001 and 2007. On the other hand, for food security, in 2011–2012, 1 farm fed 600 people, 450 of them locals and 150 of them from overseas (National Farmers' Federation 2012).

2.9 Conclusion

Agriculture plays a significant role in the economy and environmental sustainability of Australia. In recent decades, Australian broadacre farm regions have been facing more challenges in both economic and environmental change. Without sustainable agriculture, the gap between actual farm productivity and profitability and potential will only increase.

Productivity growth is a major determinant of economic growth, price fluctuations and profit for farmers. Profitability growth over the long term plays a critical role in improving the livelihoods of farmers and increasing the investment of agricultural resources. In Australian, over the long term, the cropping industry has had higher average productivity growth than the livestock industry. This could be because of the reallocation of resources and the use of advanced technologies in crop production over the past three decades. However, climate change is also still a major concern now and in the future. Many studies confirm the impact of environmental changes (such as rainfall and temperature) on the production and productivity of crops and therefore on profits and profitability. Thus, it is necessary to consider these changes when studying the economics of agricultural production.

Socioeconomic variables also have a significant influence on productivity and profitability change of a farm business. Over 95 percent of Australian farming families own the farms they work on. This situation is expected to continue for the next few decades. However, despite the significant contribution of agricultural households to agricultural work, there is a paucity of information/data on the social issues of these families and what they need in rural and remote areas. This suggests that more attention needs to be paid to encouraging farmers to increase agricultural productivity and improve efficiency to meet the increasing domestic and international food demand (export markets) because of increasing population density.

CHAPTER 3: LITERATURE REVIEW

3.1 Introduction

This chapter reviews past research related to agricultural productivity and efficiency and their relationship with environmental and socioeconomic changes of farms. This chapter is structured as follows: Section 3.2 reviews the approaches to the measurement of farm production efficiency. Section 3.3 presents a review on the decomposition of the TFPI. Section 3.4 presents Tobit and double bootstrap models. Section 3.5 highlights empirical studies of productivity, efficiency and environmental changes of wheat- and non-wheat-based farming in Australia and globally. Section 3.6 reviews studies on the determinants of efficiency of wheat- and non-wheat-based farming both in Australia and worldwide. Finally, Section 3.7 states the conclusion and highlights the knowledge gaps.

3.2 Approaches to measuring efficiency

In general, there are two main approaches to the measurement of farm production efficiency, namely data envelopment analysis (DEA) and stochastic frontier approach (SFA). DEA is one of the methods used in estimating production frontiers using mathematical programming to estimate the efficiency of multiple decision-making units (DMUs). The production process represents a structure of multiple inputs and outputs. Under DEA, efficiency is defined as the ratio of the weighted sum of outputs to that of inputs. DEA considers the DMU as being efficient when it has a score of 1.00. The DEA model is applicable in measuring farm-level inefficiencies. In cases where the DMU is inefficient, the DEA identifies what necessary improvements should be made. The model is applicable in different sectors like banking, healthcare, and transportation among others for evaluating the efficiency of resource allocation. It is important to distinguish between productivity and efficiency. Coelli et al. (2005) stated that a firm could be technically efficient but could still be able to improve its productivity (i.e. maximum possible productivity) by exploiting scale economies (i.e. optimal scale). These changes to the optimal scale point depend on whether the firm is operating in a short-run or long-run case.

O'Donnell (2010) and O'Donnell (2012c) pointed out that the production frontier determined through DEA is locally linear and all error terms are zero. Therefore, the DEA approach can

be referred to as semiparametric rather than nonparametric. In addition, several fast computer packages are now available for computing different measures of efficiency using DEA. the DEA approach, the most important feature is that there are no statistical problems when estimating multiple input/output technologies such as endogeneity (O'Donnell 2012c).

When estimating production technology, it is feasible to use the DEA approach when only a panel data set is to be used (O'Donnell 2013). However, the main limitation of the DEA approach is that it cannot recognise inefficiency from noise because this method does not allow statistical noise (Coelli et al. 2005; O'Donnell 2012a). According to O'Donnell (2012a), SFA does allow the estimation of multiple-input and multiple-output production technologies; however, requires complex restrictions on functional forms. In addition, the explanatory variables used in multiple-input/multiple-output SFA models are often correlated with the error terms (i.e., there is often an endogeneity problem). Furthermore, the most common approach to estimating SFA models is by maximum likelihood (ML) and the properties of ML estimators are unknown in small samples. Moreover, the scale efficiency component of scale-mix efficiency cannot be identified (O'Donnell 2012a, 2012c). On the other hand, Simar and Wilson (2000) showed that the SFA model is one of the best choices if statistical noise is present in the data.

According to Farrell (1957), to minimise the quantity of input while maintaining the same level of output quantity over a given time period, input-oriented efficiency may be used. However, output-oriented efficiency could be used when one seeks to maximise the level of production quantity while maintaining the same level of input quantity used over a given time period. The optimal combination of minimal input or maximisation of output is the goal of any industry. In the case of Australian agriculture, an output-oriented model appears more appropriate. It argues that farmers choose inputs in the face of uncertainty about environmental conditions and other things (e.g., output prices). Then, once inputs have been chosen and environmental conditions have been realised (e.g. it rains or it does not), farmers seek to maximise the possible output using their predetermined inputs in their given environment.

According to Banker, Charnes and Cooper (1984), the VRS assumption that the DEA model uses is more accurate to measure the technical efficiency in the DMUs than the CRS assumption. This model is called the BCC model. Inaccuracies associated with technical efficiency estimations based on the CRS DEA model could be attributed to the fact that this

model was made to be used when all firms (DMUs) are operating under optimal scale. However, this assumption does not always hold in economics in reality due to the many constraints on economic conditions (Coelli et al. 2005).

Various researchers (Abatania, Hailu & Mugera 2012; Abdulai & Abdulai 2016; Alene, Manyong & Gockowski 2006; Brümmer, Glauben & Lu 2004; Chiona 2012; Falco, Smale & Perrings 2008; Grazhdaninova & Lerman 2005; Hossain et al. 2013; Latruffe et al. 2004; Mulwa, Emrouznejad & Muhammad 2009; Njuki & Bravo-Ureta 2018; Odeck 2007; Paul et al. 2004; Roco et al. 2017; Wadud & White 2000) have carried out several analyses using both SFA (parametric approach) and DEA (nonparametric approach). Comparative results based on these two approaches do not vary significantly. For this reason, the decision to either use a parametric or nonparametric approach to estimate the efficiency of grain crops remains an issue of debate.

3.3 Decomposition of the TFPI

Agricultural performance can be measured in three main ways including partial factor productivity, multifactor productivity and TFP. Partial factor productivity refers to a single factor productivity measurement (Zhao, Sheng & Gray 2012). Multifactor productivity measures productivity due to changes in two inputs and TFP measures the change in productivity due to changes in most of the production factors. Different researchers debate the merits of these three different approaches. However, TFP is widely used to measure agricultural performance because it provides a broad indication of how efficiently and effectively farmers combine all inputs to produce a total output at a national or regional level over a period of time (Sheng, Ball & Nossal 2015). It is often used as a real measure of growth in an agricultural economy. Globally, increasing productivity and profitability have long been recognised as the most important sources of output growth and income improvement in the agricultural sector. Profitability change, a measure of value change, can be decomposed as the product of the terms of trade index (TTI) and TFPI. TFPI is a multiplicatively-complete measure of quantity change that is defined as the ratio of aggregate output to aggregate input. Generally, it is used to measure the productivity performance of an agricultural firm because it is able to reveal the efficiency with which farmers are able to combine all available market inputs to produce a total output. The TTI is a measure of price change (O'Donnell 2009). TFPI can be fully decomposed as the product of the measures of technical change and several efficiency changes. This method

is characterised by its independence on assumptions that restrict production technology and the behaviour of a firm or the level of competition in input or output markets.

Decomposition of TFPI into measures of technical change and several efficiency changes can be done using indices such as the Lowe, Färe-Primont, Laspeyres, Paasche, Fisher, Törnqvist, and Hicks-Moorsteen indices. These indices as defined by O'Donnell (2010, 2012b, 2012c) are multiplicatively-complete TFP indices and they can decompose the TFPI into economically-meaningful components. The reliability of an index for decomposing the TFPI can be determined based on how many of the basic axioms of the index number theory it satisfies. The seven basic axioms considered in the index number theory are **A1** Monotonicity, **A2** Linear homogeneity, **A3** Identity, **A4** Homogeneity of degree zero**, A5** Commensurability, **A6** Proportionality and **A7** Transitivity (O'Donnell 2012c). Coelli and Rao (2005) considered the Malmquist index method using the nonparametric approach (i.e. DEA). O'Donnell (2012c) pointed out that the Malmquist index cannot be used to measure TFP because it cannot be expressed as a ration of output quantity index to input quantity index. In other words, it is not able to capture productivity change.

All of the above listed indices, with the exception of the Lowe and Färe-Primont indices, violate the transitivity axiom and are, therefore, not suitable for making multitemporal (many periods) and multilateral (many farms) comparisons of TFP (O'Donnell 2012c, 2013). Färe-Primont and Hicks-Moorsteen indices can be used without price data, but the Laspeyres, Paasche, Fisher, Törnqvist and Lowe indices cannot. The Lowe index is ideal for measuring quantity and TFP changes because it satisfies all seven axioms of index number theory. However, it is less than ideal for measuring changes in prices (i.e. TT). Some previous empirical research (Fissel et al. 2015; Mugera, Langemeier & Ojede 2016; O'Donnell 2012c) used the Lowe index approach with TT in the US. In particular, some researchers (Islam et al. 2014; Islam, Xayavong & Kingwell 2014; Khan, Salim & Bloch 2014) have used the Färe-Primont index to decompose the TFPI in the investigation of the sources of productivity change in Australia. Le Clech and Castejón (2017) and Khan, Salim and Bloch (2014) used the Färe-Primont index because there was no information available about prices. In other words, the Lowe productivity index is more reliable than other index approaches especially when data on prices are available. Decomposing the TFPI into measures of technical change and other components of efficiency change involves estimating the production frontier. This may be achieved using either or both

parametric and nonparametric approaches such as SFA and DEA, respectively (Alene, Manyong & Gockowski 2006; Grazhdaninova & Lerman 2005; Latruffe et al. 2004; Odeck 2007; Paul et al. 2004; Wadud & White 2000).

3.4 Second Stage Regression Analysis (Tobit and Double Bootstrap Models)

The productivity and efficiency of a production process can be influenced by factors such as environmental, socioeconomic, and market input variables. This influence can be measured using second stage regression analysis. Second stage regression analysis is carried out to examine and explain the effects of a set of explanatory (independent) variables on dependent variables such as efficiency indicators. Second stage regression analysis can be performed using models such as Tobit, ordinary least squares (OLS) and bootstrap truncated regression models.

The Tobit model was first introduced by Tobin (1958) in the econometrics literature review. According to Amemiya (1984), this model can also be called censored regression model when exogenous (explanatory) variables can at least be observed, and truncated regression model when observations outside a specified range are completely unavailable. Many researchers (Boubacar et al. 2016; Coelli, Rahman & Thirtle 2002; Dhungana, Nuthall & Nartea 2004; Djoumessi et al. 2018; Fadzim et al. 2016; Henderson & Kingwell 2002; Hossain et al. 2013; Jiao et al. 2015; Latruffe et al. 2004; Lien, Kumbhakar & Hardaker 2008; Masterson 2007; Mulwa, Emrouznejad & Muhammad 2009; Odeck 2007; Poudel et al. 2015; Speelman et al. 2008; Storm, Heckelei & Heidecke 2011; Tingley, Pascoe & Coglan 2005; Tipi et al. 2009; Tu 2017) have used Tobit regression in second stage analysis of farm efficiency to explain variations in measured inefficiencies or to examine influence efficiency. There are several papers (Bravo-Ureta et al. 2007; Henderson & Kingwell 2002; Ho 2012; Latruffe et al. 2004; Lien, Kumbhakar & Hardaker 2008; Odeck 2007; Watkins et al. 2014) in the literature review that used and described the application of standard Tobit regression with panel data.

Amemiya (1984); Coelli, Rahman and Thirtle (2002); Maddala (1983); Tingley, Pascoe and Coglan (2005) argued that OLS model regression with DEA is not appropriate due to the assumption of normal and homoscedastic distribution of the dependent variable under OLS. According to George et al. (1988) estimating with OLS could lead to problems such as heteroskedasticity in the econometrics model.

The use of the Tobit model during second stage estimation has been a subject of debate in past years between Simar and Wilson (2007) and McDonald (2009). These researchers have argued that using the Tobit model leads to biased and inconsistent estimations. Simar and Wilson (2007) advocate to find a consistent estimation method that uses the data generating process (DGP) of the technical efficiency scores. McDonald (2009) criticised the proposed statistical methods (separability condition) proposed by Simar and Wilson (2007). It was stated that the Simar–Wilson models, although having several advantages, require a very complex seven-stage estimation procedure with double bootstrapping, which could be valid due to the DGP they considered but is not robust. It was also argued that the efficiency scores during the second stage analysis are unit-specific truncated, normal random variables.

On the other hand, McCarty and Yaisawarng (1993) and Hoff (2007) found that the Tobit approach, in most cases, is the most sufficient and appropriate second stage analysis DEA model because it considers the fact that the efficiency score is bounded between 0 and 1. Hoff (2007) and Khai and Yabe (2011) argued that using the Tobit model during the second stage estimation provides less biased estimation than the OLS method. Banker, Natarajan and Zhang (2015) pointed out that, based on an extensive Monte Carlo simulation, DEA+OLS and DEA+Tobit approaches consistently yielded much lower mean and median absolute deviations, and more accurate coverage rates in any given sample size than that of the Simar and Wilson (2007) DEA+Bootstrap approach. In addition, Banker, Natarajan and Zhang (2015) observed no systematic difference in performance between the single and double bootstrap Simar–Wilson approach. This is because the double bootstrap approach, which is used for efficiency bias correction is based basically on the assumption that the actual DGP and assumed DGP are similar. However, according to Simar and Wilson (2000, 2007) and Balcombe et al. (2008), the motivation behind bootstrapping is to simulate a true sampling distribution by mimicking the DGP.

Some studies in farm efficiency (Brümmer 2001; Latruffe et al. 2005) used the bootstrap method proposed by Simar and Wilson (2000). They stated that bootstrapping is one of the best methods to test bias in DEA estimators and establish their confidence intervals. Furthermore, some farming efficiency studies (Balcombe et al. 2008; Latruffe, Davidova & Balcombe 2008) followed the DEA double bootstrap procedure and Algorithm #2 proposed by Simar and Wilson (2007). Balcombe et al. (2008) found a greater possibility of improving the technical

efficiency of rice production in Bangladesh than what had been found previously. In addition, the results revealed that education, extension and credit had positive impacts on technical efficiency while age had a negative impact. Latruffe, Davidova and Balcombe (2008) also applied double bootstrap to a truncated regression of DEA efficiency to determine the sources of efficiency variations within samples of individual and corporate farms in the study area. They showed that the outcomes using the two-stage regression on standard DEA scores were similar to those that utilised the double bootstrap method. The results of the second stage regression showed that pure technical efficiency of individual farms was negatively impacted by a small use of hired labour, high capital intensity and high financial stress.

3.5 Empirical Studies of Productivity, Efficiency and Environmental Changes of Wheat and Non-wheat Farming

3.5.1 Total factor productivity in Australian farming

Several researchers have stated that the international competitiveness of crop production in Australia will increasingly depend primarily on productivity growth, mainly due to the limited availability of resources such as arable land and water (Nossal & Sheng 2010; Sheng, Jackson & Gooday 2017; Zhao et al. 2008).

TFP in Australian agriculture has been analysed in different empirical studies. Another important aspect of these studies is the multiple agricultural products that indicate that the measures provided for TFP are not always biased towards any particular agricultural product. Sheng et al. (2017) and Strappazzon, Knopke and Mullen (1995) used different methodologies to analyse TFP in Australian agriculture where it has been argued that TFP in Australian agriculture has increased persistently for over 50 years. Several studies have reported that the growth in TFP was subject to changes in policy reforms and advancements in technology (Mullen & Cox 1996; O'Donnell 2010). Other studies have argued that it was because of favourable environments and improvement in the efficiency and productivity of farming or inputs used in agriculture (Hughes et al. 2011; Khan, Salim & Bloch 2014; Tozer & Villano 2013).

Strappazzon, Knopke and Mullen (1995) analysed TFP in Australian agriculture based on panel data collected between 1977 and 1994 using SFA and the Törnqvist index. It was shown that

average annual growth in input and output from 1977–1978 to 1993–1994 in Australian agriculture were 0.25 and 2.9 percent, respectivly. It was also found that average growth in productivity in Australia was 2.7 percent; SA experienced the highest growth rate (4.1 percent) in outputs among the six states of Australia whereas Tasmania recorded a 1.2 percent decrease in inputs during this period. However, although TFP in Australian agriculture has increased, a fall in inputs has contributed to this increase. In contrast, Sheng et al. (2017) found that average growth in TFP in Australian agriculture was 2.13 percent from 1949 to 2012; 2.61 percent and 1.43 percent for crops and livestock respectively. Panel data from 1949 to 2012 was used in the analysis via the growth accounting approach. Although TFP increased, it was widely attributed to the changes in output mixes and an increase in innovation and technological progress. Gordon (2016) found that TFP decreased from 2005 to 2007 due to prolonged drought and recovered by over 30 percent up to 2012 in Australian agriculture.

Average TFP during the 1990–2011 period was found to be 1.36 percent, whereas it was 1.8 percent for 2004–2007 (Khan, Salim & Bloch 2014; Tozer & Villano 2013). Tozer and Villano (2013) analysed TFP based on panel data from 2004 to 2007 using both the SFA and DEA approach. Results demonstrate that Australian producers are technically efficient and have scale efficiency; however, the input and output mix vary significantly. However, this study only considered TFP decomposition and did not provide any estimates regarding the influencing factors of TFP . Khan, Salim and Bloch (2014) addressed the influencing variables of TFP by using panel data from 1990 to 2011 through the DEA model. It was found that TFP has grown at an average rate of 0.59 percent per annum. This study also pointed out that the variations in TFP growth were due to developments in techniques and technologies. Khan, Salim and Bloch (2014) and Tozer and Villano (2013) lacked in an adjustment for an environmental variable in the measurement of TFP. In addition, they were unclear on how they dealt with environmental variables in their methodology.

Studies by Mullen and Cox (1996) and O'Donnell (2010) revealed that the analysis of productivity and profitability in Australian agriculture indicates that TFP has increased due to technical progress and growth in TFP, which has positively affected profitability. Based on panel data from 1953 to 1994, Mullen and Cox (1996) applied the DEA approach to 700 farms to report an average growth rate of 2.4 percent to 2.6 percent in TFP. It was also argued in this study that an increase in TFP was aided by technical progress in the agricultural system. On

the contrary, the decomposition of productivity and profitability change indicated that an increase in TFP resulted in increased profitability (O'Donnell 2010). This was found based on DEA analysis of 31 years of panel data for 88 countries. It has also been found that smaller economies tend to be more productive, whereas Australia is a price-taker in output and input markets. Both these studies addressed TFP and productivity; however, measurement error in the TFP estimation was not shown, which might have inflated the results of these two studies.

3.5.2 Efficiency indicators with environmental variables in Australian studies

Several researchers (Che et al. 2012; Henderson & Kingwell 2002, 2005; Islam et al. 2014; Islam, Xayavong & Kingwell 2014) have studied efficiency together with environmental variables in Australian agriculture. These studies focused on various factors associated with the productivity and efficiency in the agricultural sector. All these studies analysed productivity and efficiency of production of multiple crops.

Henderson and Kingwell (2002) and Islam, Xayavong and Kingwell (2014) studied technical and allocative efficiency indicators as well as productivity in Australian agriculture. Analysis using the SFA model generated lower mean technical efficiency estimates compared to the DEA model (Henderson & Kingwell 2002), while the analysis of Islam, Xayavong and Kingwell (2014) produced lower efficiency estimates in Australian agriculture, which contradicted those obtained by Henderson and Kingwell (2002). However, the analysis of Henderson and Kingwell (2002) argued that efficiency estimates provided by the DEA model are more stable compared to the results produced by the SFA model. This study analysed panel data ranging from 1997 to 1999 using both SFA and DEA models. Average technical efficiency was 92.7 percent from the DEA model, whereas it was 83.6 percent based on the SFA estimates. Thus, inappropriate specification of the model may result in different outcomes.

Islam, Xayavong and Kingwell (2014) analysed the productivity and profitability in south WA considering panel data from 47 farms from 1998 to 2008. By applying the Färe-Primont index method, components of farm productivity and profitability were measured. Average values of the profitability index (PROFI), TTI, TFPI, technical index (TI), overall efficiency index (EFFI), output-oriented technical efficiency index (OTEI), output-oriented scale efficiency index (OSEI), output-oriented mix efficiency index (OMEI) and residual output-oriented scale efficiency index (ROSEI) of the farms located in high rainfall areas were 1.111, 0.881, 1.26,

1.06, 1.2, 0.91, 0.99, 1.04 and 1.22, respectively; in medium rainfall areas results were 0.96, 1.13, 1.06, 1.06, 0.98, 0.93, 1.01 and 1.072, respectively, and in low rainfall areas results were 1.04, 1.05, 0.99, 1.06, 0.94, 0.99, 0.88, 0.99 and 0.96, respectively. Growth in productivity was found to be the main contributor to profitability. The farms were grouped into three 11-year average growing season rainfall groups. In this study, it was argued that efficiency in agriculture was dependent on the level of inputs and the implementation procedure. This procedure also determined the productivity that ultimately decides profitability. In addition, it was found that the average technical efficiency was 79.5 percent for the surveyed farms, which was lower than the findings of Henderson and Kingwell (2002).

Islam et al. (2014) also studied productivity and profitability in south WA from 250 farms between 2002–2003 and 2011–2012. They found that efficiency change rather than technical change was the principal source of improvement in TFP. Average values of PROFI, TTI, TFPI, TI, EFFI, OTEI, OSEI, OMEI, ROSEI and OSMEI were 1.66, 1.20, 1.39, 0.98, 1.42, 1.12, 1.05, 1.12, 1.14 and 1.27, respectively. However, according to O'Donnell (2013), the Färe-Primont index method cannot be used when price data is available. However, both Islam et al. (2014) and Islam, Xayavong and Kingwell (2014) considered rainfall as a traditional input.

Che et al. (2012) and Henderson and Kingwell (2005) also studied efficiency in Australian agriculture, in which they adjusted their dataset for environmental variables. Henderson and Kingwell (2005) measured farm efficiency with adjustment for rainfall from 93 farms between 1997 and 1999. DEA analysis with Fisher index focused on the measurement of technical efficiency and the effect of rainfall on farm efficiency. Results from this study indicated that the average technical efficiency of farms unadjusted for rainfall was 87 percent, 88 percent and 89 percent for 1997, 1998 and 1999, respectively, whereas it was 90 percent, 91 percent and 92 percent, respectively, when adjusted for rainfall. This result demonstrates that rainfall can be considered as non-discretionary (uncontrolled) production input, which affects efficiency; when it is ignored in the analysis more farms appear to be inefficient. Therefore, Henderson and Kingwell (2005) have argued that failure to include rainfall in efficiency analysis will provide biased estimates of efficiency although the influence of other environmental variables (e.g. temperature, humidity) were not been assessed in this study. In contrast, Che et al. (2012) investigated the impact of climate on profitability, productivity, and efficiency in Australian agriculture. This study analysed 30 years of production data using the Törnqvist index within

the SFA model for six rainfall zones in WA. Results from this study indicated that the TFP of farms increased when it was adjusted for climate change as productivity rose from 1.27 to 1.45 in the 1980s, 1.58 to 1.77 in the 1990s and 1.61 to 1.87 in the 2000s. In addition, climate change variables positively affected productivity and efficiency in WA. This study only considered changes in rainfall during different agricultural seasons; however, it is not only rainfall that affects productivity and efficiency, but also temperature, humidity, soil properties, availability of water and others.

3.5.3 Efficiency indicators and productivity in global studies

The efficiency and productivity of several crops have been studied, the most common of which include rice, wheat, maize, paddy, peasant, annual and perennial crops, and have been considered either individually or as multiple crops (Abdulai & Abdulai 2016; Alene & Hassan 2003; Chiona 2012; Mulwa, Emrouznejad & Muhammad 2009; Ogundari & Ojo 2007; Paudel & Matsuoka 2009; Singh et al. 2017).

Several researchers (Alene & Hassan 2003; Chiona 2012; Mulwa, Emrouznejad & Muhammad 2009; Singh et al. 2017) have reported technical inefficiencies, which indicate farmers can increase their efficiency by the effective utilisation of available resources. Other researchers (Abdulai & Abdulai 2016; Ogundari & Ojo 2007) have also observed scale efficiency in maize production. Cost efficiency analysis carried out by Paudel and Matsuoka (2009) and Singh et al. (2017) revealed that farmers could reduce their cost of production significantly. In addition, the findings of Ogundari and Ojo (2007) indicated higher cost efficiency for farmers than the standard level of efficiency. Mulwa, Emrouznejad and Muhammad (2009) estimated an average economic efficiency of 36.4 percent for maize farmers, which indicated a requirement for significant improvement.

According to Mulwa, Emrouznejad and Muhammad (2009), farmers in Western Kenya were recording losses in income due to inadequate understanding of cost structure for producing maize, which could be because of using a lower level of mechanisation technology in crop production. A study involving 180 farmers from a small village found that the farmers were able to obtain higher output in proportion to their total production cost (Paudel & Matsuoka 2009). This finding is, however, questionable due to the small sample size used.

Ogundari and Ojo (2007) reported higher scale efficiency with only 7 percent probability of being inefficient from a survey of 200 farms. This finding may be attributable more to the use of only close-ended questions in the survey than to the farmers' primary concern. These authors also reported higher costs associated with hired labour; however, they did not consider factors that influenced scale efficiency. In contrast, Abdulai and Abdulai (2016), observed a comparatively low cost of hired labour, which could be the cause of the high probability of farms being scale inefficient. Alene and Hassan (2003) studied farm-level technical efficiency using survey data from 60 farmers covering the period 1999–2000. The average technical efficiency of maize farmers was estimated to be 76 percent, which indicates a significant potential for efficiency improvements.

Singh et al. (2017) used 45 years of maize production data to analyse growth performance and resource-use efficiency in India, where average technical inefficiency was 36 percent, allocative inefficiency was 32 percent, and cost inefficiency was 56 percent. Additionally, research findings based on very large time series data analysis indicated that Indian maize farmers can still achieve significant reductions in cost because their allocative efficiency is between 65 percent and 68 percent (Singh et al. 2017). Even though resource-use efficiency is helpful for revealing how farmers can make efficient use of their resources, this was not reported in this study.

Using 2005 survey data of Nepalese maize farmers, Paudel and Matsuoka (2009) studied cost efficiency. It was found that the farmers incurred a 63 percent higher cost above the frontier cost, which indicates significant inefficiency. This could be due to the use of data covering only 180 farmers and the focus on a single cropping village. According to Ogundari and Ojo (2007), a cost efficiency of 84 percent was recorded for maize farmers in Nigerian, which was a 16 percent higher cost than that of the frontier cost. However, changes in cost efficiency over a longer study period have not been explored. In addition, their economic efficiency was 36.4 percent which was very low; however, caution is required when interpreting this result as this finding has not been replicated in other studies that have analysed maize production.

Input-oriented models focus on explaining how to make an inefficient unit efficient via the proportional increase of its inputs while the output proportion remains unchanged (Abdulai & Abdulai 2016; Chiona 2012; Mulwa, Emrouznejad & Muhammad 2009; Paudel & Matsuoka 2009; Singh et al. 2017). These studies have analysed efficiency through input-orientation and

argued how farmers can reduce input cost without changing their existing output levels. These studies reported high improvement required in input proportions; however, they did not provide insight regarding how much it would increase/decrease output proportion. In contrast, output-oriented models consider how an inefficient unit can be made efficient via proportionally increasing its outputs without changing the input proportions (Alene & Hassan 2003; Ogundari & Ojo 2007). These studies provided insight concerning how much increase in output might be generated if input proportions remain unchanged. These studies have provided estimates regarding improvement in output levels without substantially changing input proportions.

Rice is one of the main agricultural crops in many parts of the world and there are several studies that have researched efficiency in rice production from different perspectives (Coelli, Rahman & Thirtle 2002; Dhungana, Nuthall & Nartea 2004; Hossain et al. 2013; Tijani 2006; Tipi et al. 2009; Villano & Fleming 2006; Wadud & White 2000; Watkins et al. 2014; Yang, Y. et al. 2016). Technical efficiency has been found to be low among rice producing farmers in some studies (Coelli, Rahman & Thirtle 2002; Dhungana, Nuthall & Nartea 2004; Villano & Fleming 2006; Wadud & White 2000; Watkins et al. 2014), whereas other studies have found comparatively higher technical efficiency among rice producers (Hossain et al. 2013; Tijani 2006; Tipi et al. 2009; Yang, Y. et al. 2016). Several studies have found the presence of scale efficiency and a lower rate of allocative efficiency (Coelli, Rahman & Thirtle 2002; Watkins et al. 2014).

Tijani (2006), surveyed 50 farmers during the 2002–2003 cropping season and reported an average technical efficiency of 86.6 percent; however, this result cannot be generalised owing to its small sample size and because there were only three input variables considered in the SFA model. Wadud and White (2000) studied household efficiency in rice production by comparing the results provided by DEA and SFA approaches. This study used 1997 survey data from 150 rice producing farms. The DEA approach returned an average efficiency score of 85.8 percent, whereas the SFA approach returned an average efficiency score of 79.13 percent, which indicates that the SFA underestimated the efficiency score.

The study of Hossain et al. (2013) was different from other studies because this study not only measured efficiency but also measured the impact of environmental factors on the efficiency of rice production. This study used 19 years of rice production data (from 1989 to 2008) and applied DEA with Tobit regression. The environmental factors considered in this study

included rainfall, humidity and temperature. The results showed that rice production efficiency without environmental factors averaged 94.5 percent whereas rice production efficiency with environmental factors averaged 95 percent. Thus, the efficiency was slightly higher when environmental factors were included, although this result may be because most of the irrigated lands are well managed. In addition, second stage regression demonstrated that humidity had a positive impact on efficiency whereas rainfall and temperature had an inverse association with efficiency.

Results of the technical efficiency measured between studies varied widely irrespective of the methodologies used. Coelli, Rahman and Thirtle (2002); Dhungana, Nuthall and Nartea (2004); and Watkins et al. (2014) used the DEA approach and found that the technical efficiencies ranged between 64 percent and 84 percent, whereas the SFA analysis returned average technical efficiencies ranging between 51 percent and 68 percent (Villano & Fleming 2006; Wadud & White 2000). Therefore, the methodological stance of previous studies made a substantial difference in efficiency measurements. However, Coelli, Rahman and Thirtle (2002) and Watkins et al. (2014) used the DEA approach and found lower allocative efficiency in the presence of scale efficiency.

Coelli, Rahman and Thirtle (2002) used DEA with the 1997 survey data from 406 farms in Bangladesh to report an average technical efficiency of 69.4 percent, scale efficiency of 94.9 percent, cost efficiency of 56.2 percent and allocative efficiency of 81.3 percent. Although this study provided a useful measurement of different efficiencies, it only looked at specific aspects of rice production and failed to reflect the primary concern in rice production. Data on inter-farm performance differentials were present; however, this study did not consider this data, which may be referred to as the suboptimal use of survey data. Dhungana, Nuthall and Nartea (2004) addressed the pure technical measurement from 76 farms based on a survey in 1999 where it was found that the pure technical efficiency of rice farmers in Nepal was only 18 percent. This result may be misleading because of the smaller sample size as well as the concentration on a single cropping region.

Technical efficiency, allocative efficiency, scale efficiency, and scope efficiency in multiple agricultural products have been found to be low (Chavas & Aliber 1993; Fatima, Badar & Badar 2015). In studying the economic efficiency of 1,000 US agricultural farms producing multiple agricultural products based on cross-sectional data collected in 1987, Chavas and

Aliber (1993) found that the average technical efficiency was 85 percent, the allocative efficiency was 76 percent and the scale efficiency was 87 percent. The analysis clearly indicated that although improving allocative efficiency might contribute to a reduction of production costs for many farms, there remain diseconomies of scale. The presence of such diseconomies of scale may be because of the varying output mix used by the studied agricultural holdings. An analysis by Fatima, Badar and Badar (2015) used 53 years of panel data on crop production of multiple crops from 2,589 farms in Pakistan for the period between 1948 and 2001. The nonparametric analysis indicated that Pakistani agricultural farms are inefficient. The average technical inefficiency of farms has been found to be 88 percent, with these farms overutilising farm size in the case of maize production. The dataset used in this study was very large and the results indicate a lower level of efficiency scores, which might be the result of the use of traditional agricultural procedures and less favourable government policy for the agriculture sector in Pakistan. However, most of the studies that used the SFA model to analyse the efficiency of multiple agricultural crop production argued that the efficiency level of agricultural farming has improved significantly (Battese & Coelli 1995; Brümmer, Glauben & Lu 2004; Hockmann & Pieniadz 2008; Jin et al. 2010; Kurkalova & Jensen 1996; Odeck 2007; Paul et al. 2004; Skold & Popov 1990).

Technical efficiency in multiple agricultural products was low for Cameroonian, Paraguayan, Vietnamese, Ethiopian, and some other developing countries (Binam et al. 2004; Masterson 2007; Nguyen 2017; Thiam, Bravo-Ureta & Rivas 2001; Wassie 2014). Average technical efficiency was found to be higher for Russian and Polish rural farms producing multiple agricultural products (Grazhdaninova & Lerman 2005; Latruffe et al. 2004).

The efficiency of Cameroonian farmers has been assessed by Binam et al. (2004) using survey data from 450 farmers collected during the 2001–2002 season. Results reported from this study showed that the technical efficiency of farmers ranged between 73 percent and 77 percent with an average technical efficiency of 75 percent. This study found that the lower technical efficiency of farmers was caused by the absence of modern agricultural facilities, and the unavailability of agricultural resources and agricultural education in Cameroon. In addition, the considerations of only the slash and burn agriculture zone may be another reason for the lower technical efficiency because these lands are newly created for crop production.

Nguyen (2017) studied the efficiency measurement in Vietnamese agriculture and found that the average technical efficiency was low. This study analysed efficiency based on cross-sectional farm household data collected via a survey conducted on 2,636 farm households during 2006. The findings argued that the average technical efficiency of households was 81.3 percent with a standard deviation of 10.1 percent. Although this study used data from 2,636 households, the analysis data only considered 1,970 households owing to reliability issues. Even so, these results may be a reflection of the absolute level of technical efficiency; however, the results would have been more reliable if environmental variables had been considered. Conversely, Thiam, Bravo-Ureta and Rivas (2001) conducted a systematic review based on 51 observations collected from 32 studies in different developing countries. Their analysis revealed that the average technical efficiency was 68 percent for all countries considered; thus, there was technical inefficiency in the agricultural practices of developing countries. However, this conclusion is not true because Battese and Coelli (1995); Kurkalova and Jensen (1996); Jin et al. (2010); and Brümmer, Glauben and Lu (2004) found a higher rate of technical efficiency among farmers or farms in developing countries. Therefore, the findings presented by Thiam, Bravo-Ureta and Rivas (2001) are not generalisable owing to the use of secondary sources of data that are not entirely reliable and were already analysed.

Wassie (2014) analysed the efficiency of Ethiopian farmers based on survey data collected in 2009. The survey was conducted on 3,183 farmers in Ethiopia. The analysis found an average technical efficiency of 63.56 percent, which is low in comparison with the other studies discussed in the above sections. Alene, Manyong and Gockowski (2006) also studied the efficiency of Ethiopian farmers through the DEA and SFA approaches; however, the efficiency was significantly higher than that of the findings of Wassie (2014). Although Alene, Manyong and Gockowski (2006) used a smaller sample size, they covered several regions, whereas Wassie (2014) concentrated on cropping region, which makes their results very specific for that cropping region, and thus the results cannot be generalised. In addition, neither studies included the effect of environmental variables on efficiency measurements.

Grazhdaninova and Lerman (2005) investigated the allocative and technical efficiency among Russian agricultural farms considering cross-sectional data from 144 farms during 2003. The results indicated a higher level of technical efficiency among Russian agricultural farms. Average technical efficiency was found to be 87.9 percent, which is comparatively higher than

the efficiency reported by Wassie (2014), Masterson (2007), and Binam et al. (2004). Although Grazhdaninova and Lerman (2005) reported increased technical efficiency, no long-term follow-up measures were found. On the contrary, Latruffe et al. (2004) studied the efficiency of agricultural crops produced in Poland based on data collected from 220 crop and 250 livestock farms during 2000. The results of the SFA model indicated that the average technical efficiency was 83 percent whereas this was 77 percent for the DEA model. The deviation in efficiency estimates between the two models is due to the adjustment for multi-product optimisation. The SFA model considered multi-product optimisation whereas the DEA model did not, which is why the DEA model reported lower efficiency scores.

Battese and Coelli (1995), Hockmann and Pieniadz (2008), Jin et al. (2010), Kurkalova and Jensen (1996), Skold and Popov (1990), Odeck (2007), Paul et al. (2004), and Brümmer, Glauben and Lu (2004) used time series and panel data on multiple agricultural products to report increasing levels of efficiency among farms as well as farmers. It has been argued that the technical efficiency of some countries is very promising in that efficiency has increased gradually over time. Battese and Coelli (1995) studied the technical efficiency of 125 Indian farms producing multiple crops based on data obtained from 1975–1976 to 1984–1985. Results of this study indicated that most of the farms had experienced increasing efficiency scores because the efficiency of 70 percent for the farms had increased by at least 12 percent.

Kurkalova and Jensen (1996), Skold and Popov (1990), and Odeck (2007) studied efficiency considering a smaller sample size, with all these studies based on time series data. Kurkalova and Jensen (1996) analysed the efficiency of 49 Ukrainian agricultural farms based on a three-year period of series data collected between 1989 and 1992. Results from this study indicated that the average technical efficiency of the farms had increased from 71.4 percent to 74.8 percent during the study period. Skold and Popov (1990) studied the efficiency of Russian farms based on two years of time series data collected from 1986 to 1988. Results indicated an increasing level of technical efficiency although the increase in efficiency was not absolute or persistent. The reason for the variable increase in technical efficiency was improving the resource use and increasing the agricultural output level in the Stavropol region. In contrast, Odeck (2007) studied the efficiency of 19 Norwegian agricultural farms between 1987 and 1997. Results of this study clearly demonstrated an increasing pattern in technical efficiency.

Average technical efficiency and scale efficiency for the studied period was 97 percent which is very high.

Hockmann and Pieniadz (2008) studied efficiency in Polish agriculture while Brümmer, Glauben and Lu (2004) studied productivity and efficiency in Chinese agriculture. Both these studies found increasing returns to scale as well as technical efficiency (Brümmer, Glauben & Lu 2004; Hockmann & Pieniadz 2008). Brümmer, Glauben and Lu (2004) used 14 years of panel data between 1986 and 2000 to estimate the productivity and efficiency of 307 farms. Results indicated that the average technical efficiency of farms was 78 percent while it had increased at an average rate of 5.3 percent over the considered time period. In contrast, Hockmann and Pieniadz (2008) used seven years of time series data to analyse the efficiency of 430 Polish farms from 1994 to 2001. This study also reported increasing returns to scale together with increasing technical efficiency. The average growth rate in technical efficiency was 2.9 percent for 90 percent of the farms, whereas it was 7.1 percent for the other 10 percent of the farms.

3.6 Studies of the Determinants of Efficiency in Australia and Other Parts of the World

Many researchers worldwide (Abatania, Hailu & Mugera 2012; Binam et al. 2004; Latruffe et al. 2004; Masterson 2007; Nguyen 2017; Odeck 2007; Paul et al. 2004; Tipi et al. 2009; Wassie 2014) have studied the socioeconomic factors associated with farming and their effects on productivity and efficiency using Tobit regression analysis or the OLS method in the parametric or nonparametric approaches. All these studies concluded that the socioeconomic variables had a significant impact on productivity and efficiency, either directly or indirectly. Analyses of the effect of socioeconomic variables on efficiency in crop production have indicated that education, nutrition, income, soil fertility, access to credit, distance from the main market, access to extension services, social capital, age, farming experience, years of involvement, household members, dependency ratio, poverty status, capital-labour ratio, land-labour ratio, share of hired labour, share of rented land, and household size have significant impact on efficiency estimates (Binam et al. 2004; Henderson & Kingwell 2002; Latruffe et al. 2004; Nguyen 2017; Odeck 2007; Paul et al. 2004; Sheng, Ball & Nossal 2015; Sheng et al. 2016; Wassie 2014). Based on the estimation of second stage Tobit regression, which was used in some of the studies, these studies argued that these variables must be incorporated for better estimation of efficiency in crop production. Table 3.1 summarises socioeconomic factors affecting productivity and efficiency based on literature reviewed.

Table 3.1: Summary of review of socioeconomic factors of grain farms globally

Name of Author(s)	Country	Study Period	Method	Sample	Socioeconomic Factors	Type of Data
Binam et al. (2004)	Cameroon	2001/02 (season)	SFA	450 Farmers	Credit, soil fertility, social capital, distance of the plot from the access road and extension services	Cross -Sectional Data
Latruffe et al. (2004)	Poland	2000 (season)	SFA and DEA	220 Crop and 250 Livestock Farms	Size farm, soil quality, the degree of integration with downstream markets, labour and own land and education.	Cross -Sectional Data
Wassie (2014)	Ethiopia	2009 (season)	SFA	3183 Farmers	Age, education, land policy, soil and water conservation, extension contact, plot fertility, and livestock.	Cross -Sectional Data
Nguyen (2017)	Vietnam	2006 (season)	SFA	2636 Farm Households	Education and hours of nonfarm wage participation	Cross -Sectional Data
Paul et al. (2004)	USA	1996 to 2001	SFA and DEA	48 States	Farm size	Time Series Data
Odeck (2007)	Norway	1987 to 1997	SFA and DEA	19 Farms	Experience, age, and capital/labour ratio	Time Series Data
Tipi et al. (2009)	Turkey	2006 (season)	DEA with Tobit Regression	70 Households	Number of plots, farmer's age, off-farm income, and farm size	Cross- Sectional Data
Masterson (2007)	Paraguay	2000/01 (season)	SFA	8131 Farmers	Education, household size, technical and credit assistance, and soil quality.	Cross -Sectional Data
Abatania, Hailu and Mugera (2012)	Ghana	2005/06 (season)	Bootstrap DEA with (OLS) Regression	1904 Households	Hired labour, geographical location of farms, gender and age of head of household.	Cross-Sectional Data
Yang, Mugera and Zhang (2016)	China	2013 (season)	SFA	231 households	Age of farmers, female ratio, access and use of extension services, off-farm income, and the size of cultivated land	Cross- Sectional Data
Villano and Fleming (2006)	Philippines	8 years	SFA	46 rainfed rice farmers	Education, adult ratio, and non-farm income.	Panel dataset
Watkins et al. (2014)	USA	2005–2012	DEA with Tobit Regression	158 rice fields	Fields size, fields located, soil type, zero grade, and multiple inlet irrigation.	Time Series Data
Mulwa, Emrouznejad and Muhammad (2009)	Kenyan	2004 (season)	DEA with Tobit Regression	105 Mazie's farms	Seed type, household size, agricultural training, and main occupation	Cross-Sectional Data
Abdulai and Abdulai (2016)	Zambia	2013 (season)	SFA	406 maize farmers	Education, access to extension services, distance to markets and access to credit.	Cross-Sectional Data

Abatania, Hailu and Mugera (2012) addressed socioeconomic variables in the efficiency measurement model where it was argued that a lower level of technical efficiency is attributable to the geographical location of farms, age and gender of farmers, and hired labour. A second stage using OLS regression was used to determine the factors affecting technical efficiency. It was found that older farmers were more technically efficient than younger farmers, while female farmers were more technically efficient than male farmers. The analysis was performed on 1,904 households surveyed during the 2005–2006 season to observe efficiency in crop production. The average technical efficiency was 77.26 percent whereas the average scale efficiency was 74.21 percent after correcting for biases in the entire dataset. From the findings of this study, it was observed that although the households were scaled as being efficient, technical efficiency was low because of the inefficient use of the available resources. The lower level of scale efficiency might be representative of the incompetence of management in managing crop production.

Productivity, technical efficiency and farm size of Paraguayan farmers have been found to be low (Masterson 2007). This author used cross-sectional data on 8,131 farmers collected by a survey conducted during the 2000–2001 cropping season. The SFA model indicated an average technical efficiency of 55.1 percent, which is low compared to the findings reported by the DEA method where the average technical efficiency was 61.7 percent. The efficiency levels of farmers are strongly linked to distance to main markets, access to extension services, level of education, age of farmers, access to credit services, and availability of modern agricultural inputs (Table 3.1) (Abdulai & Abdulai 2016; Alene & Hassan 2003; Chiona 2012; Paudel & Matsuoka 2009).

In a study using 2005–2006 survey data on 30 households in Zambia, Chiona (2012) estimated the technical efficiency of maize farmers to be 15 percent, which is severely low. This deficiency in technical efficiency may be the outcome of a smaller sample size, which may not necessarily occur in larger sample sizes. Mulwa, Emrouznejad and Muhammad (2009) reported 76.8 percent technical efficiency for maize farmers in Kenya from a sample of 105 farms. Even though a relatively high technical efficiency was reported in this study, no long-term follow-up measures were found.

Factors that influence the inefficiencies in farming have been found to include lack of access to credit and extension services, level of education, and distance to the major market (Abdulai

& Abdulai 2016). A scale efficiency analysis was conducted by Abdulai and Abdulai (2016) via a survey of 406 maize farmers in Zambia. Using the zero inefficient SFA analysis, the probability of being inefficient was found to be 52 percent whereas the average scale inefficiency was 20.8 percent. The high likelihood inefficiency found could have been due to the consideration of a single crop for only one year. However, the degree to which these factors affect efficiency was not specified. Other factors include timeliness of availability of inputs and farm size (Alene & Hassan 2003). The negative effect of farm size on efficiency might be because farmers who produce maize at large scales are less inefficient. Other researchers have found that years of schooling and the age of farmers (Paudel & Matsuoka 2009) and household size, farm size, use of hybrid seeds, and access to extension services (Chiona 2012) have significant effects on efficiency (Table 3.1). However, methodological limitations of these studies may raise questions concerning the effect of age and education, with the Chiona (2012) study based on small household survey data.

Tipi et al. (2009) found the average technical efficiency of Turkish rice farmers to be 92 percent. This result was obtained by applying the DEA analysis for the 2006 survey of 70 households in Turkey. He argued that the estimation using an OLS regression of DEA scores would lead to a biased parameter estimate because OLS assumes a normal and homoscedastic distribution of the disturbance and the dependent variable. Questions can be raised against this result because the Tobit regression provided a different measurement regarding the effect of socioeconomic variables on technical efficiency. It was also found that farm size and membership of a cooperative positively influenced efficiency, while off-farm income, the number of plots, and farmer's age exhibited negative effects on efficiency.

Villano and Fleming (2006) and Yang, Mugera and Zhang (2016) studied the uncertainties associated with rice production and how it affects efficiency. Yang, Mugera and Zhang (2016) used survey data from 270 farms in 2013 and Villano and Fleming (2006) used time series data between 1990 and 1997 (Table 3.1). Regardless of the different methodologies used, these studies found a higher rate of risk associated with rice production because of the scarcity of available resources, little access to credit, lack of education, and environmental factors (e.g. precipitation, temperature, rainfall). However, these studies did not provide any specific strategic recommendation through which farmers could reduce the risk associated with rice production. Besides, Watkins et al. (2014) used data in 33 counties in the USA from 1983 to

2012 to examine the efficiencies in rice production. This study found 87.5 percent technical efficiency, 71.1 percent allocative efficiency, 62.2 percent economic efficiency and 92 percent scale efficiency; however, it only considered traditional preparation methods. For example, ploughing with cows, use of dung/compost fertiliser, biological pest control, and natural weed in rice production but comparison with modern methods would have provided a better efficiency measurement.

3.7 Conclusion and Knowledge Gaps

Based on the literature reviewed, the following conclusions can be made:

1. In Australia, most previous studies have focused on the determination of agricultural productivity without much attention to profitability. Consideration of profitability is very important because it helps policy makers, funders and developers understand whether the farms are profitable and the sources of profitability. Productivity is only a technical relationship between the inputs and how to convert them into outputs.
2. In Australia, prior empirical studies have primarily considered Törnqvist and Färe-Primont TFP indices. It is recommended to consider the Lowe index to compute and decompose TFP into a measure of technical change and several types of efficiency change of the Australian broadacre farm region. The Lowe index is ideal for measuring quantity change and TFP change as it satisfies all seven axioms. The Lowe productivity index is also more reliable than other index approaches especially when data on prices are available.
3. Researchers, both in Australian agriculture and other parts of the world, considered few or limited components of productivity change and efficiency indicators covering short study periods with small study areas. Additionally, many researchers who studied the main drivers of TFP change and profitability change did not consider components of productivity such as output-oriented scale-mix efficiency (OSME), technical and scale-mix efficiency (TSME) and output-oriented environmental efficiency (OEE) in their analysis. Therefore, their results do not provide a holistic representation of productivity and efficiency. Thus, it is desirable to include all these components over longer study periods to provide a more completed picture for policy makers and farm managers, which can assist them to improve their farming performance in the future.

4. The majority of previous studies considered environmental variables (such as rainfall and temperature) and how they influence productivity or efficiency variation as market inputs. Very few studies considered them as uncontrolled (special) inputs in their estimations. In addition, most of the studies that considered rainfall and temperature as uncontrolled inputs compounded them into one input and did not treat them as separate inputs. Failure to study environmental variables as uncontrolled inputs may lead to inaccurate results.
5. For the review of efficiency indicators although several studies focused on how environmental variations impact scores of efficiency indicators, no study looked at all efficiency indicators. Additionally, very few of these studies utilised different levels of rainfall and temperature. Considering more indicators and carefully studying them one by one under different levels of rainfall and temperature could provide more comprehensive results.
6. In Australia, despite the significant contribution of agricultural households to agricultural work, there is a paucity of literature on the social issues of these families and what they require in rural and remote areas. Therefore, further studies that look at socioeconomic variables as the determinants of efficiency indicators in Australian agriculture are required.

CHAPTER 4: METHODOLOGY AND DATA SOURCES

4.1 Introduction

This chapter is structured as follows. Section 4.2 includes the definitions of variables and index construction. Section 4.3 describes the study area and the source of the dataset. Section 4.4 reviews the model estimation. Section 4.5 presents the technologies used in this study. Section 4.6 provides a measure of efficiencies. Section 4.7 describes index analysis involved components of TFP change. Section 4.8 presents the first stage analysis. Section 4.9 explains the second stage analysis including the Tobit and double bootstrap models. Section 4.10 is the conclusion.

4.2 Definitions of Variables and Index Construction

$\boldsymbol{q_1}$ refers to wheat crop output. This is the sum of production (tonnes) for each farm region.

$\boldsymbol{q_2}$ refers to non-wheat outputs. This is the sum of production (tonnes) of all crops (winter and summer seasons) namely barley, canola, sorghum, oats, lupin, rice, field peas, grain legumes and oilseeds for each farm region.

$\boldsymbol{x_1}$ refers to land input, i.e. the effective land area utilised for wheat crop and non-wheat crop production (in hectares).

$\boldsymbol{x_2}$, $\boldsymbol{x_3}$, and $\boldsymbol{x_4}$ refer to chemicals, fertiliser and fuel inputs, respectively. These were obtained by dividing their respective total costs by their yearly price indexes.

$\boldsymbol{x_5}$ refers to labour input which includes family labour and hired labour. Total labour was measured in hours per year per farm on average.

$\boldsymbol{p_1}$ refers to wheat crop price index. This was obtained as the ratio of the sum of all revenue from wheat crop production to crop output (q_1), using 1990 as the base year.

$\boldsymbol{p_2}$ refers to non-wheat crop price index. This was obtained as the ratio of the sum of all revenue from non-wheat crop productions to crop outputs (q_2), using 1990 as the base year.

$\boldsymbol{w_1}$ refers to the rental price index of land. This was derived based on the data of average price indices of land (128, 119 and 101) in the three rainfall regions from Islam, Xayavong and Kingwell (2014) because there was no data available for land rent per hectare.

$\boldsymbol{w_2}$,$\boldsymbol{w_3}$ **and** $\boldsymbol{w_4}$ refer to chemicals, fertiliser and fuel price indices, respectively. These were collected from the ABARES's online farm survey data of costs and quantities (history data) for Australian farm inputs using 1990 as the base year.

$\boldsymbol{w_5}$ refers to the labour wage index, which was generated by dividing the total cost of wages of hired labour by the hired labour hours per year.

The explanatory variables used in the second stage regression analysis are defined as follows:

1. $\boldsymbol{ev1i}$: represents age of farm manager in farm region *i*
2. $\boldsymbol{ev2i}$: represents age of spouse of farm manager in farm region *i*
3. $\boldsymbol{ev3i}$: represents off-farm work of farm manager in farm region *i*
4. $\boldsymbol{ev4i}$: represents off-farm work of spouse of farm manager in farm region *i*
5. $\boldsymbol{ev5i}$: represents the capital-labour ratio of farm region *i*
6. $\boldsymbol{ev6i}$: represents the land-labour ratio of farm region *i*
7. $\boldsymbol{Year7i}$: is a categorical variable of farm region *i*. This variable was controlled for the time fixed effect as the focus was to examine the effect of explanatory variables on variations in efficiency.

4.3 Study Area and Data Sources

The study area for this research was the Wheat Belt regions of Australia. These regions are distributed over the five states of Australia. The Wheat Belt regions of Australia are made up of 12 farm regions namely NSWN, NSWC, VICC, QLDE, NSWR, QLDD, WACS, WANE, VICM, VICW, SAEP and SAMY.

A panel dataset consisting of farm regional-level data (averaged per farm and per annum) on 10 crops from the 12 farm regions covering the period 1990–2016 were used in this study. The dataset was obtained from farm surveys conducted by ABARES and retrieved from their online database called AgSurf (ABARES 2017). It comprised 324 observations on the prices and

quantities of agricultural outputs and inputs. The ten crops, grouped as two outputs namely "wheat" and "non-wheat", included wheat, barley, canola, sorghum, oats, lupin, rice, field peas, grain legumes and oilseeds. These 10 crops are the main crops grown in the Wheat Belt regions of Australia. Wheat makes up approximately 56 percent, followed by barley (18 percent), canola (8 percent), sorghum (4 percent), oats (3 percent) and the others collectively make up 5 percent (Grain Growers 2016). They were placed in two groups to allow for easy estimations during the data analysis. This was also because the production/market competition can be said to be between wheat and the other nine crops.

Five market inputs including fertiliser, chemicals, fuel, labour and land area, and two environmental inputs (rainfall and temperature inputs separately) that were considered as uncontrolled inputs were used. Only data on fertiliser, chemicals, fuel, labour and land area were available for the 12 farm regions in this study from ABARES, i.e. there were no data available in sub-farm regions from the same source.

During the preparation of data and the formulation of the productivity model, it is essential to correctly determine the number of DMUs and the number of inputs and outputs (Sarkis 2007). According to Golany and Roll (1989) and Boussofiane, Dyson and Thanassoulis (1991), it is a basic rule that the number of DMUs must be at least equal to the product of the number of inputs and the number of outputs to avoid any biased estimates. This is because flexibility associated with the selection of weights to assign to the output and input values is the main issue in determining the efficiency of each DMU (Sarkis 2002). In this study, there were five market inputs, one special input (environmental variable) and two output groups. The 12 farm regions are treated as DMUs. Environmental variables were rainfall and temperature, which were used separately in all analysis to examine their effect on productivity and efficiency from different perspectives using specific-region level rather than state-level average farm data.

The data included agricultural output quantities, total cost of inputs and total revenue for each crop and region in each year (1990–2016). Data on input cost obtained from AgSurf were the total of winter and summer crops. This research assumed that all sample farm regions faced the same input prices of fertiliser, chemicals and fuel (ABARES 2016b). Average rent per unit land area (ha) used in this study was adopted from Islam, Xayavong and Kingwell (2014) because it was not available in this dataset. It was also assumed to be the same for all the farms considered in this study and was used as weighted average price index. The crop output price

was obtained by dividing the sum of revenue from crop production by the crop output of each crop (Kingwell et al. 2013a).

As an environmental variable, annual rainfall data covering the period 1990 to 2016 were obtained from the SILO climate database for all sub-regions in Australian Wheat Belt regions and averaged over their respective regions (SILO 2017). The farm regions in this study were grouped based on the quantities of average annual rainfall as low (below 305 mm), medium (between 305 and 450 mm) and high (above 450 mm) average annual rainfall farm regions (AARFRs). For temperature condition, annual average minimum and maximum temperature recorded specifically in the 12 farm regions over the study period were obtained from SILO. The farm regions were grouped based on the mean of annual average of minimum and maximum temperatures ($(T_{min} + T_{max})/2$) as low (10.6–11.9 °C), medium (12–13.9 °C) and high (14–15.8 °C) average annual temperature farm regions (AATFRs) (Brouwer & Heibloem 1986; Hughes et al. 2011; SILO 2017). This approach of grouping farm regions according to different levels (low, medium and high) of environmental variables follows Islam, Xayavong and Kingwell (2014).

The data also included socioeconomic variables (explanatory variables) for each farm region, which were used as independent variables during the second stage analysis. The independent variables included age of farm manager, age of spouse of farm manager, off-farm work of farm manager, off-farm work of spouse of farm manager, capital-labour ratio and land-labour ratio. These variables were used during the second stage analysis to examine the variations in farm regional-level efficiencies.

4.4 Model Estimation

This study used a standard DEA technique to estimate the production frontier and then to compute and decompose the TFPI using RStudio V.1.0.136 to V.1.1.453 in R software V 3.2.4 to V.3.4.4. R software is an open source programme. R software was also used for the calculation of the corresponding efficiency and productivity indices as well as for the estimation of econometric models. In addition, an R-package called Benchmarking with DEA was used to obtain benchmarks that fit with the objectives of this study (Bogetoft & Otto 2011).

In the settings of the programme, technical progress was assumed to occur under VRS in each farm region over the study period. All farm regions were considered to have gone through the same technical change. This study considered an output-oriented DEA model to measure efficiency indicators under the assumption of VRS. Apart from rainfall and temperature, all other environmental variables were assumed to be constant. Results outputted from the DEA were then sorted separately under the three AARFRs and AATFRs. The empirical strategy of this study involved four main parts including (1) index estimation using the Lowe index method, (2) first stage regression analysis using standard DEA, (3) second stage regression analyses using Tobit model and (4) second stage regression analyses using truncated regression and double bootstrap model (employed as a bias-corrected model to verify the robustness of estimations made with the Tobit model).

4.5 Technologies

According to O'Donnell (2016) and O'Donnell, Fallah-Fini and Triantis (2017), a technology is a technique, and a technology set is a set of techniques, method or system employed in transforming inputs into outputs. Technology refers to the choice of machinery, farming system (such as no-tillage), seeds, fertiliser and chemicals for crop protection to produce outputs. In this study, an aggregator that is linearly homogeneous, nondecreasing, and nonnegative was used to aggregate all outputs $Q_{it} \equiv Q(q_{it})$ and inputs $X_{it} \equiv X(x_{it})$. In addition, aggregate prices of outputs and inputs were defined as $P_{it} \equiv p'_{it} q_{it} / Q_{it}$ and $W_{it} \equiv w'_{it} x_{it} / X_{it}$, respectively (also see Islam, Xayavong and Kingwell (2014).

Technology was considered to have progressed over time. In this chapter, the period *t* production possibilities were used to represent the set of technologies that exist for farm region *i* in period *t*. Let $\boldsymbol{q_{it}} = (q_{1it}, q_{2it}, \ldots\ldots, q_{Nit})' \geqq 0$ and $\boldsymbol{x_{it}} = (x_{1it}, x_{2it}, \ldots\ldots, x_{Mit})' \geqq 0$ represent vectors of outputs and inputs, respectively. The set of output-input combinations that are possible using the period *t* technology set is formally defined as:

$$T^t = \{(x, q): x \text{ can produce } q \text{ in period } t\} \quad (1)$$

The frontier of T^t is a period-specific frontier, also called the metafrontier.

Standard regularity assumptions, i.e. compactness, inactivity, weak disposability of inputs and outputs are maintained (also see O'Donnell, Fallah-Fini and Triantis (2017)) determine what a specific technology can and cannot produce. If these assumptions are satisfied, period-specific production possibility sets can be represented using period-specific output distance functions (ODFs). In the studies by O'Donnell (2016) and O'Donnell, Fallah-Fini and Triantis (2017), for instance, it was assumed that the environmental variables were restricted to the technology set, $T^t(z)$. For a rainfall study, this restriction is not always the case because there may be different alternatives such as the use of irrigation water from wells or groundwater water in the study area.

In this study, only period-specific ODFs were used because of the following reasons. First, farmers could make decisions on the use of inputs or choice of technology; however, environmental factors are beyond their control. Second, given the relatively small size of the sample, including period and environment-specific production frontiers might not be appropriate from the efficiency perspective.

After efficiency estimation, based on the environment categories, the performance of DMUs in different environment groups could be examined. In this study, environmental variables were assumed to be weak disposability inputs in the estimation of the DEA production frontier. Other inputs were assumed to be strong/free disposability inputs (Coelli et al. 2005). This is because farmers cannot control environmental variables.

$$D_o^{\mathrm{t}}\,(\,x, q, z) = min\{\rho > 0: (x, z, \frac{q}{\rho}, \frac{-z}{\rho}) \in T^t\} \qquad (2)$$

where, z is an environmental variable[1], i.e. rainfall and temperature, treated as special inputs (non-discretionary inputs) as they have an effect on the production frontier. It is important to recognise that environmental variables are not strongly disposable (O'Donnell 2018). ρ is a vector of weights that must be estimated. From the literature on agricultural economics studies in Australia, several studies (Islam et al. 2014; Islam, Xayavong & Kingwell 2014; Khan, Salim & Bloch 2014) used rainfall as a market input. In contrast, other studies (Che et al. 2012; Henderson & Kingwell 2005; Hughes et al. 2011) considered rainfall as an environmental

[1] Please refer to pages 118–120 of Bogetoft and Otto (2010) for details of non-discretionary variables, also referred to as a sub-vector efficiency approach.

variable affecting inefficiency variation. However, in the present study, we hypothesised that an environmental variable is one of the factors determining the production frontier but this variable is considered as a non-discretionary variable in that frontier (O'Donnell 2018). As such, it has an impact on the production frontier, thus, resulting in inefficiency of the farm regions.

4.6 Measure of Efficiency

Following O'Donnell, Fallah-Fini and Triantis (2017) and O'Donnell (2018), to estimate the output-oriented technical efficiency (OTE) under VRS technology:

$OTE_t(x_{it}, q_{it}, z_{it})$ is the measure of the optimised value of the function and if the linear programmes (LPs) of primal and dual have possible solutions, then the optimised values are equal, and the dual formula of LP can be obtained by solving:

$$\max_{\boldsymbol{\mu},\boldsymbol{\lambda_{11}},\ldots,\boldsymbol{\lambda_{1t}}} \left\{ \boldsymbol{\mu}: \boldsymbol{\mu}\, q_{it} \;\leq \sum_{h=1}^{1}\sum_{s=1}^{t}\lambda_{hs}q_{hs,}\; \sum_{h=1}^{1}\sum_{s=1}^{t}\lambda_{hs}x_{hs} \;\leq\; x_{it,}\; \sum_{h=1}^{1}\sum_{s=1}^{t}\lambda_{hs}z_{hs} \;= z_{it,}, \sum_{h=1}^{1}\sum_{s=1}^{t}\lambda_{hs} = 1, (\;,\boldsymbol{\lambda_{11}}, \ldots, \boldsymbol{\lambda_{1t}})' \geq 0 \right\} \quad (3)$$

where, μ denotes the optimised value of the objective function that compare farm *i* in period *t* with farm *h* in period *s*. λ is a vector weighting factors, and **q** and **x** are the observed output and input matrices, respectively.

Scale efficiency was calculated by dividing the total technical efficiency (TE_{CRS}) by the pure technical efficiency (TE_{VRS}).

Output-oriented scale efficiency (OSE) = OTE_{CRS} / OTE_{VRS} (4)

where, VRS is the variable return to scale technology assumption in the model $\sum_{h=1}^{1}\sum_{s=1}^{t}\lambda_{hs} = 1$ in Equation (3) and CRS denotes the constant return to scale if this constraint is removed.

Output-oriented technical and mix efficiency (OTME), ($OTME^t(x_{it}, q_{it}, z_{it})$) , was calculated by dividing $Q(q_{it})$ by $Q(\hat{}q_{it})$, where $Q(q_{it})$ is the aggregate output of the farm region and $Q(\hat{}q_{it})$ is the maximum aggregate output that is possible in period *t* when using x_{it} in an

environment characterised by z_{it}. Thus, output-oriented mix efficiency (OME) was estimated using the following equation:

$$OME^t(x_{it}, q_{it}, z_{it}) = \frac{OTME^t(x_{it}, q_{it}, z_{it})}{OTE^t(x_{it}, q_{it}, z_{it})} \quad (5)$$

OSME is a measure of the increase in TFP due to movements from the technically efficient point to the point of maximum productivity. Residual output-oriented scale efficiency (ROSE) is a measure of the difference between TFP at an output-mix-efficient point and the maximum possible TFP (O'Donnell 2012c).

Another indicator of a firm's efficiency is its TSME (O'Donnell, Fallah-Fini & Triantis 2017). This is also called firm efficiency (FE) by O'Donnell (2016). TSME measures the efficiency of the owner of a firm, decision maker or firm manager in maximising TFP by being able to choose optimally from available options of inputs and outputs. Mathematically, the TSME of firm *i* in period *t* can be written as:

$$TSME^t(x_{it}, q_{it}, z_{it}) = TFP(x_{it}\ q_{it})/TFP^t\ (z_{it}) \quad (6)$$

where, $TFP^t\ (z_{it})$ represents the maximum TFP that is possible in period *t* and an environment characterised by z_{it}, and the OTE and OSME of farm region *i* in period *t* are shown as (O'Donnell, Fallah-Fini & Triantis 2017):

$$OTE^t(x_{it}, q_{it}, z_{it}) = D_O^t\ (x_{it}, q_{it}, z_{it}) \quad (7)$$

$$OSME^t(x_{it}, q_{it}, z_{it}) = \frac{TSME^t(x_{it}, q_{it}, z_{it})}{OTE^t(x_{it}, q_{it}, z_{it})} \quad (8)$$

Environmental efficiency (*EE*) was represented as the overall environmental efficiency (rainfall or temperature) and was estimated using Equation (9):

$$EE^t(x_{it}, q_{it}, z_{it}) = TFP^t\ (z_{it})/\ TFP_t^*(x_{it}, q_{it}) \quad (9)$$

where, $TFP^t\ (z_{it})$ represents maximum *TFP* within an environment characterised by z_{it} in a year and TFP_t^* represents maximum *TFP* within a year.

4.7 Index Analysis

Measures of economic performance, such as TFP and efficiency were measured using a standard DEA technique and TFP decomposition approach. The Lowe index method was used to decompose TFP into technical change, efficiency change and environmental change. The analytical framework used follows the aggregate quantity-price framework developed by O'Donnell (2012b, 2012c, 2016) and O'Donnell, Fallah-Fini and Triantis (2017). With this framework, the PROFI was decomposed into a multiplicatively-complete TFPI and a TT index (TTI). In addition, in theory, TFP was exhaustively decomposed to obtain measures of technical change and several measures of efficiency change using the multiplicatively-complete TFPI (O'Donnell 2012c).

4.7.1 Lowe TFPI

The Lowe index was used in this study because it is transitive, additive and can be used when price data is available (O'Donnell 2013). Being both transitive and additive makes it an attractive index for making multilateral and multitemporal comparisons of DMUs. This study follows O'Donnell (2012b, 2012c, 2016) and O'Donnell, Fallah-Fini and Triantis (2017) TFPIs that satisfy all basic index number axioms. Specifically, the study aggregates outputs and inputs using the functions $Q(q_{it})\alpha\ p'_0 q_{it}$ and $X(x_{it})\alpha w'_0 x_{it}$, where, p'_0 and w'_0 predetermined farm- and time-invariant reference output and input prices, respectively. The associated output and input quantities and TFPIs that compare farm region *i* in period *t* with farm region *h* in period *s* are:

$$QI_{hsit} = \frac{Q(q_{it})}{Q(q_{hs})} = \frac{p'_0 q_{it}}{p'_0 q_{hs}}, \tag{10}$$

$$XI_{hsit} = \frac{X(x_{it})}{X(x_{hs})} = \frac{w'_0 x_{it}}{w'_0 x_{hs}} \tag{11}$$

$$TFPI_{hsit} = \frac{QI_{hsit}}{XI_{hsit}} = \frac{p'_0 q_{it}}{p'_0 q_{hs}} \frac{w'_0 x_{hs}}{w'_0 x_{it}} \tag{12}$$

According to O'Donnell (2016), proper TFPIs satisfy the weak monotonicity, homogeneity, identity, proportionality, time-space reversal, transitivity and circularity axioms. Thus, the

related index to compare the TFP of farm *i* in period *t* with TFP of farm *h* in period *s* is (O'Donnell, Fallah-Fini & Triantis 2017):

$$TFPI(x_{hs}, q_{hs}, x_{it}, q_{it}) = \frac{TFP(x_{it}, q_{it})}{TFP(x_{hs}, q_{hs})} = \frac{Q(q_{it})/X(x_{it})}{Q(q_{hs})/X(x_{hs})} = \frac{QI(q_{hs}, q_{it})}{XI(x_{hs}, x_{it})} \tag{13}$$

where, $QI(q_{hs}, q_{it}) = Q(q_{it})/Q(q_{hs})$ represents output index and $XI(x_{hs}, x_{it}) = X(x_{it})/X(x_{hs})$ represents input index.

4.7.2 Components of TFP change

4.7.2.1 Productivity index

Measuring technical, efficiency and environmental change can be achieved by TFPI decomposition, based on Equations (6), as follows:

$$TFPI(x_{hs}, q_{hs}, x_{it}, q_{it}) = EETI \times TSMEI = \left[\frac{TFP^t(z_{it})}{TFP^S(z_{hs})}\right]\left[\frac{TSME^t(x_{it}, q_{it}, z_{it})}{TSME^s(x_{hs}, q_{hs}, z_{hs})}\right] \tag{14}$$

where, environment and technology index (*EETI*) = *EEI* × *TI* and *TSMEI* is the technical and scale-mix efficiency index = *OSMEI* × *OTEI*. This study considered the output-oriented environmental efficiency index (OEEI) and the TI separately (also see O'Donnell 2016). For accurate decomposing, TSMEI can be decomposed, based on Equations (8), as follows (see O'Donnell, Fallah-Fini and Triantis (2017) for more details):

$$\left[\frac{TSME^t(x_{it}, q_{it}, z_{it})}{TSME^s(x_{hs}, q_{hs}, z_{hs})}\right] = \left[\frac{OSME^t(x_{it}, q_{it}, z_{it})}{OSME^s(x_{hs}, q_{hs}, z_{hs})}\right]\left[\frac{OTE^t(x_{it}, q_{it}, z_{it})}{OTE^s(x_{hs}, q_{hs}, z_{hs})}\right] \tag{15}$$

$$TFPI\ (x_{hs,}\ q_{hs,}\ x_{it,}\ q_{it}) = \frac{TFP_{it}}{TFP_{hs}} = \frac{TFP_t^*}{TFP_s^*} \times \frac{TFP_{it}^*}{TFP_{hs}^*} \times \frac{OTE_{it}}{OTE_{hs}} \times \frac{OSME_{it}}{OSME_{hs}} \tag{16}$$

TFPI can be decomposed into measures of environmental change and overall efficiency change (*EFF*) according to Equation 17 (O'Donnell 2016):

$$TFPI\ (x_{hs,}\ q_{hs,}\ x_{it,}\ q_{it}) = TI_{st} \times OEEI_{hsit} \times OTEI_{hsit} \times OSMEI_{hsit} \tag{17}$$

EFF was estimated using the following Equation (18):

$$EFF = TFPI / TI \quad (18)$$

where, $OEEI_{hsit} = OEE_{it}/OEE_{hs}$, and $TI_{st} = \frac{TFP_t^*}{TFP_s^*}$ Where, TFP_t^* and TFP_s^* are the maximum TFP values in period t and s respectively.

Furthermore, TFPI can be decomposed according to Equations (20):

$$TFPI\ (x_{hs,}\ q_{hs,}\ x_{it,}\ q_{it}) = TI_{st} \times OEEI_{hsit} \times OTEI_{hsit} \times OMEI_{hsit} \times ROSEI_{hsit} \quad (20)$$

where, OMEI is the output-oriented mix efficiency index and the ROSEI is residual output-oriented scale efficiency index.

Given that $OME \times ROSE = OSME$ (or $OSME = TSME / OTE_{VRS}$) (21)

4.7.2.2 Profitability index

The analytical framework used follows the aggregate quantity-price framework developed by O'Donnell (2012b, 2012c, 2016) and O'Donnell, Fallah-Fini and Triantis (2017) to decompose the PROFI into measures of TFP and TT indices. PROFI compares the profitability of farm region i in period t with the profitability of farm region h in period s as shown in Equation 22 (Mugera, Langemeier & Ojede 2016; O'Donnell 2012c), where PROF is defined as the revenue/cost:

$$PROFI_{hsit} = \frac{PROF_{it}}{PROF_{hs}} = \frac{P_{it}Q_{it}}{W_{it}X_{it}} \times \frac{W_{hs}X_{hs}}{P_{hs}Q_{hs}} = \frac{PI_{hsit}}{W_{hsit}} \times \frac{QI_{hsit}}{XI_{hsit}} = TTI_{hsit} \times TFPI_{hsit} \quad (22)$$

where, $PI_{hsit} = P_{it}/P_{hs}$ is an implicit output price index, $W_{hsit} = W_{it}/W_{hs}$ is an implicit input price index and $TTI_{hsit} = PI_{hsit}/WI_{hsit}$ is a terms of trade index that measures output price change relative to input price change.

4.8 First Stage Analysis

During the first stage, a standard DEA technique was used to estimate the efficiency scores of the 12 farm regions grouped under three levels of rainfall and temperature separately. The efficiency scores included OTE_{CRS}, OTE_{VRS}, OSE, OME, ROSE, OSME, TSME and EE. These scores ranged between 0 and 100 percent. They are presented as averages over the study period for each farm region and under the three rainfall and temperature levels. Additionally, trends

of these scores over the study period are presented. The scores were estimated using Equations (3) to (9).

4.9 Second Stage (Regression) Analysis

Second stage regression analysis was performed to examine the causes of the variations in efficiency scores estimated from the first stage analysis using a standard two-stage DEA approach. This revealed the relationships between the dependent variables (efficiencies) and independent (explanatory) variables. The independent variables were age of farm manager, age of spouse of farm manager, off-farm work of farm manager, off-farm work of spouse of farm manager, capital-labour ratio and land-labour ratio.

The Tobit model was first employed for the second stage analysis. Truncated regression and the double bootstrap model were then employed as a bias-corrected model to confirm the robustness of estimations made with the Tobit model. Tobit model estimations during second stage analysis are likely to produce biased and inconsistent estimates (Simar & Wilson 2007).

4.9.1 Tobit model

Amemiya (1984) stated that the standard formulae of the Tobit model can be obtained by solving Equation (23). This equation is usually used to explain different indicators of efficiency (Balcombe et al. 2008):

$$\hat{y}_{it} = v_{it}\beta + \varepsilon_i \qquad (i = 1, \ldots\ldots, n),\ i = \text{observation (farm regions)} \tag{23}$$

where, y_{it} is the dependent variable (DEA scores), v_{it} is a vector of variables assumed to affect the selection and use of *q* and *x*, β represents the parameter to be estimated and ε_i is a random variable, distributed $N(0, \sigma_\epsilon^2)$ with left truncation at $(1 - v_i \hat{\beta})$, and v_{it} is the vector of explanatory (independent) variable.

Eight models were investigated during the second regression analysis (Tobit model) as follows:

$$OTE_{icrs} = \alpha + \beta_1\ ev_{1i} + \beta_2\ ev_{2\,i} + \beta_3\ ev_{3i} + \beta_4\ ev_{4i} + \beta_5\ ev_{5i} + \beta_6\ ev_{6i} + \beta_7\ Year_{7i} + \varepsilon_i \tag{24}$$

$$OTE_{ivrs} = \alpha + \beta_1\ ev_{1i} + \beta_2\ ev_{2\,i} + \beta_3\ ev_{3i} + \beta_4\ ev_{4i} + \beta_5\ ev_{5i} + \beta_6\ ev_{6i} + \beta_7\ Year_{7i} + \varepsilon_i \quad (25)$$

$$OSE_i = \alpha + \beta_1\ ev_{1i} + \beta_2\ ev_{2\,i} + \beta_3\ ev_{3i} + \beta_4\ ev_{4i} + \beta_5\ ev_{5i} + \beta_6\ ev_{6i} + \beta_7\ Year_{7i} + \varepsilon_i \quad (26)$$

$$OME_i = \alpha + \beta_1\ ev_{1i} + \beta_2\ ev_{2\,i} + \beta_3\ ev_{3i} + \beta_4\ ev_{4i} + \beta_5\ ev_{5i} + \beta_6\ ev_{6i} + \beta_7\ Year_{7i} + \varepsilon_i \quad (27)$$

$$ROSE_i = \alpha + \beta_1\ ev_{1i} + \beta_2\ ev_{2\,i} + \beta_3\ ev_{3i} + \beta_4\ ev_{4i} + \beta_5\ ev_{5i} + \beta_6\ ev_{6i} + \beta_7\ Year_{7i} + \varepsilon_i \quad (28)$$

$$OSME_i = \alpha + \beta_1\ ev_{1i} + \beta_2\ ev_{2\,i} + \beta_3\ ev_{3i} + \beta_4\ ev_{4i} + \beta_5\ ev_{5i} + \beta_6\ ev_{6i} + \beta_7\ Year_{7i} + \varepsilon_i \quad (29)$$

$$TSME_i = \alpha + \beta_1\ ev_{1i} + \beta_2\ ev_{2\,i} + \beta_3\ ev_{3i} + \beta_4\ ev_{4i} + \beta_5\ ev_{5i} + \beta_6\ ev_{6i} + \beta_7\ Year_{7i} + \varepsilon_i \quad (30)$$

$$EE_i = \alpha + \beta_1\ ev_{1i} + \beta_2\ ev_{2\,i} + \beta_3\ ev_{3i} + \beta_4\ ev_{4i} + \beta_5\ ev_{5i} + \beta_6\ ev_{6i} + \beta_7\ Year_{7i} + \varepsilon_i \quad (31)$$

where, α is a constant, β is the parameter, OTE_i represent the efficiency scores under output-oriented *CRS* and *VRS* assumptions for farm region *i*. OSE_i, OME_i, $ROSE_i$ and $OSME_i$ represent the efficiency scores under output-oriented *VRS* assumption for farm region *i*. $TSME_i$ and EE_i represent the efficiency scores for farm region *i*. All the models were analysed separately.

4.9.2 Double bootstrap model

Algorithm #2 of the bootstrapping approach proposed by Simar and Wilson (2007) was used in this study. The bootstrapping approach was used in this study to simulate the sampling distribution of the study by simulating the DGP. The ideal DGP used in Simar and Wilson (2007) double bootstrap was the DEA model (first stage analysis) (Balcombe et al. 2008)

represented by Equations (3) to (9) and second stage truncated regression described by Equation (23).

Estimations with the double bootstrap model followed the following seven steps:

1. Using the original data sample, output-oriented DEA efficiency scores $\hat{y}_{it}$ s $(i = 1, ..., n)$ for all farm regions were estimated employing Equations (3) to (9).

2. The ML method was used to obtain an estimate $\hat{\beta}$ of β as well as an estimate $\hat{\sigma}_{\varepsilon}$ of σ_{ε} in the truncated regression of Equation (23).

3. Steps 3(a) to 3(d) were looped over L_1 times to obtain n sets of bootstrap estimates $\beta_i = \{\hat{y}^*_{ib}\}_{b=1}^{L1}$:

   (a) For each farm region $i = 1, ..., n$, ε_i was drawn from the $N(0, \hat{\sigma}_{\varepsilon})$ distribution.

   (b) For each $i = 1, ..., n$, $y_i* = v_i \hat{\beta} + \varepsilon_i$ was computed.

   (c) Set $x_i* = xi$, $q_i* = qi\, \hat{y}_i / y_i*$ was constructed for all $i = 1, ..., n$

   (d) Using x_i* and q_i*, $\hat{y}^* = (i = 1, ..., n)$ was estimated using a DEA estimator.

4. For each $i = 1, ..., n$, the bias-corrected estimator $\hat{\hat{y}}_i$ was computed using the bootstrap estimates in β_i obtained in step 3 (d) and the original estimate $\hat{y}_i$.

5. Using the ML method, the truncated regression of $\hat{\hat{y}}_i$ on v_i was estimated, yielding estimates $(\hat{\hat{\beta}}, \hat{\hat{\sigma}}_{\varepsilon})$.

6. Steps 6(a) – 6(c) were looped over L_2 times to obtain a set of bootstrap estimates $\wp = \{(\hat{\hat{\beta}}^*, \hat{\hat{\sigma}}^*_{\varepsilon})_b\}_{b=1}^{L_2}$:

   (a) For each farm region $i = 1, ..., n$, ε_i was drawn from the $N(0, \hat{\hat{\sigma}}_{\varepsilon})$ distribution.

   (b) For each $i = 1, ..., n$, $y_i** = v_i \hat{\hat{\beta}} + \varepsilon_i$ was computed.

(c) Using the ML method, the truncated regression of y_i^{**} on v_i was estimated, yielding estimates $\hat{\hat{\beta}}^*, \hat{\hat{\sigma}}_\varepsilon^*$.

7. The bootstrap values in $\wp$ and the original estimates $\hat{\hat{\beta}}, \hat{\hat{\sigma}}_\varepsilon$ generated in step 5 were used to construct estimated confidence intervals for each element of β and for σ_ε.

In this study, the double bootstrap model was used following Algorithm #2 in Simar and Wilson (2007). To perform this method, the following steps were followed (Alexander, Haug & Jaforullah 2010):

1. Implementation of a truncated normal regression with the ML method using the truncreg command in package 'rDEA' in the RStudio software.
2. Programming of a bootstrap by drawing 100 samples each of 324 from the truncated empirical normal distribution of the estimated efficiency scores in the first loop.
3. Use of bias-corrected efficiency scores to re-estimate explanatory variables during the second stage regression.
4. Application of a double bootstrap based on the empirical distribution of bias-corrected second stage regression.
5. Use of 2000 replications for each parameter estimate of the explanatory variables in the second loop.

4.9.3 Random effects Tobit and lag analysis

Since the data used in this study is panel data, random effects Tobit model was also employed to confirm that the censoring function in the standard Tobit model did not introduce any bias and inconsistencies in estimations. Random effects Tobit model (also called an error components model or a variance components) "is a regression model that accommodates both left- and/or right censoring and within-cluster dependence of the outcome variable" (Wang & Griswold 2016) by explore differences in error variance components across individual or time period. The RStudio packages of random effects Tobit model used in this study was adopted from Henningsen (2010).

Furthermore, lag model was used to rid data of unwanted biases and autocorrelational effects which could weaken regression results (Keele & Kelly 2006). This was done to investigate if the Tobit model was affected by autocorrelation. The lag model was also used to predict current

values of dependent variables (efficiency indicators, t-1) based on both the lagged variables for past period and the explanatory variables (Cromwell, Labys & Terraza 1994).

4.10 Conclusion

In this chapter, the methodology used in the empirical studies is outlined. Secondary data consisting of agricultural output quantities, total cost of inputs and total revenue for each crop and region in each year (1990–2016) were collected from ABARES. This study used varied research approaches to fulfil the research objectives. These approaches were essential to meet the requirements of the types of research questions. A standard DEA technique was employed to estimate production frontier and to compute and decompose the TFPI (Lowe index method) into measures of technical, environmental and several efficiency changes. The aggregate quantity-price framework was adopted to decompose profitability change into measures of TFP and TT changes. Efficiency measures were estimated using the output-oriented DEA model under the VRS assumption. Technical efficiency was estimated under the CRS assumption. Tobit regression was used to examine the effects of socioeconomic variables on eight efficiency indicators (scores) and checked for robustness of the results using truncated regression and double bootstrap. These analyses were performed using R software.

CHAPTER 5: EFFECT OF RAINFALL AND TEMPERATURE VARIATION ON PRODUCTIVITY AND PROFITABILITY CHANGE

5.1 Introduction

This chapter presents two results of empirical outcomes. First, measurement of an analysis of rainfall variation on productivity and profitability change. Second, measurement of an analysis of temperature variation on productivity and profitability change. The estimation of the first and second results were conducted by a standard DEA technique and TFP decomposition approaches. This chapter computes and decomposes the Lowe index of TFP into a measure of technical change and several types of efficiency change of Australian broadacre farm regions by estimating the distance function. The observed performance should be compared with some benchmark, i.e. the highest level of productivity, and one should also strive to understand the variation of performance of firms. This study focused on the profitability and TFP of 12 farming regions across Australia under different environmental (rainfall and temperature) categories.

This chapter is structured as follows. Section 5.2 presents descriptive statistics of the output and input variables for the analysis of rainfall variation on productivity and profitability change under the three rainfall farm regions. This section also shows the variations in average annual rainfall in the high, medium and low rainfall areas. Section 5.3 includes the empirical results and discussion of rainfall variation on the productivity and profitability changes. Section 5.4 presents a descriptive statistic of the output and input variables for the analysis of temperature variation on productivity and profitability change under the three temperature farm regions. The variations in average annual temperature in the high, medium and low temperature areas are also presented in this section. Section 5.5 includes the empirical results and discussion of temperature variation on the productivity and profitability changes. Section 5.6 presents the conclusions of the findings.

5.2 Descriptive Statistics of Rainfall Variation on Productivity and Profitability Changes

Table 5.1 shows the summary statistics of the input and output parameters for the three rainfall farm regions. All estimates in Table 5.1 are per farm averages. All three levels of rainfall farm region observations (N) were evenly distributed. Table 5.1 shows that the wheat and non-wheat

crops (e.g. barley, oats, lupin, canola, rice, sorghum, field peas, grain legumes and oilseeds) represented the total quantity of wheat produced and non-wheat produced. For example, in high rainfall, there was an average of 265.23 tonne and 245.92 tonne per farm of wheat crops and non-wheat crops produced, respectively. As expected, wheat production was higher than non-wheat production because the wheat crop is the dominant crop in the Wheat Belt regions of Australia. Across the three levels of rainfall farm regions, the land area input and output of wheat crops and non-wheat crops mixed production in the medium level of rainfall were the highest relatively. The output price of wheat crops and non-wheat mixed crops in the low level of rainfall was relatively higher than that of the medium and high level of rainfall. In contrast, labour wage was maximum in the medium rainfall group. All these variables in Table 5.1 were defined in Chapter 4.

Table 5.1 Summary statistics of variables used in the models for the three rainfall farm regions from 1990 to 2016

(a) *High AARFRs (above 450 mm)

Variable	Unit	N	Mean	St. Dev.	Min	Max
Output						
Wheat crop (q_1)	Tonne	108	256.23	216.12	4.00	782.00
Non-wheat crops (q_2)	Tonne	108	245.92	144.62	21.00	835.00
Input						
Land area (x_1)	Hectare	108	280.82	163.83	85.00	716.00
Chemical (x_2)	kg	108	166.51	116.73	35.60	512.32
Fertiliser (x_3)	kg	108	173.93	64.46	67.57	365.84
Fuel (x_4)	litre	108	14439.44	5455.75	5783.30	29212.76
Labour (x_5)	hours/year	108	2193.68	255.85	1560.00	2856.00
Output price						
Wheat crop Price (p_1)	index	108	310.51	121.54	196.28	868.50
Non-wheat crops Price (p_2)	index	108	295.70	86.96	179.37	618.85
Input price						
Chemical price (w_2)	index	108	108.05	12.46	93.22	149.65
Fertiliser price (w_3)	index	108	122.91	38.42	85.02	239.64
Fuel price (w_4)	index	108	1.55	0.48	0.97	2.44
Labour wage (w_5)	index	108	15.53	7.91	3.69	42.70
Rainfall						
(z_2)	mm	108	496.77	130.23	188.68	932.20

* NSWN, NSWC, QLDE and VICC.

Continues

(b) *Medium AARFRs (between 305 mm and 450 mm)

Variable	Unit	N	Mean	St. Dev.	Min	Max
Output						
Wheat crop (q_1)	Tonne	108	826.46	740.67	31.00	3144.00
Non-wheat crops (q_2)	Tonne	108	552.73	412.96	52.00	1707.00
Input						
Land area (x_1)	Hectare	108	939.06	769.17	154.00	3092.00
Chemical (x_2)	kg	108	421.91	325.41	27.92	1510.33
Fertiliser (x_3)	kg	108	558.44	447.56	23.57	1545.69
Fuel (x_4)	Litre	108	24918.97	8673.97	11490.41	47946.68
Labour (x_5)	hours/year	108	2583.14	277.11	2064.00	3264.00
Output price						
Wheat crop Price (p_1)	index	108	306.10	88.96	190.00	781.58
Non-wheat crops Price (p_2)	index	108	308.73	90.32	140.57	893.32
Input price						
Chemical price (w_2)	index	108	108.05	12.46	93.22	149.65
Fertiliser price ($w_{3)}$	index	108	122.91	38.42	85.02	239.64
Fuel price (w_4)	index	108	1.55	0.48	0.97	2.44
Labour wage (w_5)	index	108	16.84	5.48	2.24	34.04
Rainfall						
(z_2)	mm	108	377.52	111.18	202.33	714.48

*NSWR, QLDD, WACS and WANE.

Continues

(c) *Low AARFRs (less than 305 mm)

Variable	Unit	N	Mean	St. Dev.	Min	Max
Output						
Wheat crop (q_1)	Tonne	108	573.13	371.11	50.00	1904.00
Non-wheat crops (q_2)	Tonne	108	491.85	215.07	76.00	926.00
Input						
Land area (x_1)	Hectare	108	693.33	303.88	263.00	1417.00
Chemical (x_2)	kg	108	317.19	146.53	88.96	690.74
Fertiliser (x_3)	kg	108	331.54	123.81	109.31	762.48
Fuel (x_4)	litre	108	19056.58	4711.80	9730.64	39126.78
Labour (x_5)	hours/year	108	2276.30	243.38	1824.00	2976.00
Output price						
Wheat crop Price (p_1)	index	108	311.98	125.70	151.44	1116.94
Non-wheat crops Price (p_2)	index	108	310.63	114.03	162.17	826.74
Input price						
Chemical price (w_2)	index	108	108.05	12.46	93.22	149.65
Fertiliser price (w_3)	index	108	122.91	38.42	85.02	239.64
Fuel price (w_4)	index	108	1.55	0.48	0.97	2.44
Labour wage (w_5)	index	108	9.77	5.81	1.37	31.12
Rainfall						
(z_2)	mm	108	272.32	74.28	132.25	490.17

*VICM, VICW, SAEP, and SAMY.

Note: z_2 is the environmental variable (rainfall input); rental price of land index (w1) was adopted from Islam, Xayavong and Kingwell (2014).

Figure 5.1 shows high fluctuations in average annual rainfall in all farm regions over the study period. The yearly variations were comparatively higher for the medium and high AARFRs.

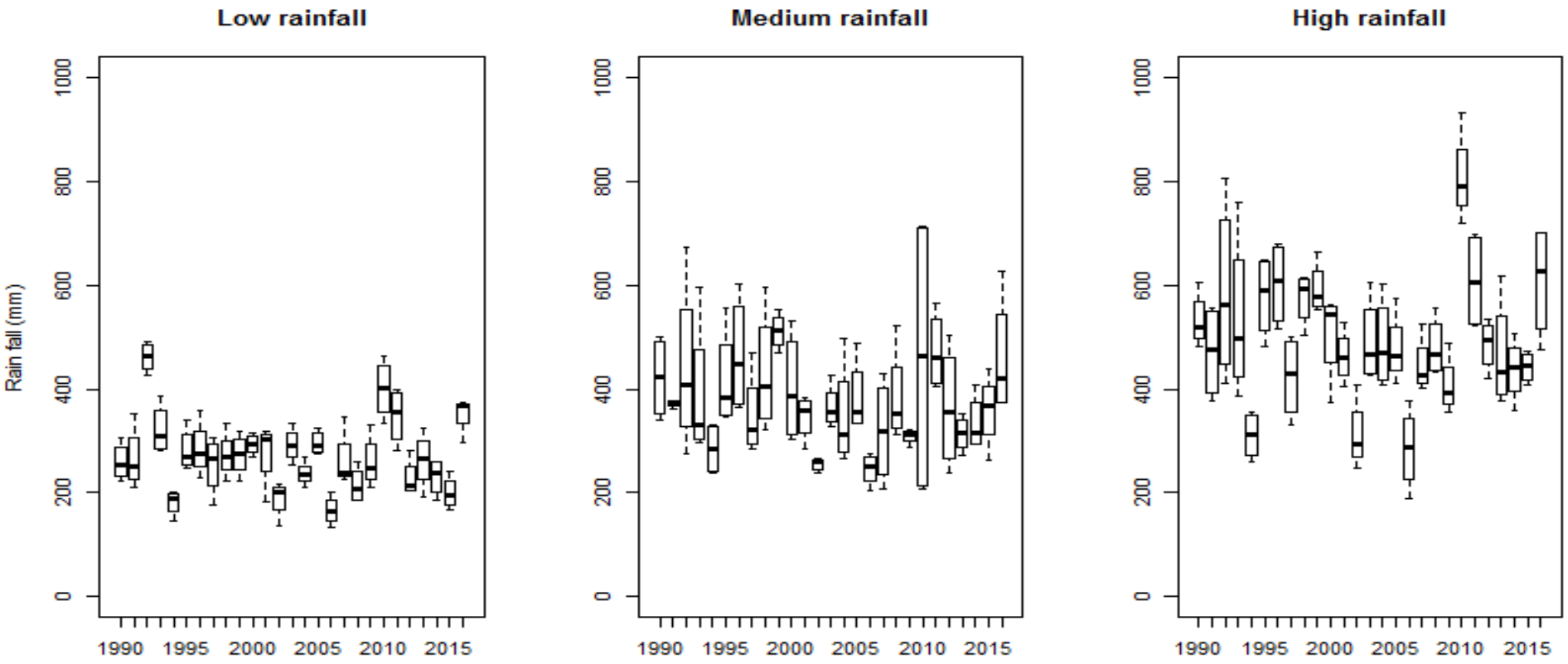

Figure 5.1 Variations in average annual rainfall in the three AARFRs (SILO 2017).

5.3 Empirical Results and Discussion of Rainfall Variation on Productivity and Profitability Changes

5.3.1 Changes of the efficiency components

The impacts of technology index, output-oriented of rainfall efficiency index, output-oriented technical efficiency index, output-oriented mix efficiency index, output-oriented scale-mix efficiency index, residual output-oriented scale efficiency index, and technical and scale-mix efficiency index are displayed in Figures 5.2, 5.3 and 5.4 and also in Tables B.1, B.2, B.3 and B.4 in Appendix B for all AARFRs. Figures A.1 and A.2 present summaries of supporting data in Appendix A.

Tables B.1, B.2, B.3 and B.4 in Appendix B show that the mean TFPI computed for the high AARFRs over the study period was 1.33, which represents a change of 2.11 percent per annum. Mean TFPI for the medium and low AARFRs were 1.42 and 1.04, respectively, representing 2.29 and 0.04 percent per annum, respectively. TFP change was 1.39 percent per annum for all AARFRs (Table B.4, Appendix B). TFPI was greater than 1 relative to the base year (1990) in the high and medium AARFRs and over the sample period except in 1992, 1995, 2003, and 2007 in the high AARFRs and 1995 and 2003 in the medium AARFRs. TFPI was less than 1 for many years (11 out of the 27) for the low AARFRs (Tables B.1, B.2 and B.3, Appendix B). The highest TFPI recorded for the medium AARFRs was consistent with the increasing trend of output (Figure A.1a, Appendix A) and cropping area (Figure A.2a, Appendix A) and favourable rainfall quantities (Figure 5.2) obtained for that AARFR.

In general, there was a significant variation of output quantity that consequently affected the supply side. Therefore, as a market mechanism the output price fluctuated overtime. For example, between 2002 and 2003, a serious drought occurred (Steffen 2015), resulting in a significant drop of agricultural outputs in 2003 (Panel a, Figure A.1). This created a significant supply shortage thus the price increased and reached a peak during that year (Panel c, Figure A.1). However, the levels of TFPI remained high (greater than 1 relative to base year) for the high and medium AARFRs and continued to increase until 2016, whereas the TFPI levels of the low AARFRs dropped due to a decreasing amount of rainfall (Figure 5.1).

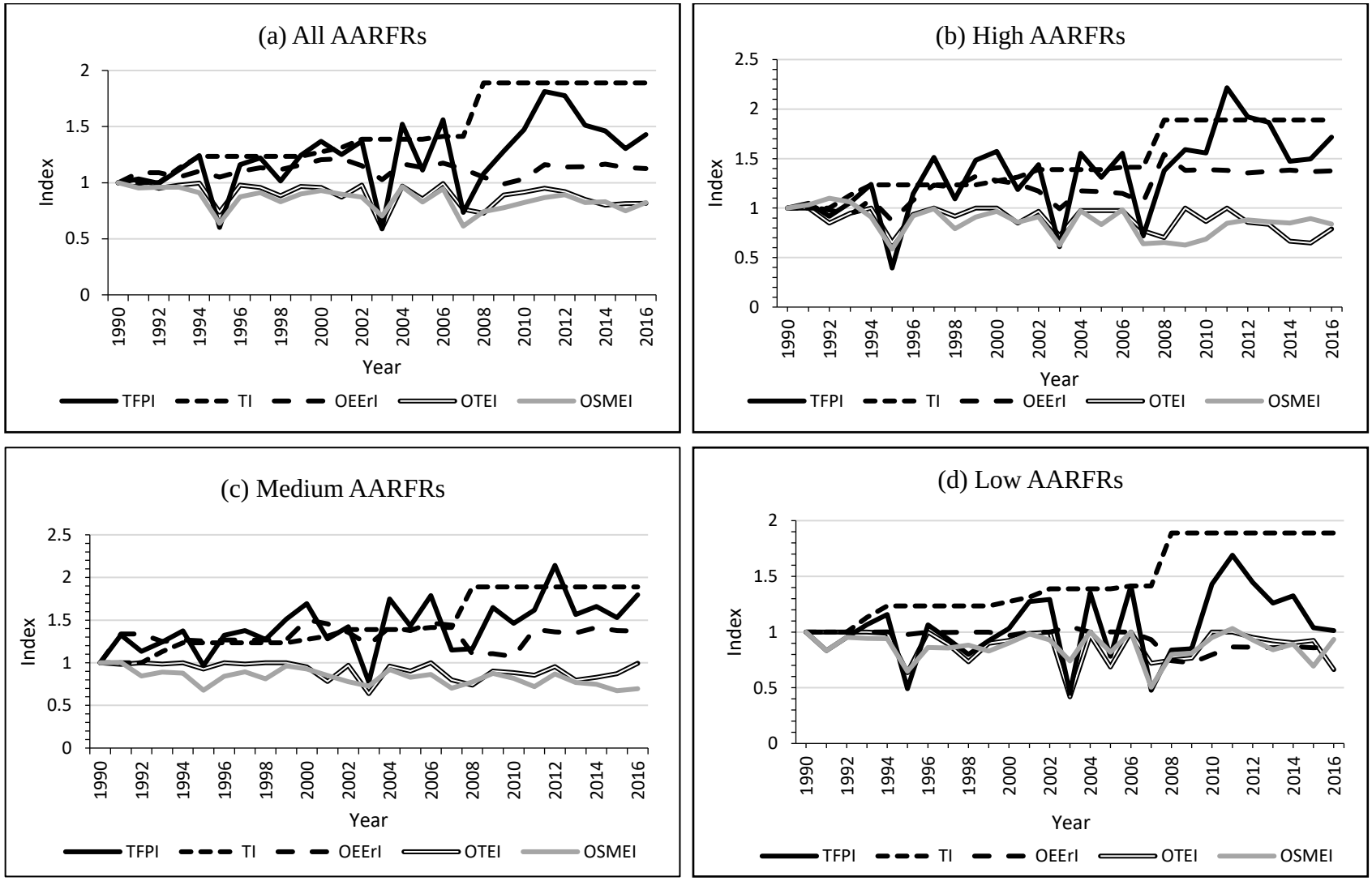

Figure 5.2 Components of TFP changes (TI, OEErI, OTEI and OSMEI) of farm

For example, farmers in southern Australia (Eyre Peninsula and Murray Lands and Yorke Peninsula), where average annual rainfall is low (Table B.3, Appendix B) experienced reduction in TFPI (CSIRO & BoM 2016). In contrast, the TFPI was lowest during 2003 for medium and low AARFRs and in 1995 for high AARFRs (Tables B.1 and B.2, Appendix B). This was because the output-oriented of rainfall efficiency index was lower in those years. Therefore, the output-oriented of rainfall efficiency index results are consistent with the TFPI results. However, the TFPI of the low AARFRs is most sensitive to rainfall change than that of the high and medium AARFRs. Rainfall change was a major contributor to TFP changes. For instance, in high AARFRs, TFPI was approximately 0.39, 1.57, 2.22 and 1.49 when output-oriented of rainfall efficiency index was approximately 0.87, 1.28, 1.38 and 1.37 in 1995, 2000, 2011 and 2015, respectively (Table B.1, Appendix B). In medium AARFRs, TFPI was approximately 0.97, 1.69, 1.62 and 1.53 when output-oriented of rainfall efficiency index was around 1.25, 1.50, 1.39 and 1.38 in the same years, respectively (Table B.2, Appendix B). This confirmed that there was a positive relationship between TFPI and output-oriented of rainfall efficiency index in high and medium AARFRs.

Results displayed in Figure 5.2 and Table B.1, Appendix B indicate that there was deterioration in rainfall conditions in high AARFRs, particularly during 1992, 1993, 1995 and 2003 compared to medium AARFRs. In contrast, a negative relationship was observed between TFPI and output-oriented of rainfall efficiency index for low AARFRs because average output-oriented of rainfall efficiency index was less than that of the base year except during 1994, 1996 and 2001–2006 when values were equal to 1 as seen in Figure 5.2 and Table B.3, Appendix B. output-oriented of rainfall efficiency index was the main source of change in the TFPI in the high and medium AARFRs but not in the low AARFRs. A number of researchers (Che et al. 2012; Islam, Xayavong & Kingwell 2014; Kokic et al. 2005; Sheng, Mullen & Zhao 2011) have shown similar results to that of the present study regarding the impact of environmental change on productivity.

Overall, an increase in productivity could be attributed to rainfall change. Figure 5.2 indicates that the high and medium AARFRs experienced positive (around 20 and 31 percent, respectively) rainfall changes which resulted in an approximate 33 and 42 percent increase in productivity, respectively (Tables B.1 and B.2, Appendix B). For instance, farmers in some parts of high AARFRs such as QLD (Eastern Darling Downs); NSW (North West Slopes and

Plains and Central West) and VIC (Central North) (Table B.1, Appendix B) have experienced improvement in productivity since 2000–2001 because of higher rainfall (Hughes, Lawson & Valle 2017). Also, (Culas 2014) claimed that wheat yield is positively influenced by the area sown. Rainfall also has positive influence on the wheat yield across the wheat-sheep zone but the time (technology progress)-related exogenous factors had only minor influence on the yield using data (AgSurf database) for the period 1990-2004 in in the wheat-sheep. However, there was a marginal increase (approximately 4 percent) in productivity in the low AARFRs. This could be attributed mainly to the 6 percent reduction in rainfall and the approximately 46 percent increase in technology index (Table B.3, Appendix B). Therefore, technology index played a significant role in TFP change from 1990 to 2016. Technology index was the main driver of TFPI (approximately 1.03, 1.43, 1.69 and 1.33) in low AARFRs in 2000, 2010, 2011 and 2014, respectively (Table B.3 and Appendix B). These results agree with results obtained by Hughes et al. (2011); Khan, Salim and Bloch (2014) and Hughes and Lawson (2017) who stated that the lower rainfall in low AARFRs over the last decade has motivated farmers to adopt new technologies and management practices to improve TFPI. For example, Njuki and Bravo-Ureta (2019) found that improvement in irrigation productivity has mainly been driven by technology change.

In conclusion, output-oriented of rainfall efficiency index and technology index were the main drivers for positive change in TFP for high and medium AARFRs. For all AARFRs, year-to-year measures of output-oriented technical efficiency index, output-oriented mix efficiency index and residual output-oriented scale efficiency index indicate a decline or no change in efficiency for all AARFRs (Figures 5.2 and 5.3) (Table B.4, Appendix B). The medium AARFRs recorded the lowest decrease (approximately 1 percent) in output-oriented mix efficiency index compared to the high (approximately 3 percent) and low (approximately 2 percent) AARFRs (Figure 5.3) (Tables B.1, B.2 and B.3, Appendix B). In contrast, the output-oriented scale efficiency index (OSE_t /OSE_s) for farms in the medium AARFRs was zero percent (Tables B.2, Appendix B). The medium AARFRs also experienced the lowest decrease in output-oriented technical efficiency index (approximately 8 percent) compared to the high (approximately 12 percent) and low (approximately 12 percent) AARFRs (Tables B.1, B.2 and B.3, Appendix B). Therefore, the medium AARFRs could be a better option for relaxing restrictions on output mix as evident in

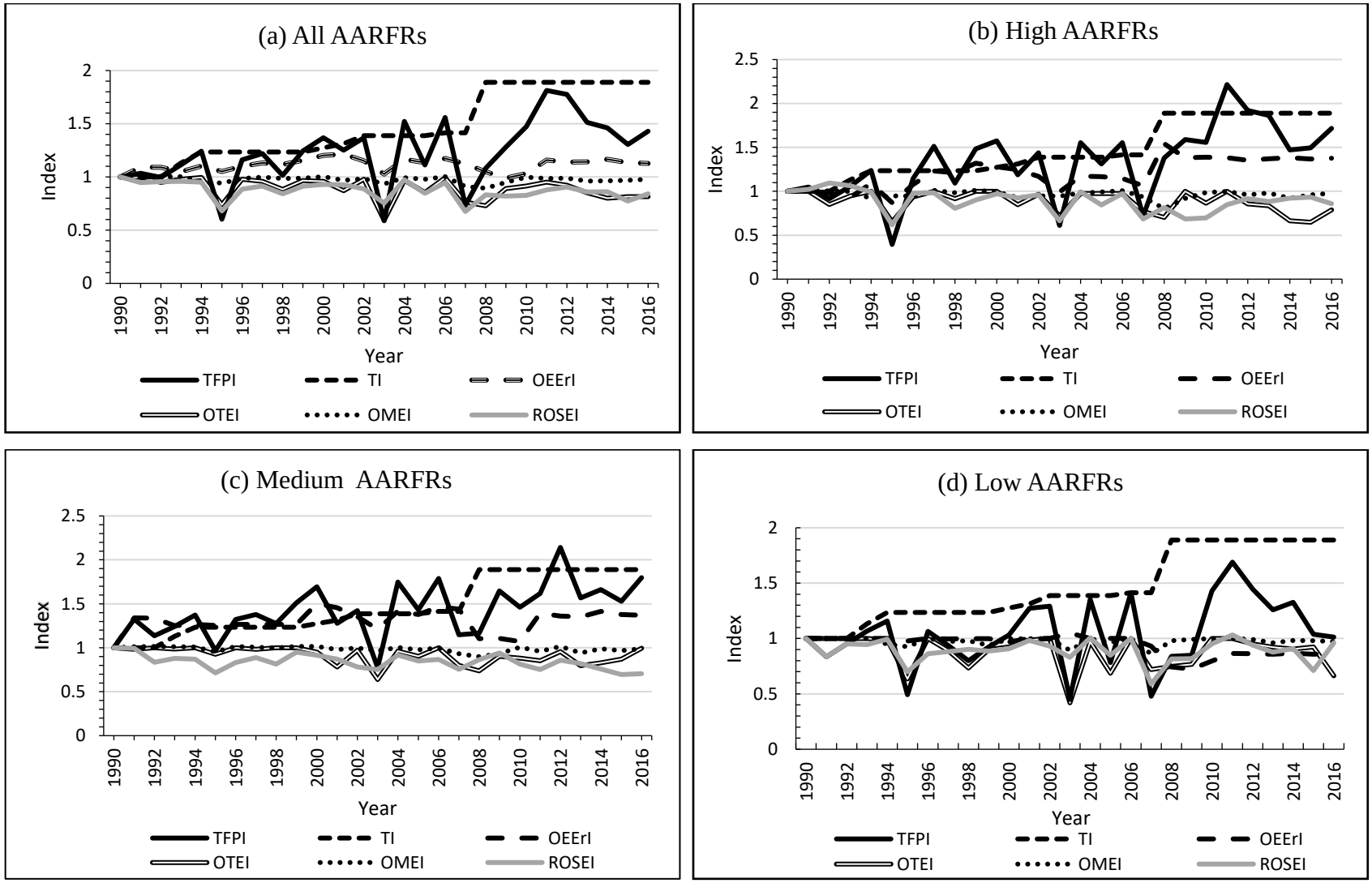

Figure 5.3 Components of TFP changes (TI, OEErI, OTEI, OMEI and ROSEI) of farms

Figures A.1 and A.2 in Appendix A. This might show that individual farms in the medium AARFRs changed their output mix options over time much more than the other AARFRs because there was not a great decrease in efficiency. Relaxing restrictions on the output mix options of the high and low AARFRs resulted in a decrease in efficiency (Figure 5.3) (Tables B.1 and B.3, Appendix B). For instance, total output change (Figure A.1a, Appendix A), proportion of wheat crop area and wheat income proportion were higher in the medium AARFRs than that in the high and low AARFRs (Figure A.2c and d, Appendix A) for the wheat crop group, which is the dominant crop and makes up the largest area in the study region. However, this could indicate that farmers, at least in low AARFRs, are not being efficient in their output mix (wheat and non-wheat crop groups) for a given level of input.

In all AARFRs, technical efficiency was estimated to have declined gradually, especially in high and low AARFRs, over the study period (Figure 5.2) (Table B.4, Appendix B). Output-oriented technical efficiency index declined by approximately 0.90, 0.04 and 1.59 percent per annum in the high, medium and low AARFRs, respectively (Tables B.1, B.2 and B.3, Appendix B). This is consistent with results obtained by Hughes et al. (2011) who stated that technical efficiency change decreased by approximately 0.3 percent between 1977–1978 and 2007–2008 in broadacre Australian farms. This decline implies that the gap between the most technically efficient AARFRs (those defining the frontier) and the least technically efficient AARFRs became wider over the study period. This could be because while the farms experienced overall improvement in technical efficiency, low technically efficient AARFRs recorded improvement in technical efficiency at a slower rate. This, in turn, resulted in a slower rate of TFP change. Technology index indicated that improving technological support will enable farmers to maximise TFP via more efficient alteration of the levels of both inputs and outputs. This proves that the best performance of technology index contributes more positively to TFP change than that of crop mix and alterations of input and output quantities.

As seen from Table 5.1, although crop yields of the high and low AARFRs were higher than crop yield of the medium AARFRs, the medium AARFRs still recorded the highest TFPI and the output-oriented scale efficiency index had a positive contribution to TFPI. This suggests that farmers had the best farm size on productivity for medium AARFRs (Table 5.1). A study by Che et al. (2012) showed that the average size of the farm was the largest in the low rainfall north zone of WA (North and East Wheat Belt in medium AARFRs) during the period 2006–

2010. This suggests that mixed farms in the medium AARFRs are more technically and scale efficient than the mixed farms in the high and low AARFRs (Tables B.1, B.2 and B.3, Appendix B).

It was also observed that output-oriented of rainfall efficiency index in medium AARFRs had the most positive effect on TFPI (Table B.2, Appendix B). Therefore, farmers in medium AARFRs improved their input efficiency more than farmers in the other AARFRs. Additionally, this suggests the best performance of output-oriented of rainfall efficiency index contributed more to TFP change than the mix and alterations of input and output quantities in both wheat and non-wheat groups. Farmers in the high AARFRs did not always have the best practice for crop growth especially for irrigated land area. High quantity of water may lead to soil salting, which could negatively affect crop growth in the long term.

Output-oriented scale-mix efficiency index impacted poorly on TFPI in all AARFRs (Figure 5.2a) (Table B.4, Appendix B). The 14 percent decrease in output-oriented scale-mix efficiency index over the 27-year period in the high AARFRs could be attributed to the approximately 3 percent drop in output-oriented mix efficiency index and approximately 11 percent decline in residual output-oriented scale efficiency index (Table B.1, Appendix B). The medium AARFRs experienced an approximate 17 percent decrease in output-oriented scale-mix efficiency index with an approximately 1 percent reduction in output-oriented mix efficiency index and approximately 16 percent decrease in residual output-oriented scale efficiency index (Tables B.2, Appendix B). In addition, the low rainfall AARFRs experienced an approximately 13 percent decrease in output-oriented scale-mix efficiency index with an approximate 2 percent fall in output-oriented mix efficiency index and an approximate 11 percent decline in residual output-oriented scale efficiency index (Figure 5.3b, c and d) (Table B.3, Appendix B).

Figure 5.4 presents the indicator technical and scale-mix efficiency index introduced by O'Donnell, Fallah-Fini and Triantis (2017). Technical and scale-mix efficiency index showed a negative impact on TFPI in high, medium and low AARFRs (Tables B.1, B.2 and B.3, Appendix B). This may suggest that output-oriented technical efficiency index and output-oriented scale-mix efficiency index decreased by approximately 12 and 14 percent, 8 and 17 percent, and 12 and 13 percent in high, medium and low AARFRs, respectively, over time (Figure 5.2) (Tables B.1, B.2 and B.3, Appendix B). For all, high, medium and low AARFRs

(Figures 5.2 and 5.4), output-oriented scale-mix efficiency index and technical and scale-mix efficiency index followed similar trends as that of the TFPI; however, their contributions to the effect on TFP were different. For example, output-oriented scale-mix efficiency index and technical and scale-mix efficiency index of high AARFRs declined in a similar manner by approximately 14 and 23 percent, respectively, (Figures 5.2b and 5.4b) (Table B.1, Appendix B). Output-oriented scale-mix efficiency index and technical and scale-mix efficiency index decreased by approximately 17 and 24 percent in medium AARFRs (Figure 5.2c and 5.4c), and by approximately 13 and 22 percent in low AARFRs (Figures 5.2d and 5.4d) (Tables B.2 and B.3, Appendix B). For a clearer understanding of the impact of output-oriented scale-mix efficiency index and technical and scale-mix efficiency index on the TFPI, their changes have been expressed as percent per annum. Output-oriented scale-mix efficiency index and technical and scale-mix efficiency index declined, respectively, by around 0.67 and 1.59 percent per annum in high AARFRs (Table B.1, Appendix B), 1.36 and 1.42 percent per annum in medium AARFRs (Tables B.2, Appendix B), and by approximately 0.24 and 1.82 percent per annum for low AARFRs (Table B.3, Appendix B). In all AARFRs, output-oriented scale-mix efficiency index and technical and scale-mix efficiency index also decreased by approximately 0.76 and 1.53 percent per annum, respectively (Table B.4, Appendix B).

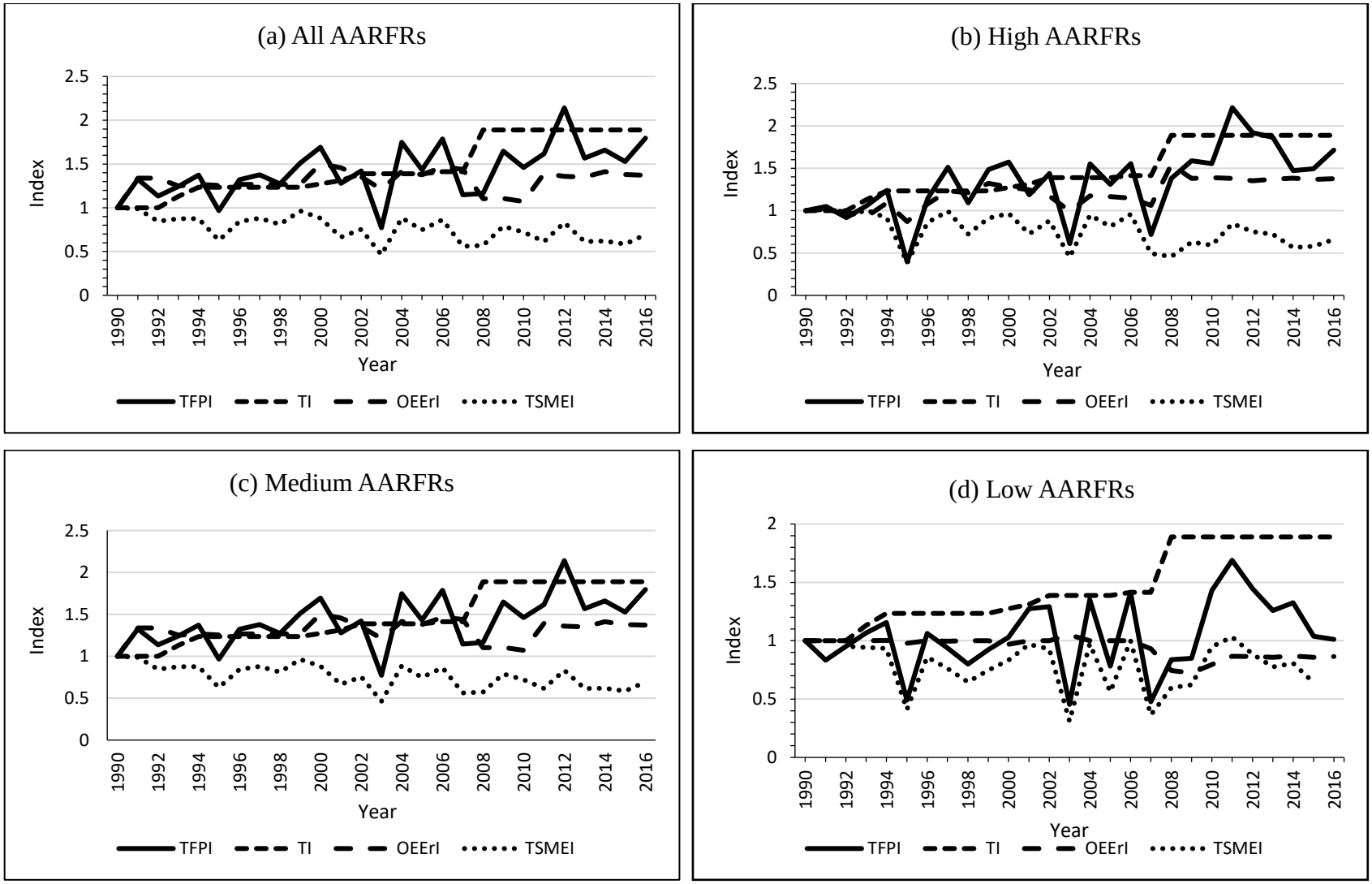

Figure 5.4 Components of TFP changes (TI, OEErI and TSMEI) of farms

Therefore, technical and scale-mix efficiency index had the highest negative impact on TFPI in the low farms under study. Output-oriented scale-mix efficiency index and technical and scale-mix efficiency index had an equally negative effect on the TFPI in medium AARFRs. This evidence suggests that the farmers did not achieve the maximum TFP due to the suboptimal use of available resources in all AARFRs. Output-oriented scale-mix efficiency index was relatively low (average values of approximately 0.85 in all, 0.86 in high, 0.83 in medium and 0.87 in low AARFRs) in all farm regions in this study (Tables B.1, B.2 and B.3, Appendix B). O'Donnell (2012c) also found that Output-oriented scale-mix efficiency index had a negative effect on and was highly variable with TFPI in some states. This suggests that the increase observed in the TFPI was not due to economies of scale and scope.

It could, therefore, be inferred that it is less flexible for, especially, farmers in low AARFRs to move their crop mix more towards alternative profitable crops. In contrast, it is easier for farmers in medium AARFRs to vary their crop mixes in response to changes in rainfall and the price of their farm produce. Because farms in low AARFRs are more sensitive to rainfall change, it is particularly important to promote the establishment of region-based technologies for reducing plant transpiration rates and conserving soil moisture in cases where there are no other options such as the presence of river or ground water.

5.3.2 Components of TFP change

Technical change and efficiency change are regarded as two of the main components of TFP. Decomposing TFPI into technology index and overall efficiency index revealed that technology change played a crucial role in TFPI across the three AARFRs over the study period (Figure 5.5). Several previous studies have shown similar results to that of the present study regarding technological change and its impact on total productivity change (Che et al. 2012; Islam, Xayavong & Kingwell 2014; Khan, Salim & Bloch 2014; Mugera, Langemeier & Ojede 2016; O'Donnell 2012c). With the assumption that no technical regress occurred over the study period, an upward shift in the best-practice production frontier was observed in 1993, 1994, 2000, and 2012 as shown in Figure 5.5 by the technology index values for all AARFRs.

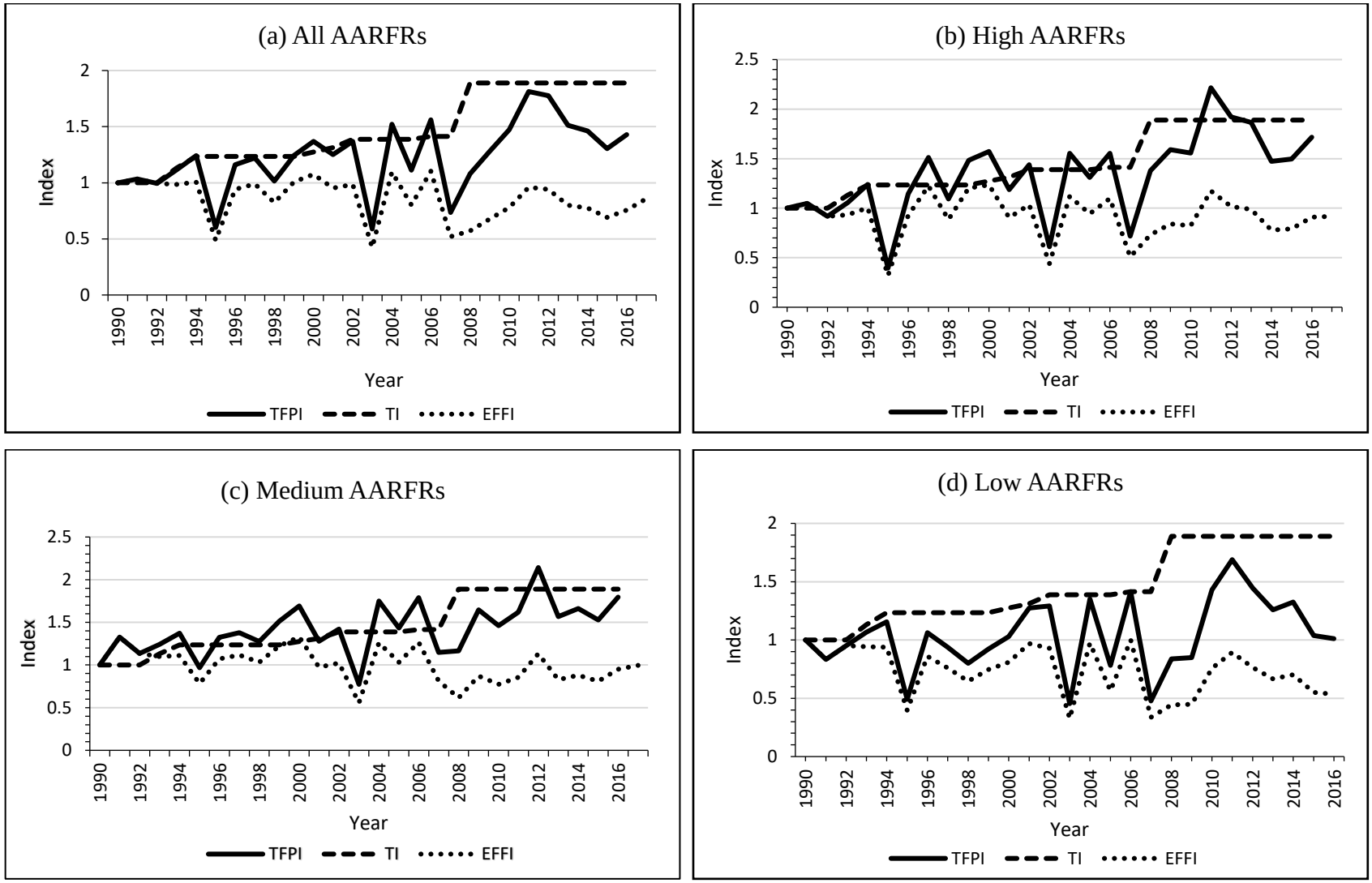

Figure 5.5 Variations in TFPI due to TI and EFFI

Mugera, Langemeier and Ojede (2016) also assumed technological development in the analysis and found results comparable to the present study. TFPIs of the high, medium and low AARFRs were approximately 1.06, 1.24, 1.57 and 1.92; 1.24, 1.37, 1.69 and 2.14; and 1.07, 1.16, 1.03 and 1.45 in 1993, 1994, 2000 and 2012, respectively (Tables B.1, B.2 and B.3, Appendix B). Therefore, the farmers in the medium AARFRs used new technology and knowledge more than those in the other AARFRs and with the best performance (best farms) as was also found by Che et al. (2012). Khan, Salim and Bloch (2014) showed that technological progress was the main driver of productivity change in broadacre agriculture in Australia. Slow productivity change was attributed mainly to a 0.70 percent annual rate of increase in production possibilities (technical progress) and a 0.11 percent annual decrease in overall efficiency using data (AgSurf database) from 1990 to 2011.

In all AARFRs over the sample period, overall efficiency index had a negative (approximately 14 percent) impact on TFPI. Year-to-year efficiency gains, however, indicated that farmers in high AARFRs experienced improvement in overall efficiency index in 1997, 1999, 2000, 2004 and 2011 and farmers in medium AARFRs showed improvement in 1991, 1992, 1994, 1997, 1999, 2000, 2004, 2006 and 2012 (Tables B.1, B.2 and B.3, Appendix B). No improvement in efficiency gains was observed for low AARFRs.

The overall efficiency index of the three AARFRs followed a similar decreasing trend. The high, medium and low AARFRs experienced approximately 8, 0.5 and 27 percent changes (Tables B.1, B.2 and B.3, Appendix B) in efficiency, respectively (Figure 5.5 b, c, and d). TFPI computed for the high and low AARFRs over the study period showed changes of approximately 2.11 and 0.04 percent per annum, respectively (Table B.1 and B.3, Appendix B). This was because of the combined impact of technology index and overall efficiency index of approximately 2.48 and −0.36 percent and 2.48 and −2.34 percent per annum in the high and low AARFRs, respectively (Table B.1 and B.3, Appendix B). For the medium AARFRs, a TFPI change of approximately 2.29 percent per annum occurred due to the technology index and overall efficiency index changes of approximately 2.48 and −0.20 percent per annum, respectively (Tables B.2, Appendix B). This again implies that the overall efficiency index of medium AARFRs was more flexible for output mix than the other two AARFRs because the positive change in TFPI of the medium AATFRs was more than that of the high and low AATFRs.

Variations in rainfall were crucial not only for productivity, but also for improvement in efficiency. For example, the overall efficiency index of the medium AARFRs experienced a zero percent change when output-oriented of rainfall efficiency index increased by approximately 31 percent, whereas overall efficiency index of the high and low AARFRs decreased by approximately 8 and 27 percent with a 20 and 6 percent increase in output-oriented of rainfall efficiency index , respectively (Tables B.1, B.2 and B.3, Appendix B).

This study also confirmed that technical change in the long run plays an important role in generating productivity gains, which is offset by a gradual decline in technical efficiency in Australian broadacre agriculture as found by Hughes et al. (2011). According to Kingwell et al. (2013b) and Islam, Xayavong and Kingwell (2014), many farmers choose to increase farm size and/or the size of cropping programmes as a business and adaptation strategy to obtain the benefits of economies of scale. Therefore, farmers who grow more wheat than other crops improve their use of best-practice methods by adopting existing technology to improve their productivity. Additionally, results from the medium AARFRs showed that crop mix efficiencies also play a key role in supporting farm productivity. Improving technology index and overall efficiency index are important to achieve the best performance and to shift farmers' production frontiers (Asseng & Pannell 2012). Thus, Hughes et al. (2011), Kingwell et al. (2013b), Khan, Salim and Bloch (2014) and Hughes, Lawson and Valle (2017) stated increasing research, development and extension efforts in agriculture is essential to improve the profitability and productivity.

5.3.3 Profitability and productivity decomposition

Tables B.1, B.2 and B.3 in Appendix B show changes in profitability index, terms of trade index and TFPI of average farms for all AARFRs. Profitability index decreased in all AARFRs over the study period relative to the base year. With the exception of 1996, 2002 and 2013, profitability was lower than that of the base year for all AARFRs (Table B.4, Appendix B). This was mainly due to decreases in trade indices. Over time, the trade index value dropped below that of the base year, except in 1995 and 2003 when positive changes in the trade index values were recorded (Table B.4, Appendix B). However, negative change in profitability in medium and low AARFRs was mostly due to decreases in terms of trade index, whereas positive changes in profitability in high AARFRs was mostly due to increases in TFPI.

Productivity changes were mostly positive during the study period, whereas trade indices were negative (Figure A.1a, Appendix A). The lowest and highest values of profitability index were, respectively, approximately 0.42 (in 2007) and 1.05 (in 2002) in the low AARFRs, 0.58 (in 2007) and 1.21 (in 1996) in the medium AARFRs, 0.59 (in 1995) and 1.52 (in 2013) in the high AARFRs, and 0.51 (in 2007) and 1.12 (in 1996) for all AARFRs (Tables B.1, B.2 and B.3, Appendix B). Thus, profitability change varied greatly for all AARFRs as evidenced by the variations in quantities and prices of outputs and inputs shown in Figure A.1, Appendix A.

The main source of profitability change for the high AARFRs was for TFPI (Islam, Xayavong & Kingwell 2014; Mugera, Langemeier & Ojede 2016; O'Donnell 2012c), whereas it was terms of trade index for the medium and low AARFRs. The 7 percent increase in profitability over the 27-year period in the high AARFRs could be attributed to the approximate 12 percent (1–0.88) drop in terms of trade index and around 33 percent (1–1.33) increase in TFPI (Table B.1, Appendix B). The medium AARFRs experienced an approximate 7 percent decrease in profitability with a 34 percent reduction in terms of trade index and a 42 percent increase in TFPI (Tables B.2, Appendix B). In contrast, the low rainfall AARFRs experienced an approximate 26 percent decrease in profitability with a 23 percent fall in terms of trade index and a 4 percent increase in TFP (Table B.3, Appendix B). Changes in profitability index due to terms of trade index varied in a similar pattern over the 27-year period within each AARFR. However, the highest frequency of terms of trade index decrease was observed for the medium AARFRs (Figure 5.6c). Farmers in these regions experienced increases in production costs during the 27-year period owing to increased prices of inputs and decreased output prices (Figure A.1d, Appendix A). For example, in 2003 and 2006, wheat group price decreased from an average of 527.85 $/t to 200.51 $/t, whereas non-wheat group price decreased from an average of 463.97 $/t to 186.50 $/t (Figure A.1c and d, Appendix A). Despite this, the medium AARFRs had the highest wheat income proportion (Figure A.2d, Appendix A) partly due to their highest output quantity (Figure A.1a, Appendix A).

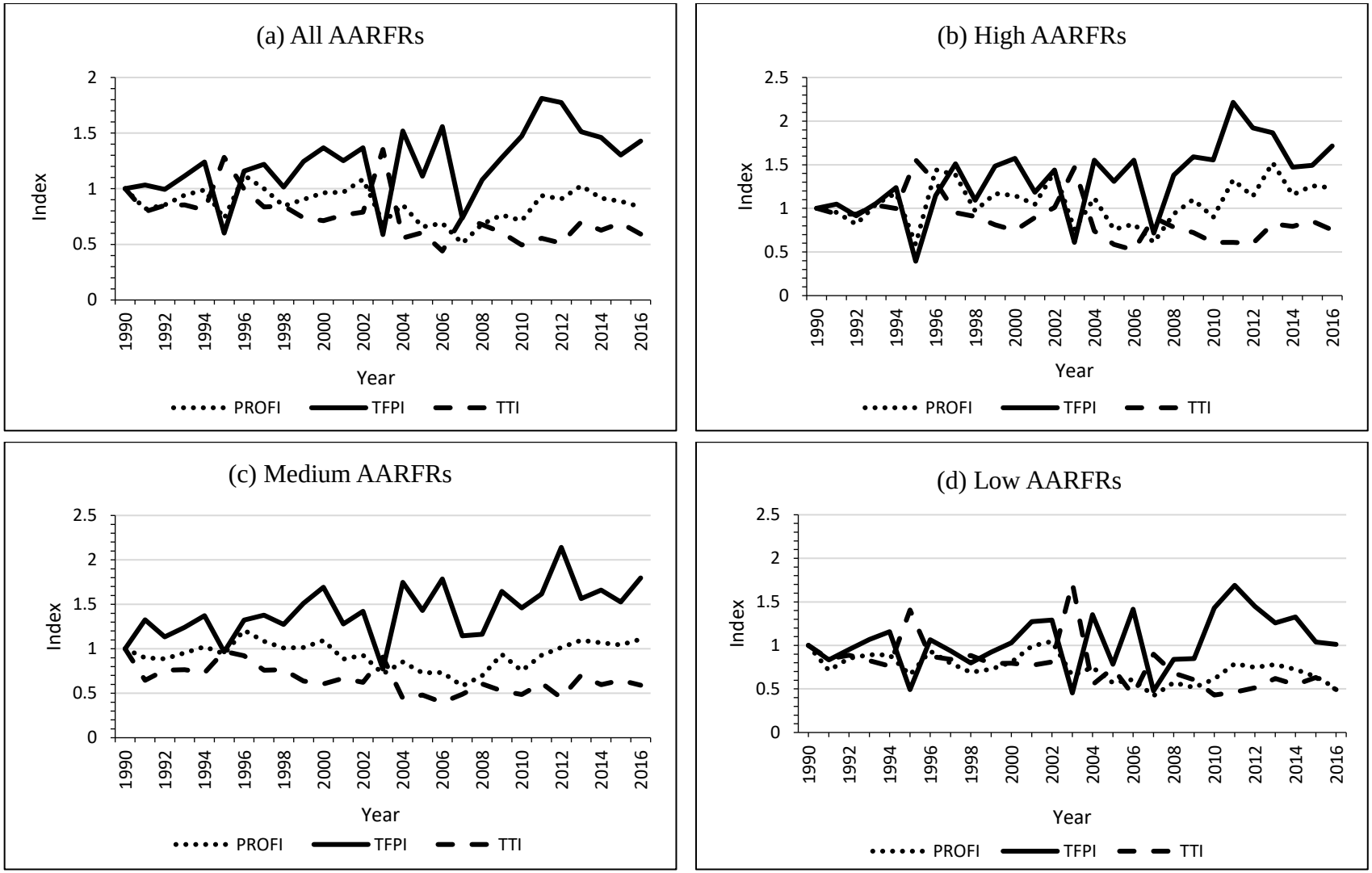

Figure 5.6 Changes in PROF, TFP and TT (base 1990).

By contrast, farms in low AARFRs experienced the lowest crop prices except for 1994, 2003 and 2007, which resulted in favourable TT and supported profitability change. The TFPI for all AARFRs remained higher than that of 1990 (base year) except for 1992, 1995, 2003 and 2007, and varied between 52 percent in 2004 and 78 percent in 2012 whereas it varied between 51 percent in 2013 and 43 percent in 2016 (Table B.4, Appendix B). The TFPI was highest for the medium AARFRs (42 percent), followed by the high (33 percent) and low (4 percent) AARFRs (Tables B.1, B.2 and B.3 Appendix B). Thus, the TFPI of the medium AARFRs increased significantly relative to the base year (Figure 5.6c). As shown in Figure A.1a, Appendix A, the output quantity of the medium AARFRs increased over the study period due to an increase in input quantity (Figure A.1b, Appendix A) and crop area trend (Figure A.2a, Appendix A). The increase in output price also caused a decrease in the output quantity in all AARFRs (Figure A.1a and c, Appendix A). One of the other factors that must be considered in agricultural economics when studying crop output quantity is the uncertainties caused by environmental change such as rainfall.

5.4 Descriptive Statistics of Temperature Variation on Productivity and Profitability Changes

Table 5.2 presents the summary statistics of the input and output parameters for the three temperature farm regions in per farm averages, with N referring to the sample size (number of observations). Observations were evenly distributed at all three temperature levels. The medium temperature group in the farm region had the highest land area input and output per farm of wheat crop and non-wheat mixed production compared to the high and low temperature groups. Moreover, the medium level of temperature had the highest relative wheat crop price. In contrast, the labour wage input of wheat crop and non-wheat mixed production was the maximum in the high temperature group and minimum in the low temperature group.

Table 5.2 Summary statistics of variables used in the models for the three temperature farm regions from 1990 to 2016

(a) *High AATFRs (14–15.8 °C)

Variable	Unite	N	Mean	St. Dev.	Min	Max
Output						
Wheat crop (q_1)	Tonnes	108	488.22	346.27	30.00	1,638
Non-wheat crops (q_2)	Tonnes	108	384.83	372.79	21.00	1,707
Input						
Land area (x_1)	Hectare	108	550.79	398.02	171.00	1,825
Chemical (x_2)	kg	108	284.64	213.95	27.92	1,100
Fertiliser (x_3)	kg	108	318.67	327.39	23.57	1,385
Fuel (x_4)	litre	108	20,350	6,057	10,411	38,387
Labour (x_5)	hour/year	108	2,464	241.14	1,800	2,976
Output price						
Wheat crop price (p_1)	index	108	307.40	98.63	190.00	781.58
Non-wheat crops price (p_2)	index	108	295.77	98.13	140.57	893.32
Input price						
Chemical price (w_2)	index	108	108.05	12.46	93.22	149.65
Fertiliser price (w_3)	index	108	122.91	38.42	85.02	239.64
Fuel price (w_4)	index	108	1.55	0.48	0.97	2.44
Labour wage (w_5)	index	108	18.07	7.18	7.89	42.70
Temperature						
(z_1)	^{0}C	108	15.24	0.86	13.18	16.70

* NSWN, NSWC, QLDD and WACS.

Continues

(b) *Medium AATFRs (12–13.9 °C)

Variable	Unit	N	Mean	St. Dev.	Min	Max
Output						
Wheat crop (q_1)	Tonnes	10	782.16	783.07	4	3,144
Non-wheat crops (q_2)	Tonnes	108	496.68	296.21	52	1,539
Input						
Land area (x_1)	Hectare	108	872.41	780.55	85	3,092
Chemical (x_2)	kg	108	374.4	314.1	35.6	1,510
Fertiliser (x_3)	kg	108	485.45	386.41	84.81	1,545
Fuel (x_4)	litre	108	21,991	9,676	8,121	47,946
Labour (x_5)	hour/year	108	2,444	332.32	1,824	3,264
Output price						
Wheat crop price (p_1)	index	108	311.36	103.69	195.05	868.5
Non-wheat crops price (p_2)	index	108	302.3	72.58	180.97	497.69
Input price						
Chemical price (w_2)	index	108	108.05	12.46	93.22	149.65
Fertiliser price (w_3)	index	108	122.91	38.42	85.02	239.64
Fuel price (w_4)	index	108	1.55	0.48	0.97	2.44
Labour wage (w_5)	index	108	15.16	6.55	2.24	38.36
Temperature						
(z_1)	^{0}C	108	13.42	0.62	12.01	15.23

*NSWR, QLDE, SAEP and WANE.

Continues

(c) *Low AATFRs (10.6–11.9 °C)

Variable	Unite	N	Mean	St. Dev.	Min	Max
Output						
Wheat crop (q_1)	Tonnes	108	385.44	281.30	30.00	1,592.00
Non-wheat crops (q_2)	Tonnes	108	408.99	239.32	39.00	926.00
Input						
Land area (x_1)	Hectare	108	490.01	285.01	92.00	1,350.00
Chemical (x_2)	kg	108	246.56	145.38	39.13	690.74
Fertiliser (x_3)	kg	108	259.79	105.15	67.57	617.44
Fuel (x_4)	litre	108	16,073	5,806	5,783	39,126
Labour (x_5)	hour/year	108	2,143	229.60	1,560	2,904
Output price						
Wheat crop price (p_1)	index	108	309.83	134.23	151.44	1,116.94
Non-wheat crops price (p_2)	index	108	317.00	117.12	162.17	826.74
Input price						
Chemical price (w_2)	index	108	108.05	12.46	93.22	149.65
Fertiliser price (w_3)	index	108	122.91	38.42	85.02	239.64
Fuel price (w_4)	index	108	1.55	0.48	0.97	2.44
Labour wage (w_5)	index	108	8.91	4.05	1.37	20.42
Temperature						
(z_1)	^{0}C	108	11.16	1.10	9.16	13.30

*VICM, VICW, VICC and SAMY

Note: z_1 is the environmental variable (temperature input); rental price of land index (w1) was adopted from Islam, Xayavong and Kingwell (2014).

Figure 5.7 shows high fluctuations in average annual temperature in all the farm regions over the study period. The year-to-year variation was relatively higher for the medium and high AATFRs. For instance, the highest temperature was in 2014 in the high (15.84) and low (11.73) AATFRs whereas the medium temperature was 14.11 in 2007.

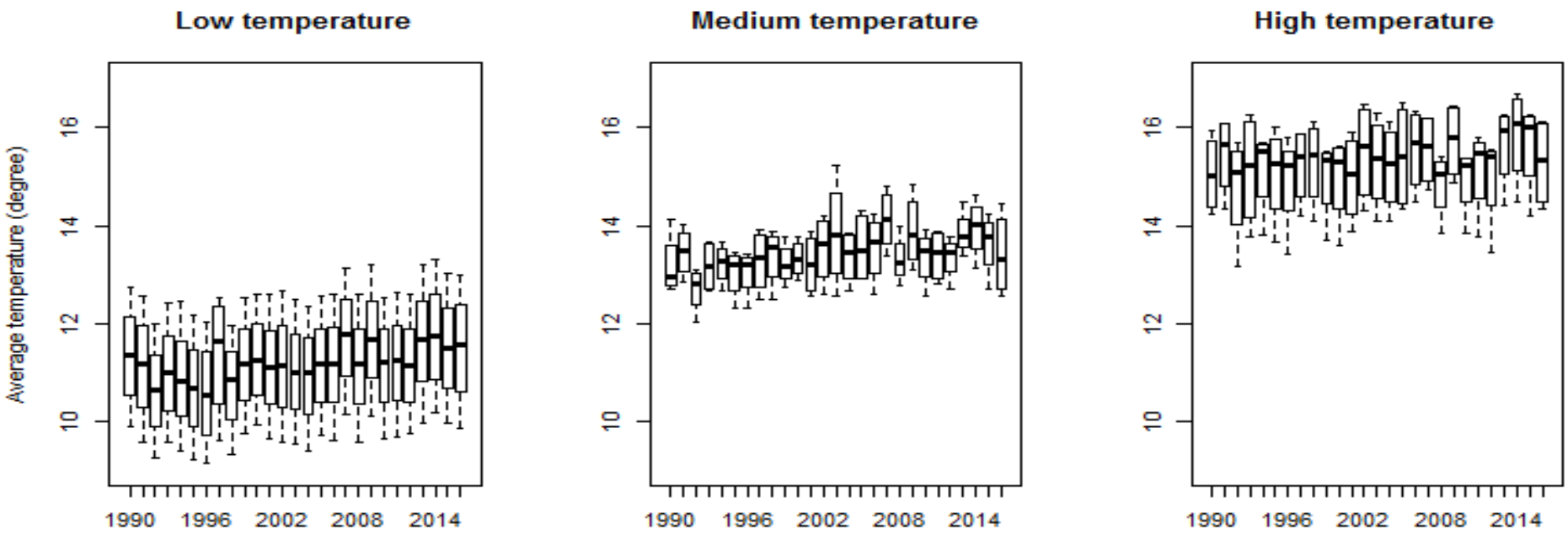

Figure 5.7 Variations in average annual temperature in the three AATFRs (SILO 2017).

5.5 Empirical Results and Discussion of Temperature Variation on Productivity and Profitability Changes

5.5.1 Changes of the efficiency components

Relative to 1990, TFPI was decomposed into technology index, output-oriented technical efficiency index, output-oriented mix efficiency index, output-oriented scale-mix efficiency index, technical and scale-mix efficiency index, residual output-oriented scale efficiency index and output-oriented of temperature efficiency index. These indices are presented in Figures 5.8, 5.9 and 5.10 and also in Tables C.1, C.2, C.3 and C.4 in Appendix C for all AATFRs. TFP change was 1.39 percent per annum for all AATFRs (Tables C.1, C.2, C.3 and C.4, Appendix C). Mean TFPI computed for the high AATFRs, over the study period, was approximately 1.35, which represented a change of approximately 2.26 percent per annum (Table C.1, Appendix C). Mean TFPI for the medium and low AATFRs was approximately 1.28 and 1.10, representing approximately 1.94 and −0.16 percent per annum, respectively (Tables C.2 and C.3, Appendix C). Therefore, low AATFRs have the lowest decrease in total productivity change.

TFPI was greater than 1 relative to the base year (1990) in the high and medium AATFRs and over the sample period except in 1992, 1995, 2003 and 2007 (Tables C.1 and C.2, Appendix C). TFPI was less than 1 in many years (10 out of the 27) in the low AATFRs (Table C.3, Appendix C). The highest TFPI recorded for the high AATFRs was consistent with the increasing output trend (Figure A.1a, Appendix A), cropping area (Figure A.2a, Appendix A) and favourable temperatures (Figure 5.7) recorded in the high AATFRs. For instance, based on climate projections towards 2030, the price of land and grain productivity are expected to increase by 2–9 percent with an increase in rainfall in high temperature farm regions (Kingwell 2006). In contrast, the price of land and grain productivity are expected to decline by 7–16 percent with declining rainfall and increasing temperature (CSIRO 2001; Kingwell 2006; Kokic et al. 2005).

In general, there was a significant variation of output quantity and this consequently affected the supply side. Therefore, as a market mechanism the output price fluctuated over time. For example, between 2002 and 2003, a serious drought occurred (Steffen 2015), resulting in a significant drop of agricultural outputs in 2003 (Figure A. la, Appendix A). This created a

significant the supply shortage, thus the price increased and reached a peak during that year (Figure A.lc, Appendix A).

Generally, temperature change played a key role in contributing to TFP change. For example, in high AATFRs, TFPI was approximately 0.57, 1.53 and 1.41 when output-oriented of temperature efficiency index was approximately 1.01, 1.29 and 1.19 in 1995, 2000 and 2015, respectively (Table C.1, Appendix C). Temperature change contributed positively (13 percent) to productivity change in high AATFRs; however, it had a negative impact (approximately 3 and 8 percent, respectively) on productivity change in the medium and low AATFRs (Figure 5.8) (Tables C.1, C.2 and C.3, Appendix C). This was because average output-oriented of temperature efficiency index was less than that of the base year except in 2000, 2006, 2008–2012 and 2014–2016 in medium AATFRs. In low AATFRs, no year was observed that was greater than that of the base year (Tables C.2 and C.3, Appendix C). These results suggest that TFPI of the medium and low AATFRs was more sensitive to temperature change than that of high AATFRs, which implies that temperature change has a negative impact on crop output (Figure A.1a, Appendix A) (Hughes et al. 2011). For example, farmers in southern Australia (Eyre Peninsula and Murray Lands and Yorke Peninsula) experienced a reduction in TFPI over several years of the study period (Tables C.2 and C.3, Appendix C). However, farmers in low AATFRs recorded the highest crop yields (Table 1) because they experienced increases in crop prices (Figure A.1c, Appendix A), which encouraged increased production. Because change in output-oriented of temperature efficiency index contributed negatively to TFPI in the medium and low AATFRs, technology index was the main driver of TFP in these AATFRs. According to Hughes et al. (2011) and Hughes, Lawson and Valle (2017) technical change plays a major role in total productivity change in Grain Research and Development Corporation regions.

TFPI was more than that of the base year except in 1995, 2003 and 2007 (approximately 0.75, 0.72 and 0.77, respectively) in the medium AATFRs and in 1991, 1992, 1995, 1998, 1999, 2003, 2005, 2007–2009 and 2016 in the low AATFRs (Tables C.2 and C.3, Appendix C). Therefore, there was an approximate 28 and 10 percent increase in productivity in the medium and low AATFRs, respectively. This could be attributed mainly to an approximate 3 and 8 percent reduction in temperature change and an approximate 46 percent increase in technology index in the medium and low AATFRs, respectively (Tables C.2 and C.3, Appendix C). In addition, the TFPI of the medium AATFRs improved more than that of the low AATFRs.

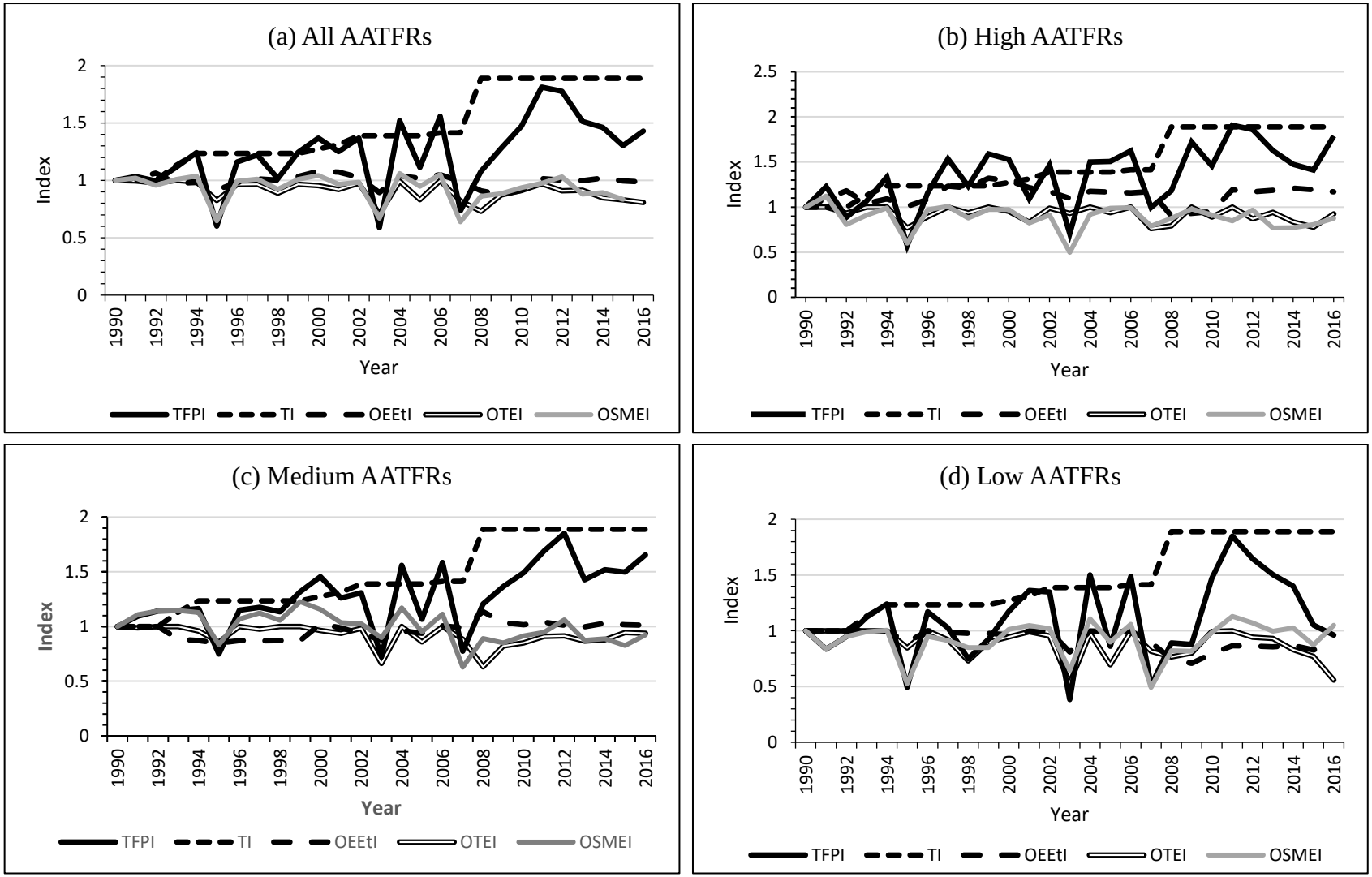

Figure 5.8 Components of TFP changes (TI, OEEtI, OTEI and OSMEI) of farms relative to the base year (1990)

Therefore, farmers in the medium and low AATFRs adopted new technologies and applied new knowledge; however, those in the medium AATFRs invested more in these changes (Figure 5.9). This is because farmers benefitted from the positive effect of residual output-oriented scale efficiency index (approximately 3 percent) on TFPI in the medium AATFRs (Figure 5.9) (Table C.2, Appendix C). Technology index indicated that improving technological support enabled farmers to maximise TFP via more efficient alteration of the levels of both inputs and outputs (Figure 5.8). This demonstrated that technology index contributed more positively to TFP change than that of crop mix and alterations of input and output quantities. Again, technology index played a significant role in TFP change from 1990 to 2016 (Tables C.1, C.2, C.3 and C.4, Appendix C).

Output-oriented of temperature efficiency index and technology index were the primary drivers of improvement in TFP in the high AATFRs compared to the other AATFRs, whereas only technology index was the main driver of positive change in TFP in the medium and low AATFRs. The TFPI of the high AATFRs was the highest. This suggests that the positive effects of output-oriented of temperature efficiency index and technology index provided more support to improve TFPI for farmers in high AATFRs (Table C.1, Appendix C). Other evidence showed that farmers in some parts of high AATFRs in NSW (North West Slopes and Plains and Central West) have experienced improvement in productivity since 2000–2001 owing to favourable temperature (Hughes, Lawson & Valle 2017) (Table C.1, Appendix C).

In all broadacre farms in the various AATFRs, technical efficiency was estimated to have declined over the study period (Figure 5.8) (Tables C.1, C.2, C.3 and C.4, Appendix C). output-oriented technical efficiency index decreased by approximately 0.81 percent per annum in all AATFRs (Table C.4, Appendix C). Additionally, output-oriented technical efficiency index decreased by approximately 0.32, 0.24 and 2.21 percent per annum over the survey period in the high, medium and low AATFRs, respectively (Tables C.1, C.2 and C.3, Appendix C). Generally, this could indicate that farmers in all AATFRs are technically inefficient in their output mix (wheat and non-wheat crop groups) for a given level of inputs. Hughes et al. (2011) suggested that technical change decreased by approximately 0.30 percent between 1977–1978 and 2007–2008 in broadacre Australian farms.

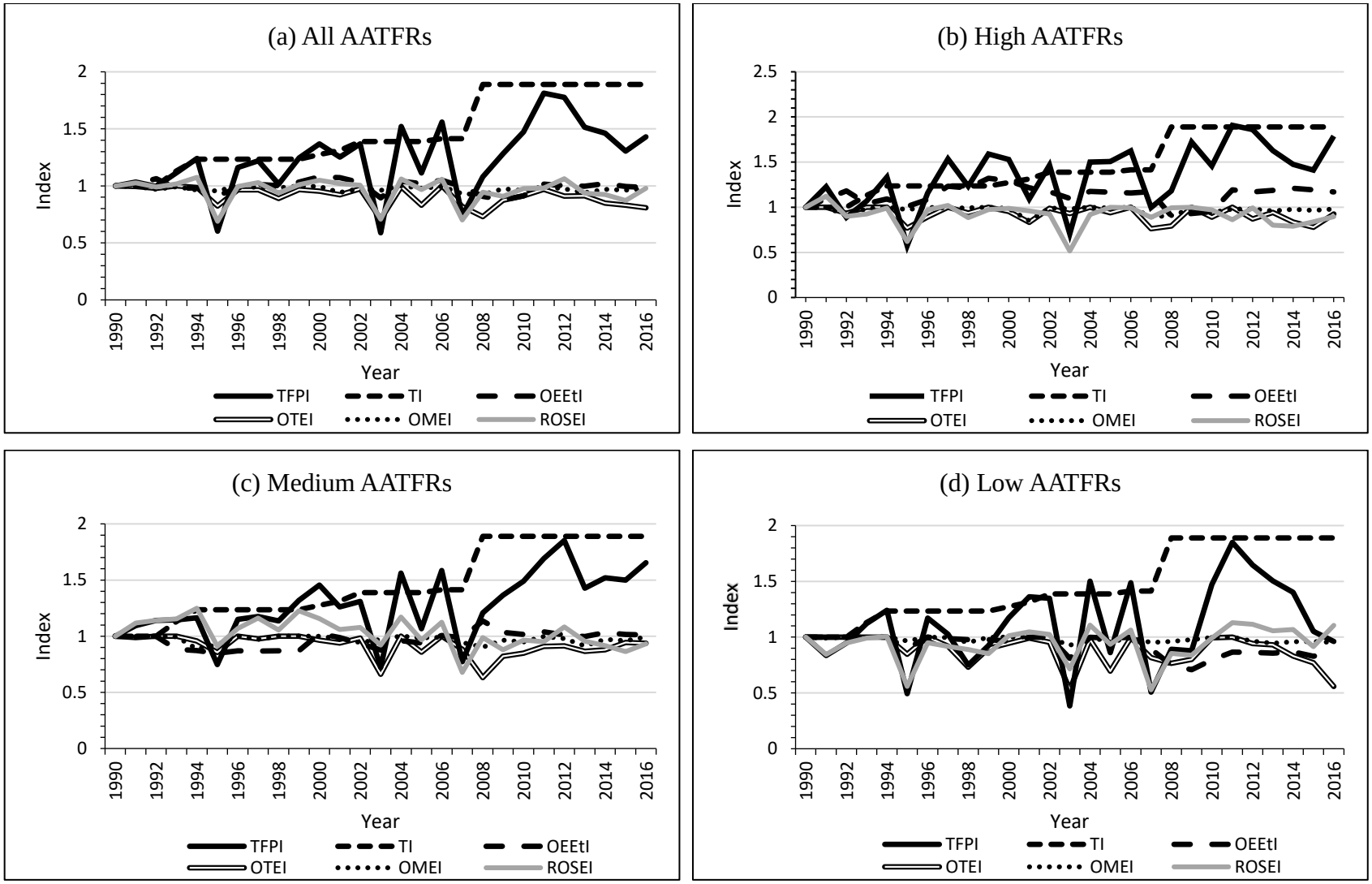

Figure 5.9 Components of TFP changes (TI, OEEtI, OTEI, OMEI and ROSEI) of farms relative to the base year (1990).

For all AATFRs, measures of output-oriented mix efficiency index and residual output-oriented scale efficiency index over the study period indicated a decline in efficiency (Figure 5.9); however, this did not generally indicate that there was no improvement in efficiency for individual AATFRs in some years (Figures 5.9b and c). For instance, residual output-oriented scale efficiency index was slightly greater than 1 in 1991 and 1997 for the high AATFRs; considerably in 1991–1994 and 1996–2002, 2004, 2006 and 2012 for the medium AATFRs; and moderately in 2000–2002, 2004, 2006, 2011–2014 and 2016 for the low AATFRs (Tables C.1, C.2, and C.3, Appendix C).

Residual output-oriented scale efficiency index had a positive contribution to TFP changes in the medium AATFRs, but not in the high and low AATFRs (Figure 5.9). TFPI increased by approximately 28 percent with an approximate 3 percent increase in residual output-oriented scale efficiency index and 3, 8 and 3 percent decreases in output-oriented of temperature efficiency index, output-oriented technical efficiency index and output-oriented mix efficiency index and respectively, in the medium AATFRs (Figure 5.9c). In contrast, output-oriented scale efficiency index (OSEt/OSEs) also declined by approximately 2 percent (Table C.2, Appendix C).

Therefore, farmers in the medium AATFRs were more efficient in their crop mix for a given level of input and in altering the levels of both inputs and outputs to maximise TFP. O'Donnell (2010) and Islam, Xayavong and Kingwell (2014) reported that residual output-oriented scale efficiency index played a key role in increasing TFP change of Australian broadacre farms. They observed significant reduction in terms of trade index and increase in residual output-oriented scale efficiency index over their study periods.

TFPI was lowest in 2003 for the medium (0.72) and low (0.38) AATFRs and in 1995 for the high (0.57) AATFRs (Tables C.1, C.2 and C.3, Appendix C). This could be attributed to drought experienced throughout Australia during those years (ABS 2012a; Hughes et al. 2016). This could also be due to low contributions of output-oriented technical efficiency index (0.77) and residual output-oriented scale efficiency index (0.62) in high AATFRs in 1995; and output-oriented technical efficiency index (about 0.66 and 0.53), output-oriented of temperature efficiency index(about 0.88 and 0.81), and residual output-oriented scale efficiency index (around 0.92 and 0.71) in the medium and low AATFRs (Figure 5.9b, c, and d) in 2003,

respectively (Tables C.1, C.2 and C.3, Appendix C). These results were consistent with the results of TFPI in 1995 and 2003. Furthermore, change in output-oriented mix efficiency index contributed negatively (approximately 3, 3 and 2 percent) to the productivity of broadacre farm for the high, medium and low AATFRs, respectively, over the 27-year period (Figure 5.9). Over the study period, the TFPI increase was 1.94 per annum in the medium AATFRs. This was the effect of a 2.48 per annum increase in technology index (Tables C.1, C.2 and C.3, Appendix C).

The medium AATFRs had residual output-oriented scale efficiency index contributing positively to TFPI and also had the largest farm area. This confirmed that farmers in medium AATFRs were more scale efficient and they used output mix more extensively than did the other farmers in high and low AATFRs. For instance, wheat crop area proportion and wheat income proportion were higher in the medium AATFRs than those in the high and low AATFRs (Figure A.2c and d, Appendix A) for the wheat crop group, which was the dominant crop in the study area.

Figures 5.8 and 5.10 show the relationships among TFPI and output-oriented scale-mix efficiency index, and technical and scale-mix efficiency index. Generally, output-oriented scale-mix efficiency index and technical and scale-mix efficiency index had a negative impact on TFPI in all sample farm regions (Figures 5.8 and 5.10a, b, c and d). The values of output-oriented scale-mix efficiency index were relatively low, having average estimates of approximately 0.93 in all, 0.89 in high, 1 in medium and 0.92 in low AATFRs (Tables C.1, C.2, C.3 and C.4, Appendix C).

The high, medium and low AATFRs had output-oriented mix efficiency index (approximately 3, 3 and 2 percent, respectively) contributing negatively to output-oriented scale-mix efficiency index, whereas residual output-oriented scale efficiency index contributed negatively in the high and low (8 and approximately 6, respectively) AATFRs and positively in the medium (approximately 3 percent) AATFRs (Tables C.1, C.2 and C.3, Appendix C).

This suggested that the increase in the TFPI was not due to economies of scale and scope. Farmers in medium AATFRs may be closer to obtaining cost advantages because of increased production and operation size or scale than those in the other AATFRs. Technical and scale-mix efficiency index was less than 1 in high, medium and low AATFRs by 17, 7 and 17 percent,

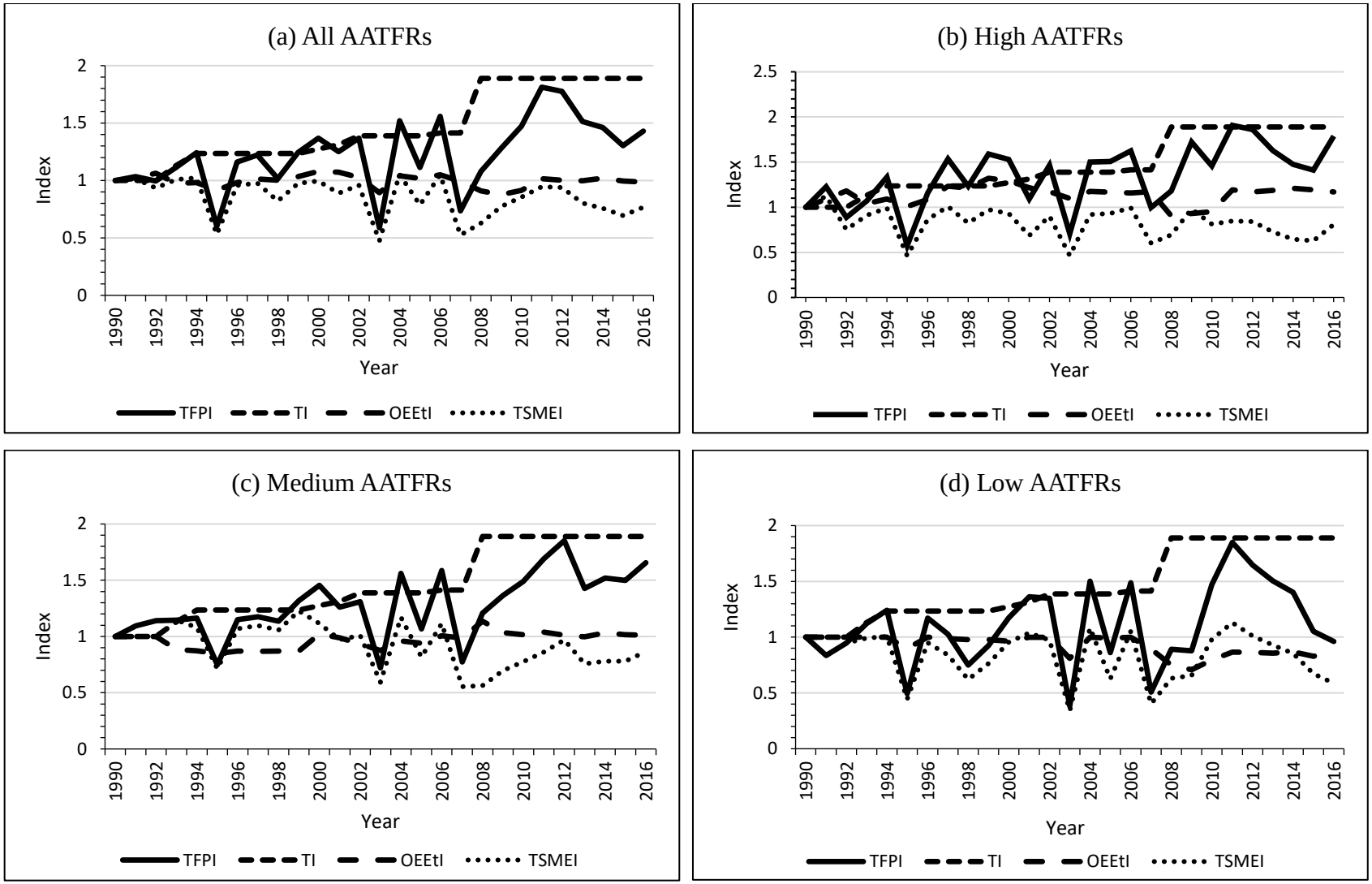

Figure 5.10 Components of TFP changes (TI, OEEtI, and TSMEI) of farms relative to the base year (1990).

respectively over the study period. However, technical and scale-mix efficiency index was greater than 1 in 1991 in high AATFRs, and in 1991–1994, 1996–2000, 2004 and 2006 in medium AATFRs, and in 2001, 2006 and 2011 in low AATFRs (Tables C.1, C.2 and C.3, Appendix C). This may be because the combined effect of output-oriented technical efficiency index and output-oriented scale-mix efficiency index decreased by 8 and 11 percent in high AATFRs, 8 and zero percent in medium AATFRs, and 11 and 8 percent in low AATFRs, respectively (Tables C.1, C.2 and C.3, Appendix C). Therefore, technical and scale-mix efficiency index had a negative effect by approximately 0.81, 0.53 and 2.01 percent per annum on the TFPI in high, medium and low AATFRs, respectively (Tables C.1, C.2 and C.3, Appendix C). However, farms businesses in medium AATFRs experienced the lowest decline in technical and scale-mix efficiency index (Figure 5.10c).

Finally, the study suggested that broadacre farmers in the farm regions should support their output mix and improve their TFP change and income by following the strategy below:

1. In high AATFRs: by increasing output quantity to compensate for the highest input prices (Figure A.1a and d, Appendix A).
2. In medium AATFRs: by growing more wheat than non-wheat crops (Table 5.2) (Figure A.2c and d, Appendix A).
3. In low AATFRs: by gradually increasing wheat farm area (Figure A.2b, Appendix A) because of an increase in output price (Figure A.1c, Appendix A).

5.5.2 Components of TFP change

Technical change and efficiency change are regarded as two of the main components of TFP. Decomposing TFPI into technology index and overall efficiency index revealed that technological change played a crucial role in TFPI across the three AATFRs over the study period (Figure 5.11) (Che et al. 2012; Islam et al. 2014; Islam, Xayavong & Kingwell 2014; Khan, Salim & Bloch 2014). With the assumption that no technical regress occurred over the study period, an upward shift in the overall efficiency index was observed in 1994, 2000, 2004, and 2006 by the technology index values for all AATFRs.

TFPIs of the high, medium and low AATFRs were approximately 1.07, 1.33, 1.53, 1.63 and 1.91; 1.15, 1.16, 1.46, 1.59 and 1.69; and 1.12, 1.24, 1.17, 1.49 and 1.85 in 1993, 1994, 2000,

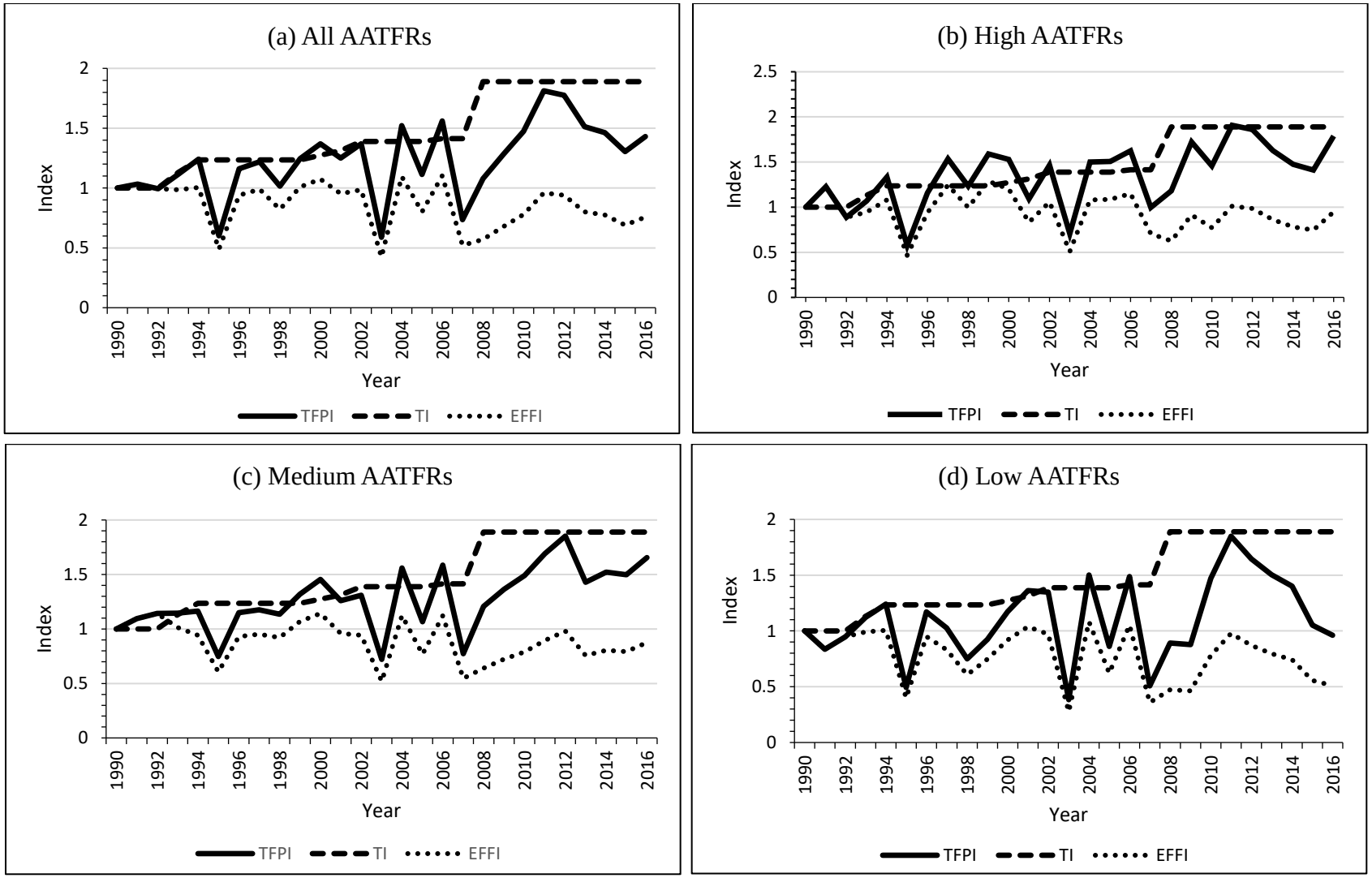

Figure 5.11 Variations in TFPI due to TI and EFFI

2006 and 2011, respectively (Tables C.1, C.2 and C.3, Appendix C). Generally, this suggested that TFP change of low AATFRs was more sensitive to temperature change. Therefore, if farmers in low AATFRs did not adopt new technologies, there would be further decline in the TFPI. In addition, this showed that farmers achieved better performance of technology index in the high and medium AATFRs compared to the low AATFRs.

In all AATFRs over the sample period, overall efficiency index had a negative (14 percent) impact on TFPI (Table C.4, Appendix C). Year-to-year efficiency gains, however, indicated that farmers in high AATFRs experienced improvement in overall efficiency index in 1991, 1997, 1999, 2000, 2002, 2004 and 2006; and farmers in medium AATFRs in 1991–1993, 1999–2000, 2004 and 2006; and slight improvement in efficiency gains was observed for low AATFRs in 2001, 2004 and 2006 (Tables C.1, C.2 and C.3, Appendix C).

The overall efficiency index of the three AATFRs followed a similar decreasing trend (Figure 5.11b, c, and d). The high, medium and low AATFRs experienced 6, 0.11 and 23 percent negative changes in efficiency, respectively (Tables C.1, C.2 and C.3, Appendix C). Recall that TFPI computed for the high, medium and low AATFRs over the study period showed changes of 2.26, 1.94 and −0.16 percent per annum, respectively. Therefore, technology index showed changes of approximately 2.48 percent per annum in high, medium and low AATFRs, while overall efficiency index showed changes approximately - 0.20, - 0.49, and - 2.56 percent per annum in high, medium and low AATFRs, respectively (Tables C.1, C.2, and C.3, Appendix C). This implied that the positive change in TFPI of high AATFRs was more than that of the medium and low AATFRs. In addition, the overall efficiency index of high AATFRs decreased the least. This, again, suggested that the TFPI of farms in the low AATFRs was more sensitive not only to the output-oriented of temperature efficiency index, but also to the overall efficiency index than that of the other AATFRs.

Technology index, in addition to having a positive relationship with TFPI, also supported overall efficiency index in all AATFRs. While temperature change had a negative effect on the TFPI in the medium and low AATFRs, technology index had a positive effect on improving their TFPI (Figure 5.11). For example, in 2001 and 2010, when overall efficiency index of high, medium and low AATFRs were 0.83, 0.96 and 1.04, respectively, and technologies index were 1.31, their TFPIs were 1.09, 1.26 and 1.36 in 2001, respectively. However, a further

increase in technology index to 1.89 in 2010 and a decrease in overall efficiency index to 0.77, 0.79 and 0.78 for the high, medium and low AATFRs, respectively, led to a further increase in TFPI to approximately 1.46, 1.49 and 1.47, respectively (Tables C.1, C.2 and C.3, Appendix C). This suggested that farmers in the medium and low AATFRs could, in the long term, improve their management practices against unfavourable temperature change by adopting new technologies and applying new knowledge. This may lead to the achievement of practice and shift in the production frontier. The largest crop yield in the low AATFRs (Table 5.2) suggests that the farm area was increased (Figure A.2a, Appendix A) in the low AATFRs in response to increasing output price (Figure A.1c, Appendix A).

5.5.3 Profitability and productivity decomposition

Figure 5.12 displays profitability index and TFPI and their components. These measures were recorded as average for farms in each AATFRs and for all the farms for each data period using 1990 as the base year (Tables C.1, C.2, C.3 and C.4, Appendix C). Figures 5.12 a, b, c and d show the changes in profitability index, terms of trade index and TFPI of average farms for all AATFRs. Figures A.1 and A.2 present the summary of supporting data in Appendix A.

Profitability index decreased by 14 percent in all AATFRs over the 27-year period relative with the base year (Table C.4, Appendix C). However, its respective lowest and highest values were approximately 0.54 (in 2007) and 1.13 (in 1997); 0.52 (in 2007) and approximately 1.23 (in 1996); and approximately 0.48 (in 2007) and approximately 1.22 (in 2002) for the high, medium and low AATFRs, respectively (Tables C.1, C.2 and C.3, Appendix C). These revealed that profitability change varied greatly for all AATFRs as evidenced by the variations in quantities and prices of output and input shown in Figures A.1a and c, Appendix A.

Even though TFPI increased, profitability decreased over the study period for all AATFRs owing to a reduction in the terms of trade index. This implied that terms of trade index was the main source of profitability change for the AATFRs. The 14 percent decrease in profitability was the combined effect of a 35.4 percent (1–0.65) decrease in terms of trade index and 35 percent (1–1.35) increase in TFPI for the high AATFRs (Table C.1, Appendix C). For the medium AATFRs, the 8 percent (1–0.92) decrease in profitability could be attributed to the approximately 20 percent (1–0.80) reduction in terms of trade index and the approximately 28 percent (1–1.28) increase in TFPI, whereas the 18 percent (1–0.82) decrease in profitability for

the low temperature AATFRs was due to a 17 percent (1–0.83) drop in terms of trade index and a 10 percent (1–1.10) increase in TFPI (Tables C.1, C.2 and C.3, Appendix C). Therefore, the medium AATFRs experienced the lowest decrease in profitability.

In conclusion, generally TFPI increased in all AATFRs. This could be attributed partly to the gradual increase in input quantity in all three AATFRs as presented in Figure A.1b, Appendix A. TFPI remained higher than that of the base year (1990) for all the AATFRs (Figure 5.12c). It increased by approximately 35, 28 and 10 percent in the high, medium and low AATFRs, respectively (Tables C.1, C.2 and C.3, Appendix C).

Terms of trade index was less than 1 in most of the sample years, which indicates a weakening performance relative to 1990 (Tables C.1, C.2, C.3 and C.4, Appendix C). Profitability index was also less than 1 in the same years as terms of trade index within each AATFRs. Low AATFRs experienced the lowest reduction (17 percent) in the terms of trade index over the study period, whereas the high AATFRs experienced the greatest drop in terms of trade index (35 percent) (Table C.1 and C.3, Appendix C). Farmers in these regions experienced an increase in production cost during the 27-year period due to increased prices of inputs and decreased output prices (Figure A.1c and d, Appendix A). In contrast, farms in medium AATFRs experienced drops in crop prices except in 1994, 2003 and 2007, which resulted in favourable terms of trade change and supported profitability change (Figure A.1c, Appendix A). However, farmers in the medium AATFRs had the highest wheat income proportion (Figure A.2d). Furthermore, with exception of 1996, 2002 and 2013 (slightly more than that of the base year), profitability was lower than that of the base year for all AATFRs (Table C.4, Appendix C). This may be due to the combined effect of TFPI and terms of trade index.

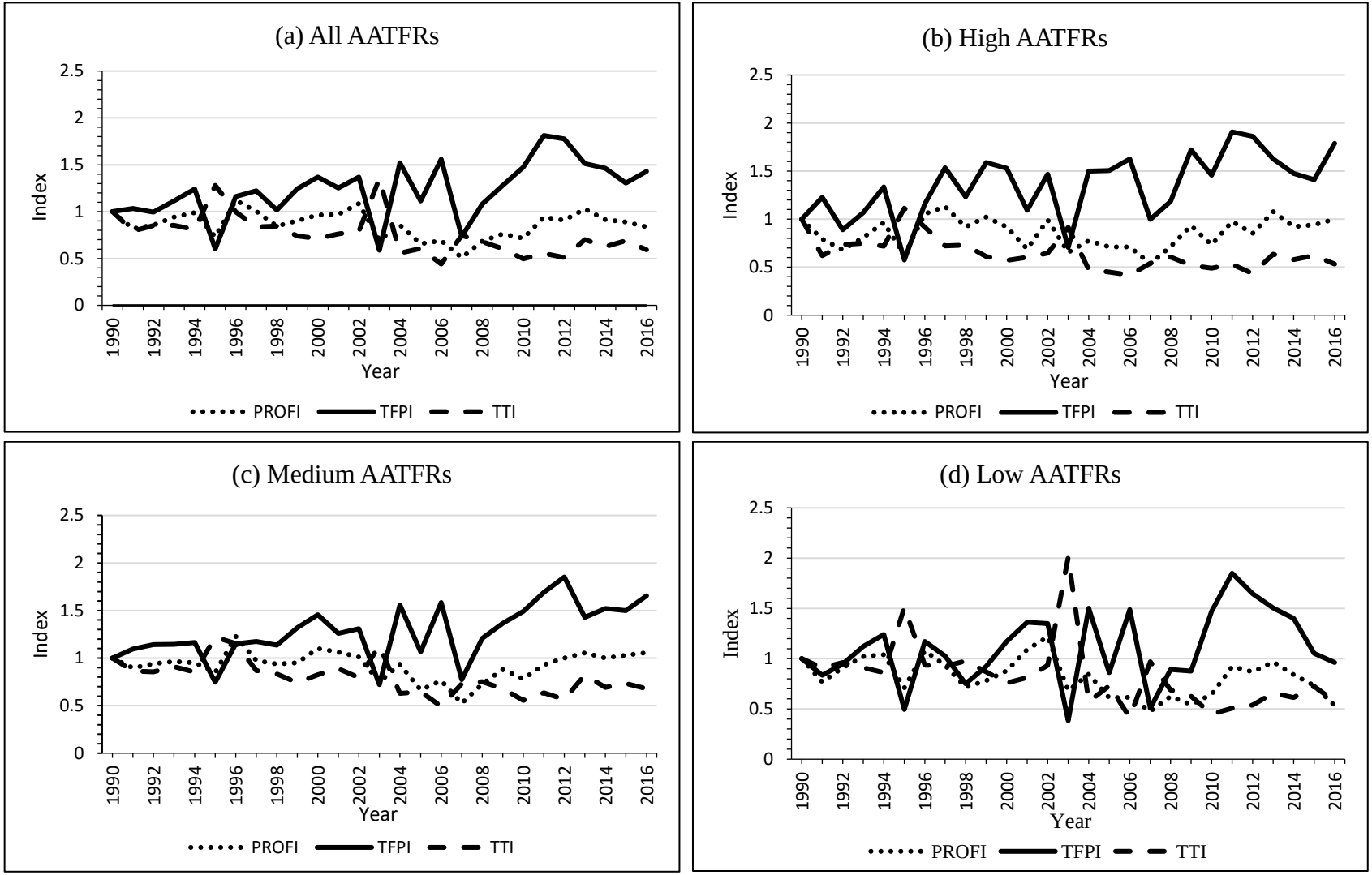

Figure 5.12 PROF, TFP and TT change (base 1990).

5.6 Conclusion

The main contribution of this chapter was to use the new approach Lowe index method. The standard DEA technique was employed to estimate the production frontier and to compute and decompose the TFPI into technical change, efficiency change and environmental change. An aggregate quantity-price framework was adopted to decompose profitability changes into measures of TFP and terms of trade. Analysing the effect of rainfall variation on productivity and profitability change revealed that the main drivers of TFP change were output-oriented of rainfall efficiency change and technical change in high and medium AARFRs. TFP change and terms of trade change were the main drivers of profitability change in the high and medium AARFRs, respectively. Results from the effect of temperature variation on TFP and profitability change also revealed that output-oriented of temperature efficiency change, and technical change were the main drivers of TFP change in high AATFRs. The main driver of profitability change was change in terms of trade for the high, medium and low AATFRs.

CHAPTER 6: EFFECT OF RAINFALL VARIATION ON EFFICIENCY AND ITS DETERMINANTS

6.1 Introduction

This chapter presents empirical results of the effect of rainfall variation on efficiency and its determinants. A standard two-stage DEA approach was used. In the first stage, averages and scores of efficiency indicators namely output-oriented technical efficiency (CRS), output-oriented technical efficiency (VRS), output-oriented scale efficiency, output-oriented mix efficiency, residual output-oriented scale efficiency, output-oriented scale-mix efficiency, technical and scale-mix efficiency, and environmental efficiency (rainfall efficiency=EEr) were estimated for different farm regions. In the second stage, a Tobit regression model was used to examine the relationship between efficiency indicators (dependent variables) and independent variables namely (1) age of farm manager, (2) age of spouse of farm manager, (3) off-farm work of farm manager, (4) off-farm work of spouse of farm manager, (5) capital-labour ratio and (6) land-labour ratio. The double bootstrap analysis was achieved using a truncated regression analysis to investigate whether the second stage analysis estimators are biased or unbiased. A summary of input, output and farm-specific factors variables used in the analysis are presented in Table 6.1.

The rest of this chapter is organised as follows. Section 6.2 presents summary statistics of the inputs and outputs used to measure the different types of efficiency scores (dependent variables) and explanatory variables in the Tobit regression and double bootstrap with truncated regression estimations of rainfall analysis. Section 6.3 shows the empirical results and provides a discussion of an analysis of rainfall variation on efficiency scores. Section 6.4 highlights the results and discussion for the second stage analysis. Section 6.5 presents the conclusions of the findings.

6.2 Descriptive Statistics of First Stage Analysis and Second Stage Analysis of Rainfall Data

Table 6.1 presents summary statistics of the inputs and outputs used to measure the different types of efficiency scores (dependent variables) and explanatory variables (independent variables). All variables were explained in Chapter 4.

Table 6.1 Summary statistics of variables used in the models from1990 to 2016 in different AARFRs

(a) High AARFRs

Variable	**Unit**	**N**	**Mean**	**St. Dev.**	**Min**	**Max**
Output						
Wheat crop (q_1)	Tonnes	108	256.23	216.12	4	782
Non-wheat crops (q_2)	Tonnes	108	245.92	144.62	21	835
Input						
Land area (x_1)	Hectare	108	280.81	163.83	85	716
Chemical (x_2)	kg	108	166.5	116.73	35.6	512.32
Fertiliser (x_3)	kg	108	173.93	64.46	67.57	365.84
Fuel (x_4)	litre	108	14,439.44	5,455.75	5,783.30	29,212.76
Labour (x_5)	hrs/year	108	2,193.68	255.85	1,560.00	2,856.00
Rainfall input (z_2)	mm	108	496.77	130.23	188.68	932.2
Farm-specific factors						
-Age of farm manager (**ev_1**)	year	108	55.94	3.43	49	64
- Age of spouse of farm manager(**ev_2**)	year	108	52.97	3.65	45	62
- Off-farm work of farm manager (**ev_3**)	hrs/wk	108	3.62	2.28	0	10
- Off-farm work of spouse of farm manager (**ev_4**)	hrs/wk	108	6.51	3.33	0	14
-Capital-labour ratio (**ev_5**)	$/hr	108	27.52	11.5	9.63	61.79
-Land-labour ratio (**ev_6**)	hectare/hr	108	0.13	0.07	0.04	0.31

(b) Medium AARFRs

Variable	Unit	N	Mean	St. Dev.	Min	Max
Output						
Wheat crop (q_1)	Tonnes	108	826.46	740.67	31	3,144
Non-wheat crops (q_2)	Tonnes	108	552.73	412.96	52	1,707
Input						
Land area (x_1)	Hectare	108	939.06	769.17	154	3,092
Chemical (x_2)	kg	108	421.91	325.41	27.92	1,510.33
Fertiliser (x_3)	kg	108	558.44	447.56	23.57	1,545.69
Fuel (x_4)	litre	108	24,918.97	8,673.97	11,490.41	47,946.68
Labour (x_5)	hrs/year	108	2,583.14	277.11	2,064.00	3,264.00
Rainfall input (z_2)	mm	108	377.52	111.18	202.33	714.48
Farm-specific factors						
-Age of farm manager (**ev_1**)	year	108	54.06	3.94	46	63
- Age of spouse of farm manager(**ev_2**)	year	108	51.29	3.85	43	61
-Off-farm work of farm manager (**ev_3**)	hrs/wk	108	2.74	3.46	0	19
- Off-farm work of spouse of farm manager (**ev_4**)	hrs/wk	108	4.94	3.23	0	14
-Capital-labour ratio (**ev_5**)	$/hr	108	57.22	37.54	9.81	181.74
-Land-labour ratio (**ev_6**)	hectare/hr	108	0.35	0.28	0.07	1.31

(c) Low AARFRs

Variable	**Unit**	N	Mean	St. Dev.	Min	Max
Output						
Wheat crop (q_1)	Tonnes	108	573.13	371.11	50	1,904
Non-wheat crops (q_2)	Tonnes	108	491.85	215.07	76	926
Input						
Land area (x_1)	Hectare	108	693.33	303.88	263	1,417
Chemical (x_2)	kg	108	317.19	146.53	88.96	690.74
Fertiliser (x_3)	kg	108	331.54	123.81	109.31	762.48
Fuel (x_4)	litre	108	19,056.58	4,711.80	9,730.64	39,126.78
Labour (x_5)	hrs/year	108	2,276.30	243.38	1,824.00	2,976.00
Rainfall input (z_2)	mm	108	272.32	74.28	132.25	490.17
Farm-specific factors						
-Age of farm manager (**ev_1**)	year	108	52.95	4.01	41	62
- Age of spouse of farm manager(**ev_2**)	year	108	50.48	4	40	59
-Off-farm work of farm manager (**ev_3**)	hrs/wk	108	3.11	2.33	0	9
- Off-farm work of spouse of farm manager (**ev_4**)	hrs/wk	108	6.33	3.66	0	16
-Capital-labour ratio (**ev_5**)	$/hr	108	45.77	17.97	17.3	92.84
-Land-labour ratio (**ev_6**)	hectare/hr	108	0.3	0.13	0.12	0.65

(d) All AARFRs

Variable	Unit	N	Mean	St. Dev.	Min	Max
Output						
Wheat crop (q_1)	Tonnes	324	551.94	545.35	4	3,144
Non-wheat crops (q_2)	Tonnes	324	430.17	310.47	21	1,707
Input						
Land area (x_1)	Hectare	324	637.73	556.29	85	3,092
Chemical (x_2)	kg	324	301.87	240.27	27.92	1,510.33
Fertiliser (x_3)	kg	324	354.64	312.72	23.57	1,545.69
Fuel (x_4)	litre	324	19,471.66	7,783.66	5,783.30	47,946.68
Labour (x_5)	hrs/year	324	2,351.04	308.07	1,560.00	3,264.00
Rainfall input (z_2)	mm	324	382.21	141.33	132.25	932.2
Farm-specific factors						
-Age of farm manager (**ev_1**)	year	324	54.31	3.99	41	64
- Age of spouse of farm manager(**ev_2**)	year	324	51.58	3.97	40	62
-Off-farm work of farm manager (**ev_3**)	hrs/wk	324	3.16	2.76	0	19
- Off-farm work of spouse of farm manager (**ev_4**)	hrs/wk	324	5.93	3.47	0	16
-Capital-labour ratio (**ev_5**)	$/hr	324	43.51	27.71	9.63	181.74
-Land-labour ratio (**ev_6**)	hectare/hr	324	0.26	0.21	0.04	1.31

6.3 First Stage Analysis

6.3.1 Technical efficiency

6.3.1.1 Average OTE for all farm regions

Table 6.2 presents averages of the overall and pure technical efficiency estimated from the DEA approach under high, medium, low and all AARFRs. For high AARFRs, output-oriented technical efficiency (CRS) ranged between a minimum of 77 percent in NSWC and a maximum of 91 percent in QLDE. Therefore, farmers in the high AARFRs could increase their output by 9 to 23 percent without having to increase inputs. Mean output-oriented technical efficiency (CRS) for farms in the medium AARFRs ranged between 85 percent in NSWR and 93 in QLDD. This suggests a possible improvement of approximately 7 to 15 percent in outputs of these farm regions using a similar level of inputs. In the low AARFRs, average output-oriented technical efficiency (CRS) of farms in VICM was the least (81 percent) whereas that of farms within SAEP was the highest (87 percent) (Table 6.2). Therefore, farmers within the low AARFRs could increase their output by 13 to 19 percent without having to change inputs.

Table 6.2 Average OTE_{CRS} and OTE_{VRS} for all farm regions over 1990–2016

Farm region (DMUs)	**OTE_{CRS}**	**OTE_{VRS}**
High AARFRs		
NSWN	0.82	0.85
NSWC	0.77	0.80
QLDE	0.91	0.96
VICC	0.81	0.94
Medium AARFRs		
NSWR	0.85	0.86
QLDD	0.93	0.95
WACS	0.92	0.94
WANE	0.91	0.92
Low AARFRs		
VICM	0.81	0.84
VICW	0.82	0.89
SAEP	0.87	0.90
SAMY	0.86	0.89
All AARFRs	0.86	0.89

Average output-oriented technical efficiency (VRS) of farms in the high AARFRs was estimated to be in the range of approximately 80 percent in NSWC to 96 percent in QLDE (Table 6.2). Therefore, farmers in the high AARFRs could improve their output by 4 to 20 percent without increasing their input. In addition, the minimum and maximum output-oriented technical efficiency (VRS) for farms in the medium AARFRs were estimated to be 86 and 95 percent in NSWR and QLDD, respectively (Table 6.2). This implies a possible increase of 5 to 14 percent in output at the same level of input. Output-oriented technical efficiency (VRS) for farms in the low AARFRs varied between a minimum of 84 percent in VICM and a maximum of 90 percent in SAEP (Table 6.2). This suggests 10 to 16 percent possible improvement in output using the same level of input. The 90 percent output-oriented technical efficiency (VRS) recorded for SAEP, despite the low level of rainfall, is likely attributable to the adoption of modern technology, which helps reduce the use of production resources (Hughes & Lawson 2017; Hughes et al. 2011). Therefore, farmers were closer to capturing the best performance of the production frontier by continuing to adopt modern technology and by adapting to the decreasing rainfall rates via the use of alternative water sources.

In all AARFRs, the output-oriented technical efficiency (CRS) and output-oriented technical efficiency (VRS), on average, were approximately 86 and 89 percent, respectively. This suggests that farmers in the Wheat Belt regions of Australia could improve their outputs (wheat and non-wheat farms) by 14 and 11 percent, respectively, without changing their level of inputs. Thus, farmers should pay more attention to expanding their outputs or reducing their inputs. These results are consistent with the results obtained by Che et al. (2012) who stated that technical efficiency ranged between 70 percent and more than 85 percent across WA grain farms.

From the results presented above, it can be seen that out of all the 12 farm regions under study, farms in QLDE recorded the highest output-oriented technical efficiency (VRS) whereas farms in QLDD recorded the highest output-oriented technical efficiency (CRS) . This suggests that these two farm regions had higher crop mix production because they are located in regions with high and medium rainfall amounts. According to Che et al. (2012) and Hughes, Lawson and Valle (2017), farmers in regions with high and medium rainfall amounts have experienced improvement in their productivity since the 2000s.

6.3.1.2 Technical efficiencies scores

[2]Figures 6.1 to 6.4 and Tables D.1 and D.2 in Appendix D present variations in output-oriented technical efficiency (CRS) and output-oriented technical efficiency (VRS) scores over the study period (1990 to 2016) in each farm region under all AARFRs and the three levels of rainfall (high, medium, and low AARFRs).

Output-oriented technical efficiency (CRS) scores measured in the high AARFRs varied from approximately 18 percent in NSWC in 1995 to 100 percent in all four farm regions in different years (Figure 6.1). Farms in QLDE were fully efficient in 13 years (1990 to 1993, 1995–1996, 1998–2000, 2003, 2006, 2008 and 2010) out of 27 years (Table D.1, Appendix D). Therefore, farmers could increase their crop productivity without increasing or reducing their production resources. Moreover, all four farm regions recorded 100 percent efficiency in 1990 and 1991 (Table D.1, Appendix D and Figure 6.1).

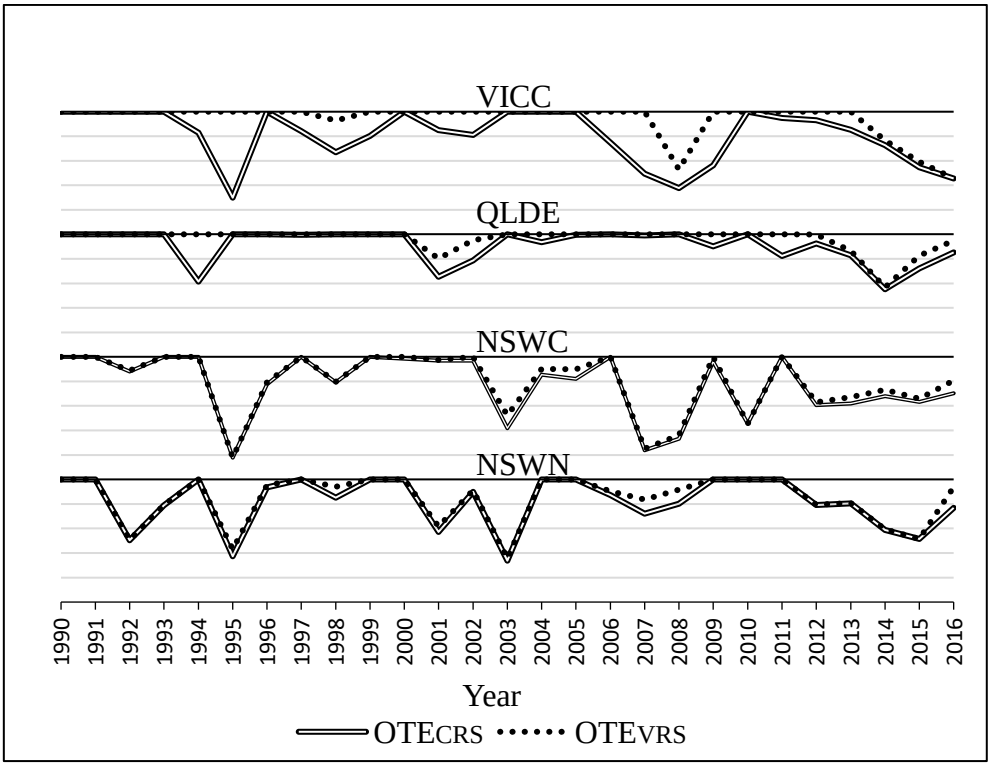

Figure 6.1 Overall and pure technical efficiency in high AARFRs

For medium AARFRs, the output-oriented technical efficiency (CRS) varied between a minimum of 25 percent in 2008 in NSWR and a maximum of 100 percent in all farm regions

[2] All thick horizontal axes in Figures 6.1 to 6.25 represent 100 percent efficiency line.

in different years (Figure 6.2). QLDD recorded 100 percent efficiency in 19 out of the 27 years (Table D.1, Appendix D). Therefore, the farmers of this region were able to control their input quantities better to achieve their highest possible productivity compared to farmers in other farm regions within the medium AARFRs. The four farm regions all achieved 100 percent efficiency in 1992, 1996, 1998 and 1999 (Table D.1, Appendix D and Figure 6.2).

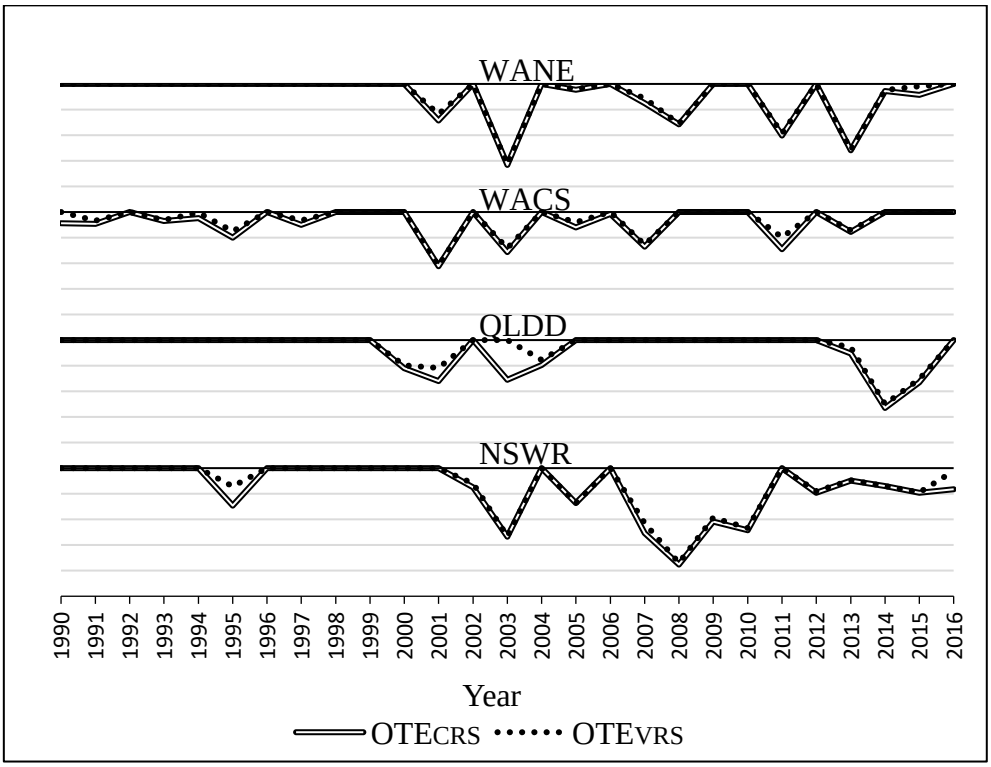

Figure 6.2 Overall and pure technical efficiency in medium AARFRs

As shown in Figure 6.3, output-oriented technical efficiency (CRS) estimated for farm regions within low AARFRs ranged from approximately 21 percent in 2003 in VICW to 100 percent in all four farm regions in some years. VICM and VICW farm regions recorded 100 percent full efficiency in 12 out of the 27 years (Table D.1, Appendix D). All farm regions were fully efficient in 1990, 1992, and 2011 (Figures 6.3, Table D.1, Appendix D). This may indicate that farm managers in low AARFRs failed to obtain as much efficiency as possible during the sample period due to lack of rainfall in this area, which negatively affected crop productivity. Because farms in low AARFRs are more sensitive to rainfall change, it is particularly important to promote the establishment of region-based technologies.

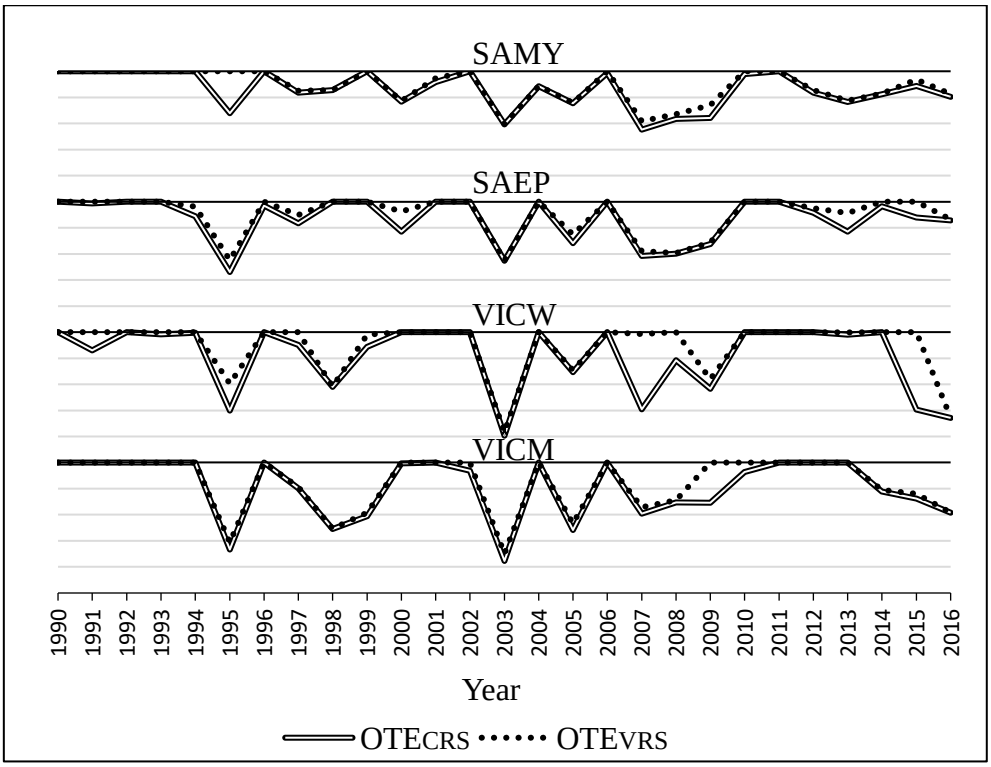

Figure 6.3 Overall and pure technical efficiency in low AARFRs

Estimates of output-oriented technical efficiency (VRS) for all farm regions in high AARFRs showed minimum and maximum scores of approximately 18 percent in 1995 in NSWC and 100 percent in all four farm regions over the study period (Table D.2, Appendix D). The high decrease in the output-oriented technical efficiency (VRS) score in NSWC might be due to the significant decline in production as a result of deteriorating environmental conditions during that season. Hughes, Lawson and Valle (2017) stated that farmers face significant challenges in terms of environment change and their reflection on declining productivity since the 1990s. Although VICC achieved full efficiency in 22 out of 27 years, the average output-oriented technical efficiency (VRS) of QLDE over 27 years was more than that of VICC. Furthermore, all farm regions in the high AARFRs were most efficient in the years 1990–1991, 1995, 1997, 1999–2000, 2009 and 2011 (Table D.2, Appendix D and Figure 6.1). This could confirm that these farm regions reached the best-practice production frontier owing to a favourable rainfall level.

Output-oriented technical efficiency (VRS) scores of farms in the medium AARFRs ranged between 26 percent in 2008 in NSWR and 100 percent in the four farm regions. QLDD recorded 100 percent efficiency in the greatest number of years (21) out of 27 years, i.e. 1990

to 1999, 2002–2003, 2005–2012 and 2016 (Table D.2, Appendix D). All farm regions together were fully efficient in 1990, 1992, 1996, 1998–1999 and 2006 (Table D.2, Appendix D).

In the low AARFRs, the output-oriented technical efficiency (VRS) scores varied from a minimum of 23 percent in 2003 in VICW to a maximum of 100 percent in all farm regions in some years. However, VICW recorded 100 percent efficiency in 18 out of the 27 years (Table D.2, Appendix D). This suggests that farmers adapted to low rainfall during crop growth by adopting modern technology and improving their farm management practices.

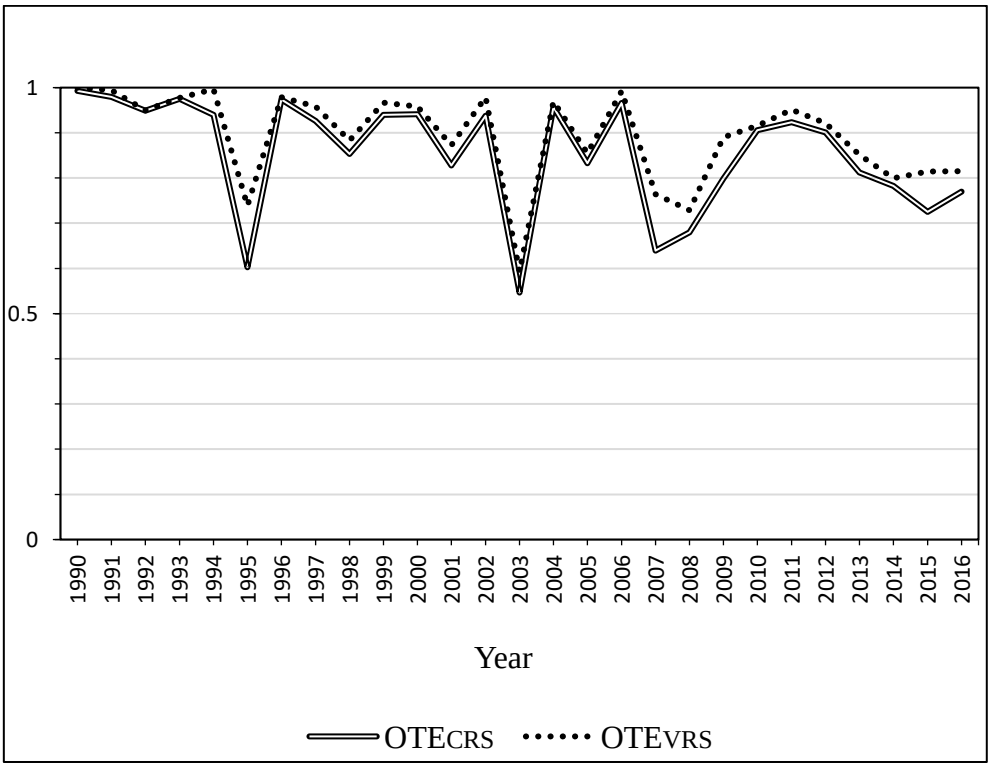

Figure 6.4 Overall and pure technical efficiency in all AARFRs

In contrast, Figures 6.1 to 6.3 show that in general there was a decline in overall and pure technical efficiency in 1995, 2003, 2007 and 2008 in most of the 12 farm regions. This is confirmed by Figure 6.4. As can be seen in Figures 6.1, 6.2, and 6.3, the decline varied from farm region to farm region. This reveals that there was a significant variation of output quantity. This may be the result of sharp changes in the amounts of rainfall in the Australian Wheat Belt regions. According to Steffen (2015), ABS (2012a), Hughes et al. (2016) and Che et al. (2012), there was a serious drought between 1995 and 2008, which resulted in a significant drop in agricultural outputs.

6.3.2 Scale efficiency

6.3.2.1 Average scale efficiency for all farm regions

Estimation of the scale efficiency rates are presented in Table 6.3 for each farm region in each level of rainfall for the purpose of investigating the efficiency of scale in these regions during the past 27 years. In high AARFRs, the average output-oriented scale efficiency was lowest (86 percent) in VICC and highest (97 percent) in NSWN, which implies that farms in high AARFRs could improve their output-oriented scale efficiency by 3 to 14 percent to reach the optimal scale (where OTE_{CRS} equals OTE_{VRS}) by adjusting the production scale. The average output-oriented scale efficiency in the medium AARFRs ranged from a minimum of approximately 98 percent in three farm regions to a maximum of 99 percent in WANE. Output-oriented scale efficiency in the medium AARFRs can therefore be increased by 1 to 2 percent, on average, to obtain full scale efficiency by a slight modification of farm size. This confirms that these farm regions were very close to their optimal size of farm. In low AARFRs, the average of output-oriented scale efficiency ranged between 91 percent in VICW and 97 percent in SAMY. This indicates that farmers of these farm regions could improve their scale efficiency, on average, by 3 to 9 percent to reach the best scale by changing the production scale.

Table 6.3 Average OSEs for all farm regions over 1990–2016

Farm region (DMUs)	OSE
High AARFRs	
NSWN	0.97
NSWC	0.96
QLDE	0.95
VICC	0.86
Medium AARFRs	
NSWR	0.98
QLDD	0.98
WACS	0.98
WANE	0.99
Low AARFRs	
VICM	0.96
VICW	0.91
SAEP	0.96
SAMY	0.97
All AARFRs	0.96

The average of output-oriented scale efficiency in all AARFRs was approximately 96 percent. This suggests that the scale efficiency of farm regions in the Australian Wheat Belt may be optimised by increasing output-oriented scale efficiency by only 4 percent via the adjustment of the production scale or by increasing farm size. This result falls within the range of that reported by Coelli, Rahman and Thirtle (2002) and Abatania, Hailu and Mugera (2012). The highest output-oriented scale efficiency was recorded in WANE whereas the lowest was recorded in VICC.

6.3.2.2 Scores of Scale efficiency

The average of output-oriented scale efficiency does not indicate the full variety of measures of output-oriented scale efficiency for all years and farm regions. Figures 6.5 to 6.8 and Table D.3 in Appendix D present score of scale efficiency. In high AARFRs, the lowest and highest scores of output-oriented scale efficiency were, respectively, 30 percent in VICC in 1995 and 100 percent in the four farm regions in different years (Figure 6.5 and Table D.3, Appendix D). It was observed that QLDE recorded the most count full efficiency years, i.e. 15 out of the 27 years (Table D.3, Appendix D). This result was not surprising because QLDE recorded a 100 percent overall and pure technical efficiencies in many years. Additionally, VICC had the most fluctuating and least scale efficiency over the study period (Figure 6.5). In the VICC region, eight restrictions that may affect crop production were observed. Some of these restrictions are beyond the control of land managers, such as climate change (environmental changes). In addition, increasing soil carbon content to improve surface and subsoil structure and soil health is considered one of the priorities of researchers in VICC (NCCMA 2015). This could explain why farmers were prevented from expanding their farm size.

Output-oriented scale efficiency scores in the medium AARFRs ranged from 69 percent in QLDD in 2003 to 100 percent in the different years. It was observed that QLDD and WANE were fully scale efficient in 20 years out of 27 years of the sample period (Table D.3, Appendix D). This implies that farmers of these farm regions might be able to improve their output-oriented scale efficiency by changing farm size. QLDD had the lowest percent of output-oriented scale efficiency score in 2003 (Figure 6.6). Therefore, famers did not consider large farm size owing to the soil issue. DAFF (2014) stated that farmers in QLDD are faced with soil degradation and loss of crop land as a result of deterioration of environmental conditions..

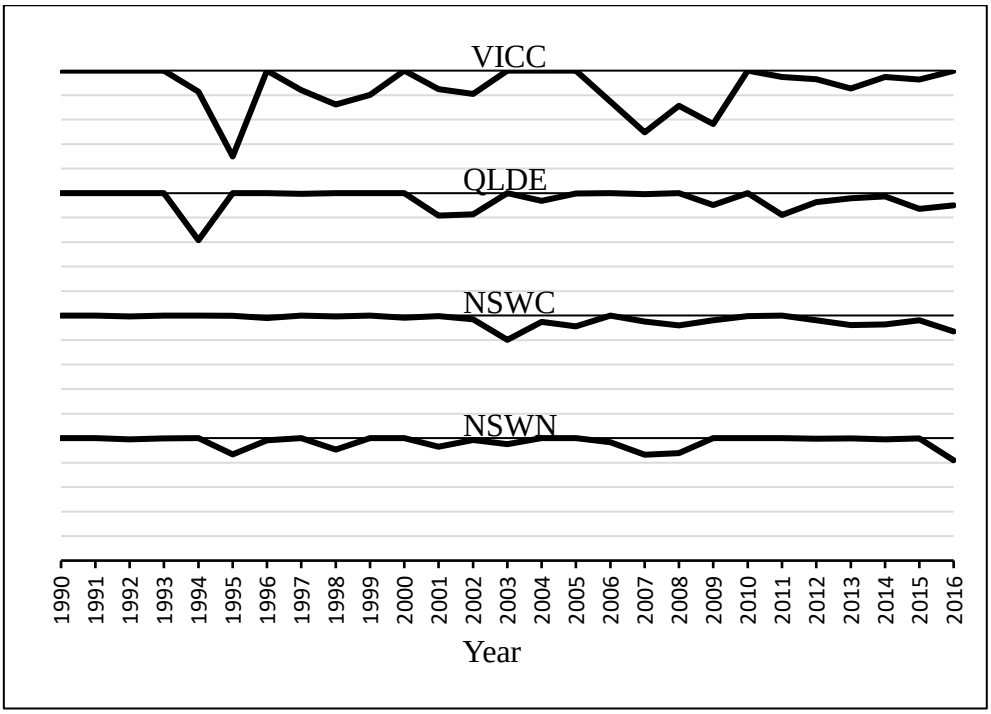

Figure 6.5 Scale efficiency in high AARFRs

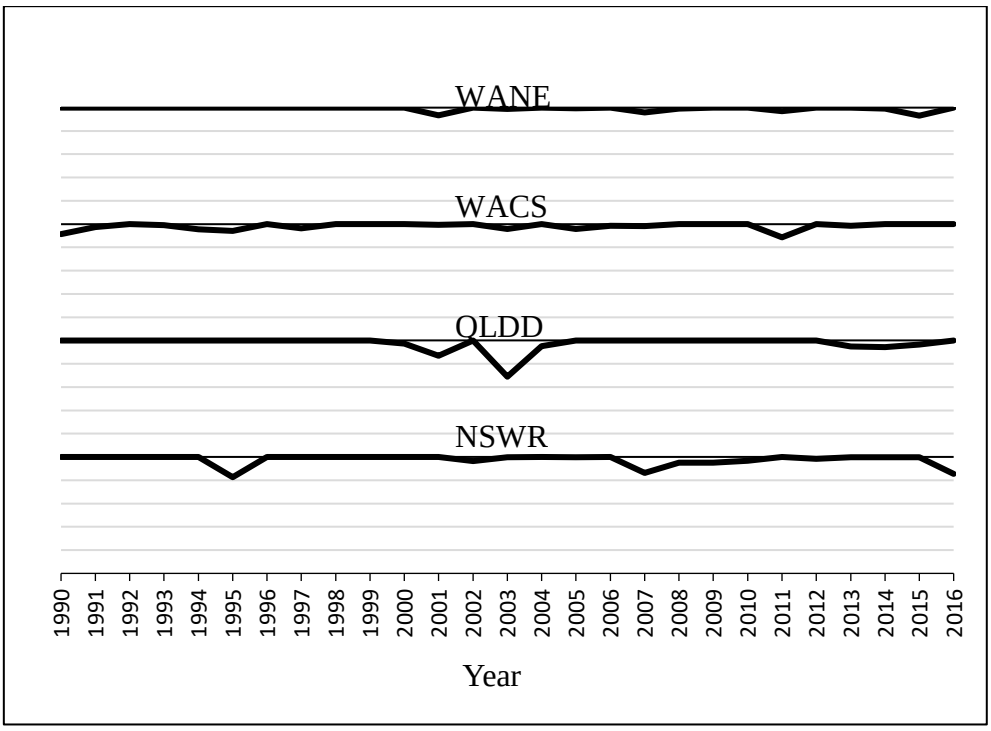

Figure 6.6 Scale efficiency in medium AARFRs

Efforts to improve the management of land and water resources to maintain soil characteristics and increase crop productivity since the 1980s and 1990s has led to a reduction in soil degeneration. This problem may have risen again in these regions during the 2002–2003 season due to drought. Therefore, farmers did not consider large farm sizes.

In the low AARFRs, output-oriented scale efficiency scores were calculated between a minimum of 41 percent in 2015 in VICW and a maximum of 100 percent in various years. Although SAMY was the highest rate among farm regions, it had the same number of years as that of VICW in which full scale efficiency was achieved. (Table D.3, Appendix D). This suggests that farmers can increase their scale efficiency to reach to the best scale by adjusting their production scale.

Figure 6.7 shows that, in general, all farm regions experienced a decline in output-oriented scale efficiency in 1995. VICW recorded the lowest output-oriented scale efficiency score of all farm regions in 2007. This may confirm that farmers did not optimise their size of operations. According to ABARES (2017), VICW experienced the highest loss in farm business profits in 2007. Therefore, this may be one of the reasons for the lack of incentive to encourage farm managers to expand the volume of their production. Farms in the WANE region were the most scale efficient over the study period. Che et al. (2012) showed that the average size of farms in the north zone of WA (WANE) was largest during the period 2006–2010.

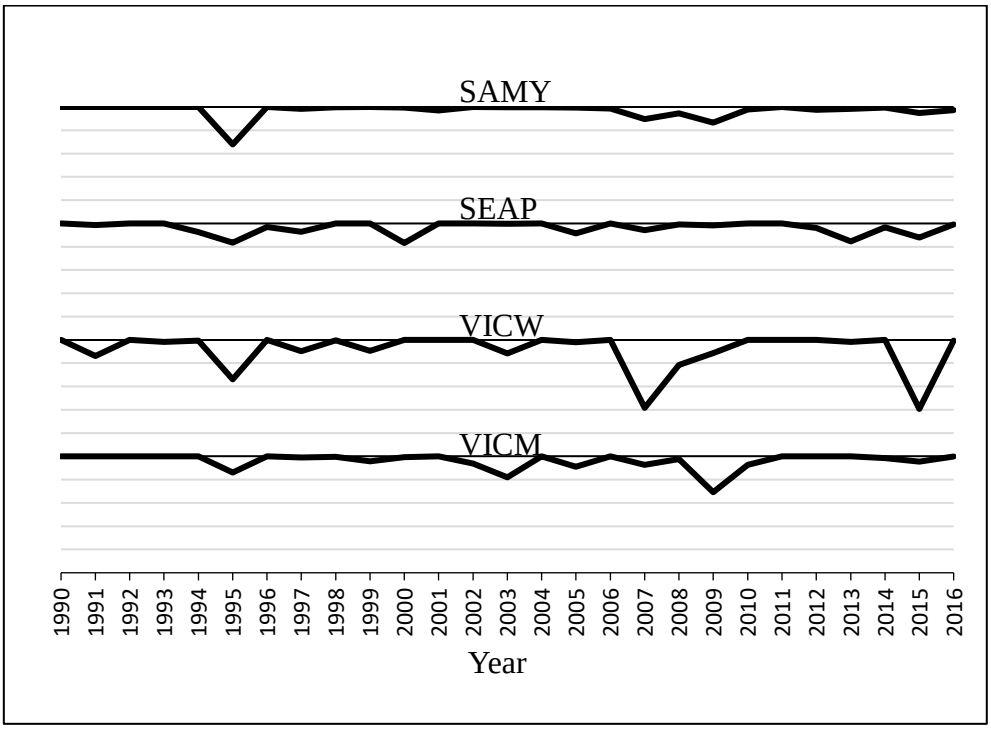

Figure 6.7 Scale efficiency in low AARFRs

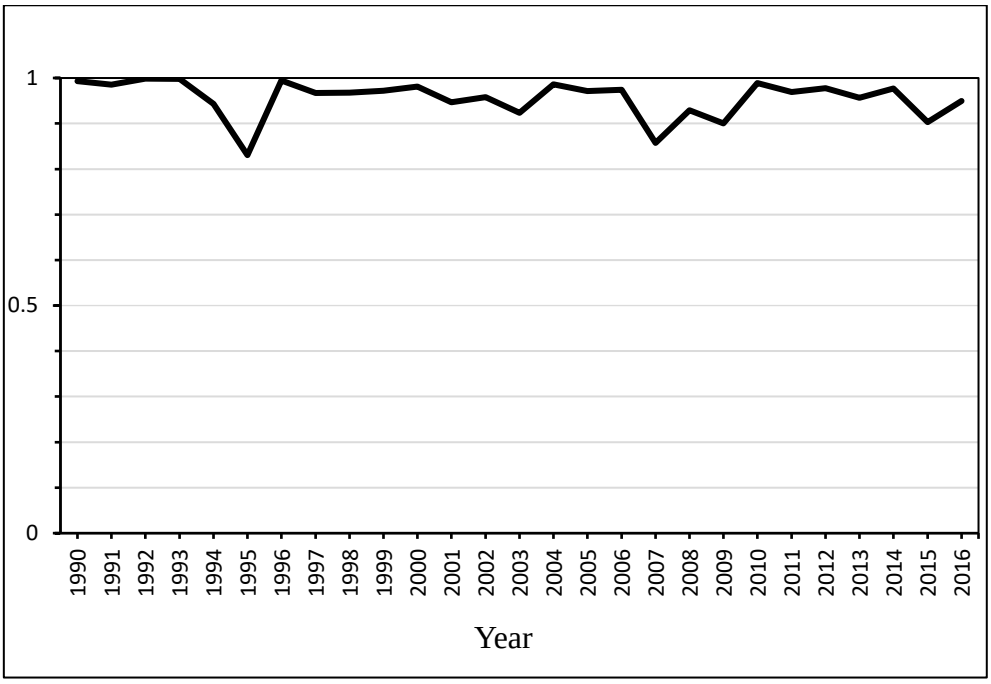

Figure 6.8 Scale efficiency in all AARFRs

Generally, the lowest average output-oriented scale efficiency (83 percent) of all AARFRs occurred in 1995 (Figure 6.3). This could be attributed to the low scale efficiency recorded in most farm regions during that year (Table D.3, Appendix D).

Table 6.4 Average OMEs for all farm regions over 1990–2016

Farm region (DMUs)	**OME**
High AARFRs	
NSWN	0.97
NSWC	0.92
QLDE	0.96
VICC	0.98
Medium AARFRs	
NSWR	0.96
QLDD	0.99
WACS	0.95
WANE	0.98
Low AARFRs	
VICM	0.97
VICW	0.92
SAEP	0.96
SAMY	0.98
All AARFRs	0.97

6.3.3 Mix efficiency

6.3.3.1 Average mix efficiency for all farm regions

Table 6.4 presents average output-oriented mix efficiency for all farm regions under study from 1990 to 2016. In the high AARFRs, average output-oriented mix efficiency ranged between a minimum of 92 percent in NSWC and a maximum of 98 percent in VICC. Therefore, farms in the high AARFRs could improve their output-oriented mix efficiency by 2 to 8 percent with the given amount of input by changing the proportion of output mix (i.e. wheat and non-wheat). Average output-oriented mix efficiency, in the medium AARFRs, varied between 95 percent in WACS and 99 percent in QLDD. This suggest that farmers could improve their output-oriented mix efficiency by 1 to 5 percent without increasing their amounts of input through re-mixing their crop output ratios. Mean output-oriented mix efficiency for farms in the low AARFRs ranged between 92 percent in QLDD and 98 percent in SAMY. Therefore, farmers within the low AARFRs could increase their OME by 2 to 8 percent without having to change inputs if they were adjusting their mix of wheat and non-wheat output.

The mean output-oriented mix efficiency of all AARFRs was 97 percent, which suggests that all farmers in the Wheat Belt regions of Australia could improve their output mix efficiency by only 3 percent with a similar level of input and with a slight focus on their output mix. In addition, farmers have succeeded relatively in the process of mixing the cultivation of wheat and non-wheat crops. Therefore, of the 12 farm regions under study, farms in QLDD recorded the highest output-oriented mix efficiency whereas farms in NSWC and VICW recorded the lowest output-oriented mix efficiency over the study period.

6.3.3.2 Mix efficiency scores

Table D.4 in Appendix D and Figures 6.9 to 6.12 present the results of differences in OME scores over the sample period. These results are presented according to farm regions classified into high, medium, low and all AARFRs. The output-oriented mix efficiency scores in high AARFRs ranged between 63 percent in QLDE in 1994 and 100 percent in different years of the study period. NSWC recorded the lowest number of full mix efficiency during 1990–1991, 1994, 1997–1999, 2006 and 2011. VICC had the highest number of 100 percent (21 out of 27 years) (Table D.4, Appendix D). Therefore, farmers in VICC were the most efficient in mixing

different proportions of agricultural products. Figure 6.9 shows that VICC displayed the least fluctuations in output-oriented mix efficiency estimates over the study period. In general, a relative decrease in output-oriented mix efficiency was observed in 2008 in the three farm regions in high AARFRs excluding QLDE. These results may support the views that the prices of some crops in that year were low and therefore did not motivate the farmers to cultivate mixed crops.

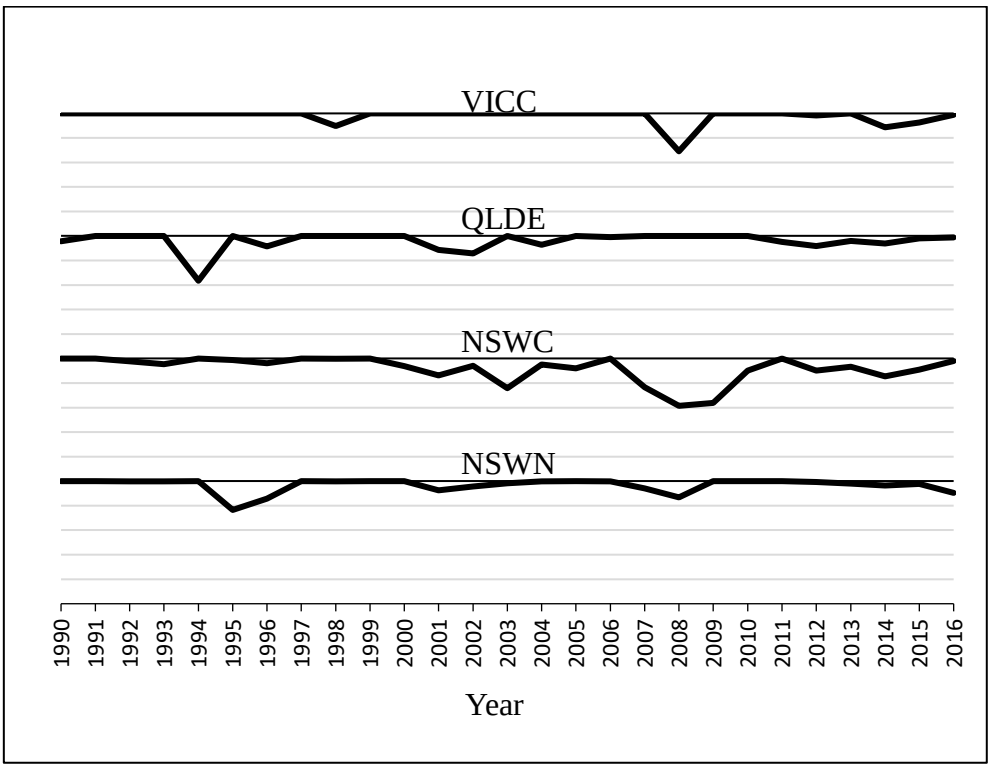

Figure 6.9 Mix efficiency in high AARFRs

In the medium AARFRs, output-oriented mix efficiency scores varied between a minimum of 67 percent in 2008 in NSWR and a maximum of 100 percent over several years. Farms were fully efficient in only 8 years in WACS and 21 years in QLDD out of 27 years (Table D.4, Appendix D). This suggests that WACS was the most inefficient in many years, which implies that farmers failed to process the optimal mix of crop products.

Figure 6.10 shows that QLDD was the most stable farm region in the medium AARFRs, which might be a reflection of farmers in QLDD being able to achieve an optimal mix of crop cultivation during most of the sample period, likely due to the availability of sufficient rainfall or a relative increase in the production of wheat and non-wheat crops to increase farming profit (Table 6.2).

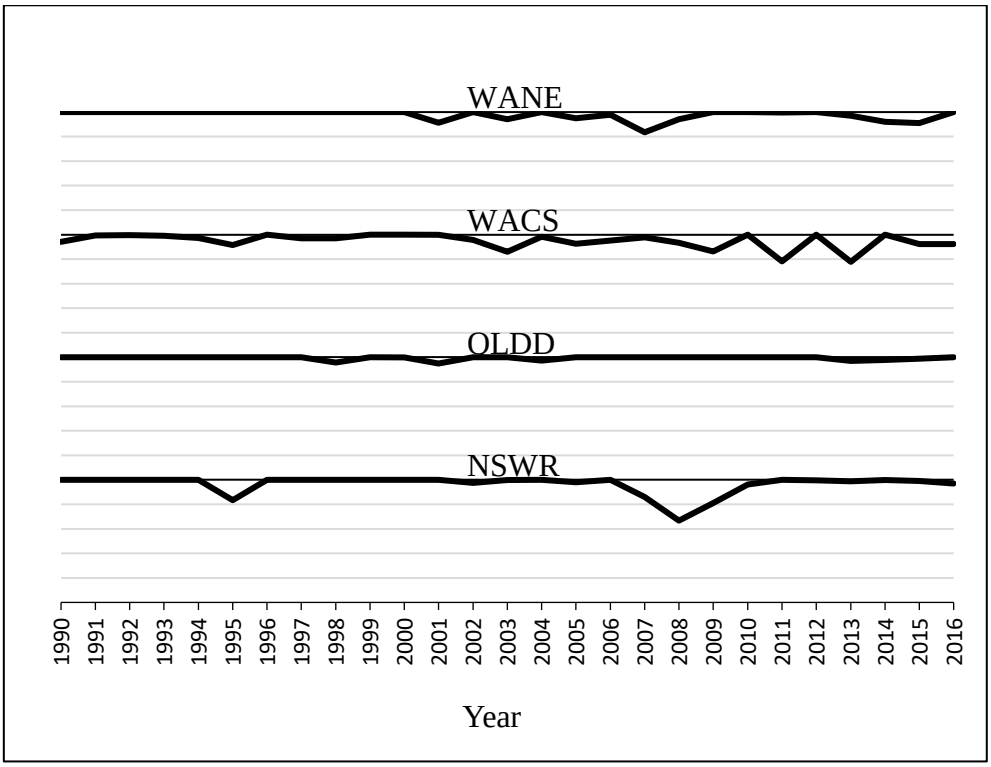

Figure 6.10 Mix efficiency in medium AARFRs

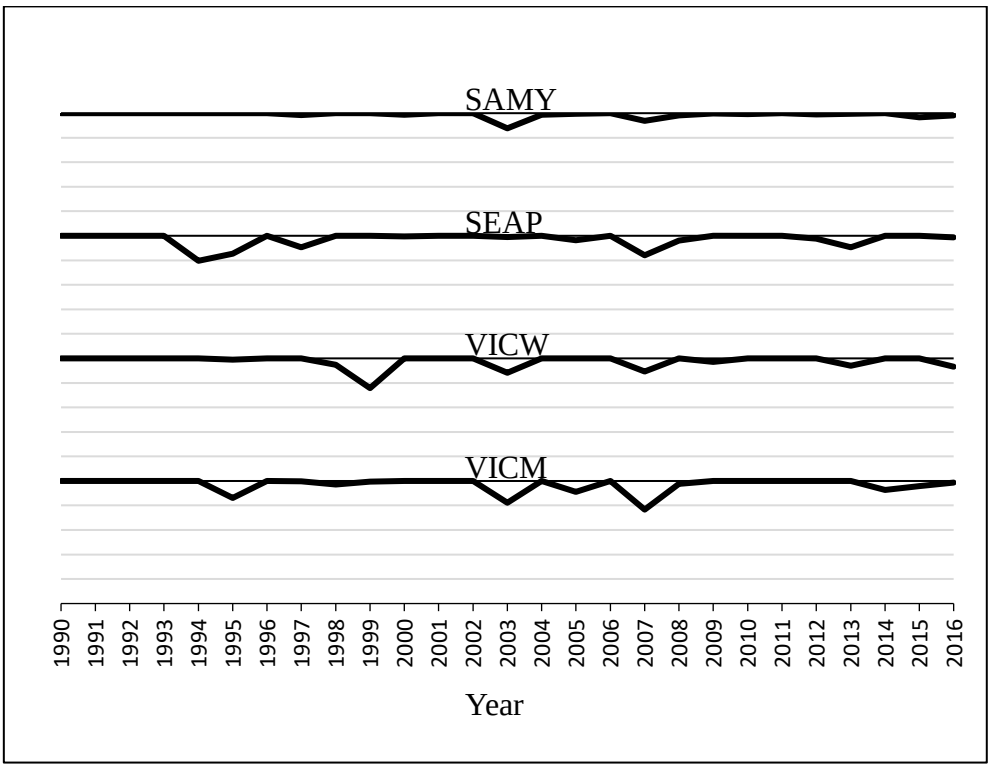

Figure 6.11 Mix efficiency in low AARFRs

The lowest score of output-oriented mix efficiency (76 percent in 1999) in the low AARFRs was recorded in VICW, whereas the highest score (100 percent) was recorded in the three other

farm regions over the 27-year study period (Figure 6.11; Table D.4, Appendix D). However, VICW recorded 100 percent output-oriented mix efficiency for most years, although the average score for SAMY was more than that of VICW. This was because there were greater dips in the output-oriented mix efficiency of VICW than that of SAMY over the study period.

In addition, Figure 6.11 shows that output-oriented mix efficiency declined relatively in 2003 and 2007. These results confirm that these farm regions in the low AARFRs are more sensitive to rainfall change than those in the high and medium AARFRs. Che et al. (2012) Che et al. (2012) stated that the average rainfall level in Australian Wheat Belt regions was very low in 2002–2003 (2003 drought) and 2007–2008.

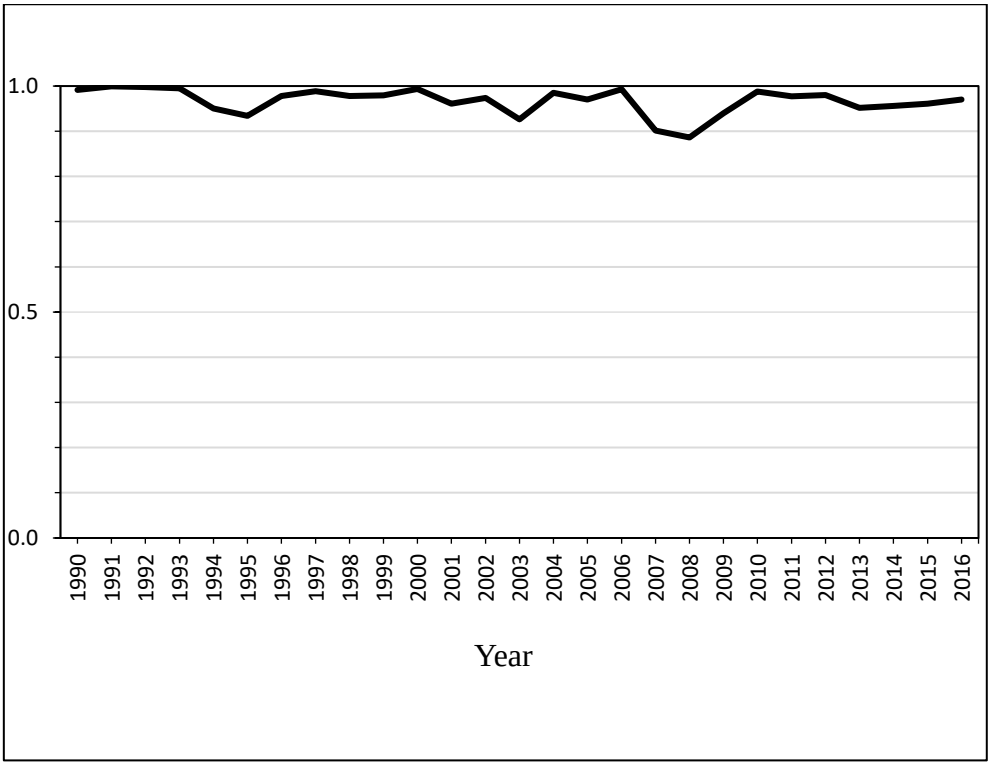

Figure 6.12 Mix efficiency in all AARFRs

A maximum output-oriented mix efficiency of 100 percent and a minimum of 89 percent was found in 1991–1993 and in 2008 in all AARFRs, respectively (Table D.4, Appendix D). Generally, there was a slight fluctuation and a drop in the OME of all AARFRs (Figure 6.12). output-oriented mix efficiency also dropped in 1995, 2003 and 2007, which have been confirmed as years that experienced severe drought (Che et al. 2012).

6.3.4 Residual output-oriented scale efficiency

6.3.4.1 Average residual output-oriented scale efficiency for all farm regions

O'Donnell (2010) stated that residual output-oriented scale efficiency is a measure of scale efficiency and may contain a residual mix effect. Table 6.5 displays average residual output-oriented scale efficiency for all farm regions under study from 1990 to 2016. The estimated average residual output-oriented scale efficiency in high AARFRs ranged between a minimum of 57 percent in VICC and a maximum of 85 percent in NSWC. Farmers in the high AARFRs can, therefore, improve their residual output-oriented scale efficiency by 15 to 43 percent by changing output and input mixes with existing technology (Table 6.5). This suggest that farms in high AARFRs did not try to obtain the benefit (residual) of change in the input/output mix, which reflected a lack of full efficiency over the long term.

Table 6.5 Average ROSE for all farm regions over 1990–2016

Farm region (DMUs)	ROSE
High AARFRs	
NSWN	0.84
NSWC	0.85
QLDE	0.64
VICC	0.57
Medium AARFRs	
NSWR	0.87
QLDD	0.51
WACS	0.87
WANE	0.85
Low AARFRs	
VICM	0.83
VICW	0.80
SAEP	0.84
SAMY	0.88
All AARFRs	0.78

The average residual output-oriented scale efficiency in medium AARFRs varied between a minimum of 51 percent in QLDD and a maximum of 87 percent in NSWR and WACS. Therefore, the farmers of these farm regions could improve their residual output-oriented scale efficiency, on average, by 13 to 49 percent to obtain the best scale and residual effects by

changing the output and input mixes (Table 6.5). These findings imply that farms in medium AARFRs were less efficient with respect to average residual output-oriented scale efficiency than those in the other AARFRs.

Regarding farms in low AARFRs, measured average residual output-oriented scale efficiency ranged between 80 percent in VICW and 88 percent in SAMY. Therefore, farms of low AARFRs could increase their average residual output-oriented scale efficiency by 12 to 20 percent to capture the optimal scale and residual effects if they appropriately alter their output and input mixes. Farmers in these farm regions have a better chance of obtaining full efficiency when they have the flexibility to change the input and output mix during the production process to obtain the remaining (residual) benefit.

In all AARFRs, average residual output-oriented scale efficiency was found to be 78 percent. This means that all 12 farm regions, on average, could improve their residual output-oriented scale efficiency by 22 percent if the farmers could obtain the positive scale and residual effects. In addition, this result also reveals that all farm regions under study were inefficient. It can be concluded that QLDD farms were the least efficient respect to residual output-oriented scale efficiency whereas farms in SAMY were the most efficient.

6.3.4.2 Residual output-oriented scale efficiency scores

The results of the first stage estimation of the residual output-oriented scale efficiency analysis are presented in Figures 6.13 to 6.16 and Table D.5 in Appendix D. The residual output-oriented scale efficiency scores in the high AARFRs varied between a minimum of 16 percent in 2003 in VICC and a maximum of full efficiency in NSWN (1990 and 1992–1994, 1997 and 2002); NSWC (1991, 1993 and 1999) and QLDE (2008). VICC was not fully efficient during any year (Figure 6.13; Table D.5, Appendix D). Therefore, farmers in VICC were the most inefficient in their residual output-oriented scale efficiency over the study period. This might have occurred because farmers in VICC did not focus on scale efficiency, which could include a residual effect through the changing of output and input mixes. Furthermore, in general, residual output-oriented scale efficiency of VICC fluctuated most relative to the others. These results are consistent with the results of output-oriented scale efficiency indicators discussed above and why the efficiency scores of this farm region was low. All four farm regions in high AARFRs experienced a decline in residual output-oriented scale efficiency in 1995.

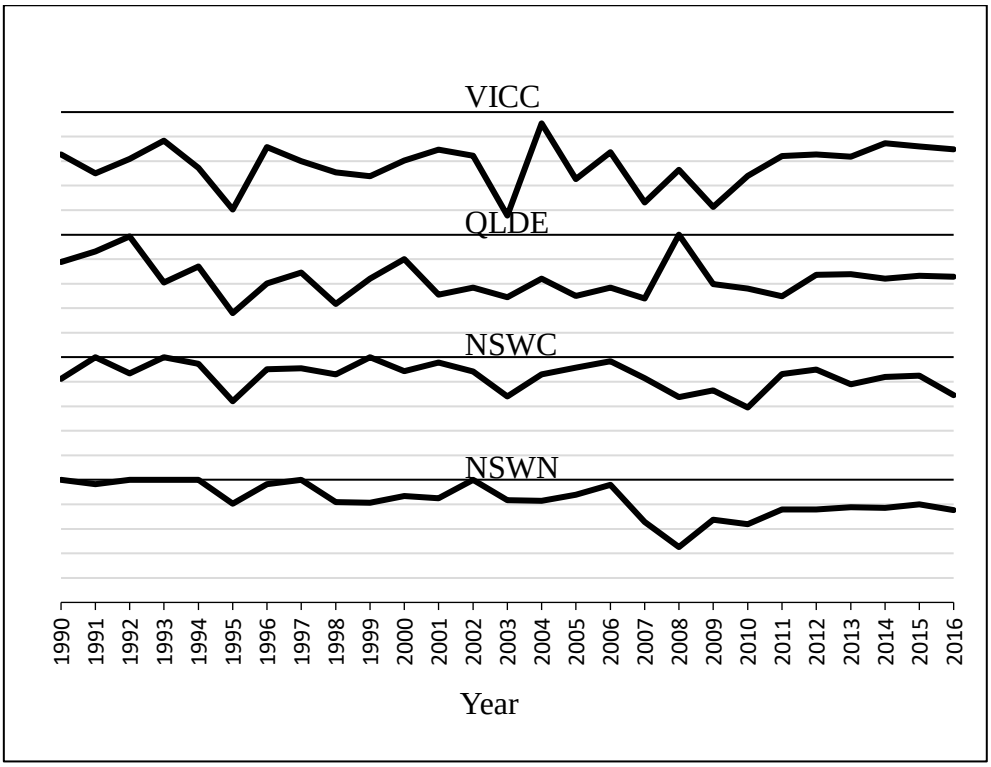

Figure 6.13 Residual output-oriented scale efficiency in high AARFRs

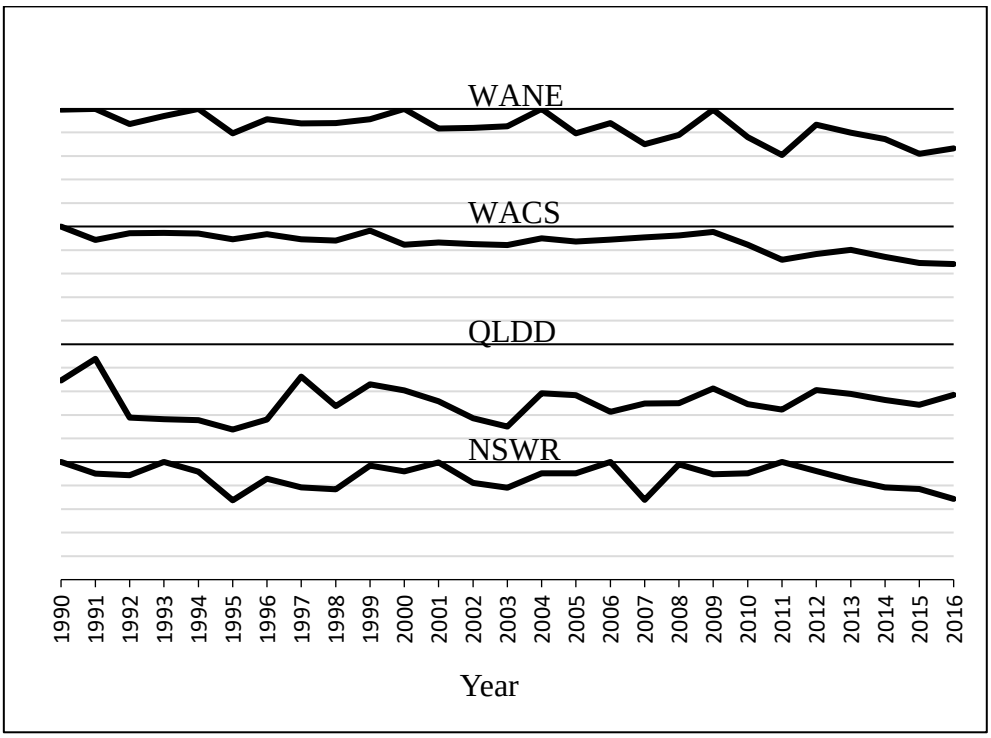

Figure 6.14 Residual output-oriented scale efficiency in medium AARFRs

In the case of medium AARFRs, residual output-oriented scale efficiency scores ranged from 28 percent in 1995 in QLDD to 100 percent in NSWR in 1990, 1993, 2006 and 2011; WACS

in 1990; and WANE in 1991, 1994, 2000 and 2004. ROSE was less than 100 percent in QLDD throughout the study period (Figure 6.14; Table D.5, Appendix D), which implies that QLDD farms were inefficient from 1990 to 2016. Moreover, there was considerable fluctuation in residual output-oriented scale efficiency of QLDD, which diminished towards the end of the study period. The state of inefficiency in this area may confirm that farmers have not succeeded in obtaining residual advantages via the process of changing the input/output mix for the reasons mentioned earlier.

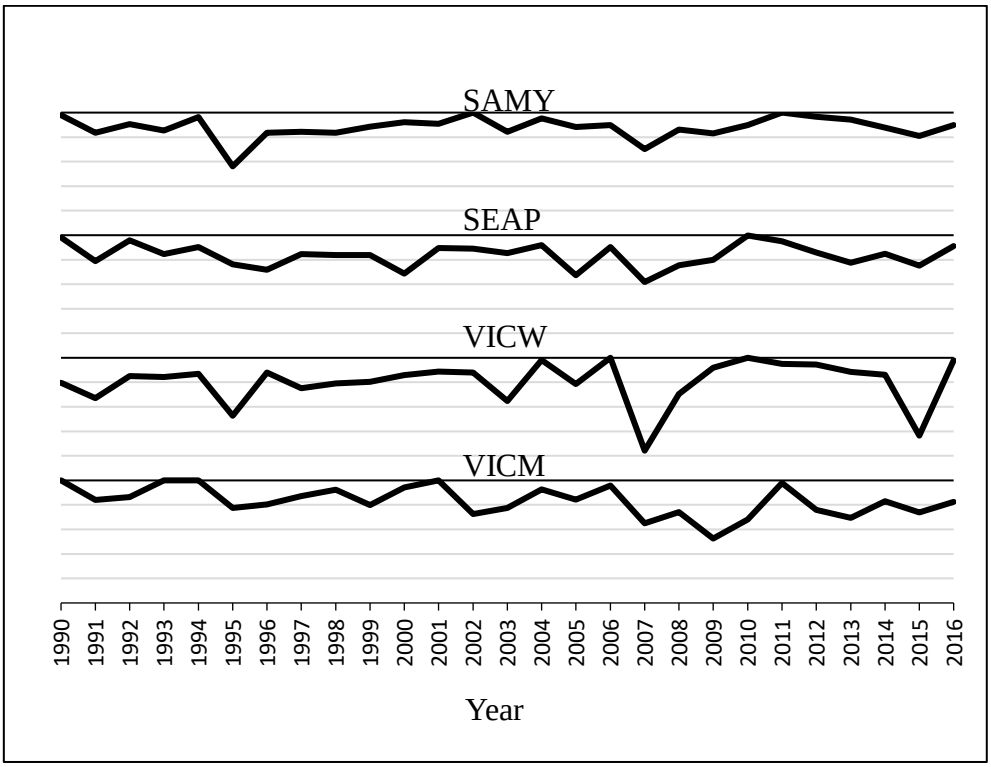

Figure 6.15 Residual output-oriented scale efficiency in low AARFRs

In low AARFRs, residual output-oriented scale efficiency scores were calculated to be between a minimum of 24 percent in 2007 in VICW and a maximum of 100 percent in VICM (1990, 1993–1994 and 2001); VICW (2006 and 2010); SAEP in 2010 and SAMY in 2002 and 2011 (Figure 6.15; Table D.5, Appendix D). Therefore, VICM recorded the highest numbers of years in which the farms were fully efficient whereas SAEP recorded the lowest. Additionally, the farmers did not achieve full efficiency in many years over the four farm regions. Figure 6.15 displays the variations in residual output-oriented scale efficiency of the four farm regions, with residual output-oriented scale efficiency of all farm regions in the low AARFRs reduced in 1995, 2003 and 2007. Previous studies (ABS 2012a; Che et al. 2012; Hughes et al. 2016;

Steffen 2015) have shown that these years were among the years with the most decline in rainfall the Australian Wheat Belt regions, which may have affected the distribution of resources and productivity on the farm. Additionally, the fact that these farm regions fall within areas with low rainfall supports the low levels of efficiency recorded.

Figure 6.16 shows that the residual output-oriented scale efficiency scores of all AARFRs ranged between 61 percent in 1995 and 89 percent in 1990. Residual output-oriented scale efficiency scores declined during the years of drought in Australian (1995, 2003 and 2007). Farms in VICC had the lowest residual output-oriented scale efficiency (16 percent) in 2003 among the 12 farm regions.

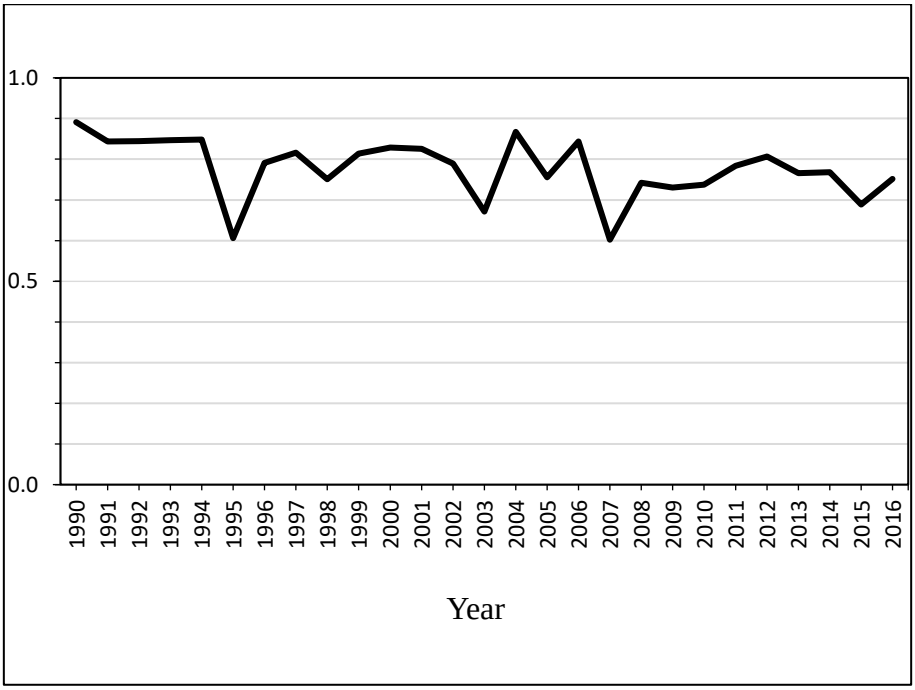

Figure 6.16 Residual output-oriented scale efficiency in all AARFRs

6.3.5 Scale and mix efficiency

6.3.5.1 Average scale and mix efficiency for all farm regions

Average output-oriented scale-mix efficiency of all farm regions in the three AARFRs under study over 27 years are shown in Table 6.6. Output-oriented scale-mix efficiency measures the improvements in productivity related to the economies of scale and scope (O'Donnell 2012c, 2016). Results for farms in high AARFRs showed variation between a minimum of 55 percent in VICC and a maximum of 82 percent in NSWN. Therefore, farmers in high AARFRs

could improve their output-oriented scale-mix efficiency by 18 to 45 percent by adjusting the production scale and the proportion of output mix (i.e. wheat and non-wheat).

In the medium AARFRs, average output-oriented scale-mix efficiency ranged between 51 percent in QLDD and 84 percent in NSWR. Therefore, farms in medium AARFRs could improve their output-oriented scale-mix efficiency by approximately 16 to 49 percent by changing the farm size and mix of the wheat and non-wheat ratio.

Estimates of average output-oriented scale-mix efficiency in low AARFRs revealed that it varied between a minimum of 78 percent in VICW and a maximum of 87 percent in SAMY. Farmers in low AARFRs could, therefore, improve their average output-oriented scale-mix efficiency by 13 to 22 percent to capture the optimal economies of scale and scope by altering their output mixes and farm size. The mean output-oriented scale-mix efficiency of all AARFRs was 75 percent. Therefore, in general, farmers could have faced problems in capturing the benefits from economies of scale and scope.

Table 6.6 Average OSME for all farm regions over 1990–2016

Farm region (DMUs)	**OSME**
High AARFRs	
NSWN	0.82
NSWC	0.78
QLDE	0.61
VICC	0.55
Medium AARFRs	
NSWR	0.84
QLDD	0.51
WACS	0.82
WANE	0.83
Low AARFRs	
VICM	0.81
VICW	0.78
SAEP	0.81
SAMY	0.87
All AARFRs	0.75

6.3.5.2 Scale and mix efficiency scores

Figures 6.17 to 6.20 present variations in output-oriented scale-mix efficiency of all farm regions from 1990 to 2016. Output-oriented scale-mix efficiency was estimated by multiplying output-oriented mix efficiency and residual output-oriented scale efficiency. In high AARFRs, the lowest and highest output-oriented scale-mix efficiency scores were, respectively, 16 percent in VICC in 2003 and 100 percent in all farm regions in only a few years (1990–1994, 1997 and 2008) except in VICC (Figure 6.17; Table D.6, Appendix D). VICC did not record any full efficiency (OSME) in any of the years under study mainly because residual output-oriented scale efficiency scores for VICC were less than 100 percent throughout the study period.

Although output-oriented scale-mix efficiency and residual output-oriented scale efficiency followed a similar trend over the study period, there was a greater decrease in output-oriented scale-mix efficiency (Figure 6.17). Output-oriented scale-mix efficiency scores were relatively low and highly variable over the study period. Furthermore, the scores were relatively low in 1995, 2002–2003 and 2007–2008, which were the drought years (Che et al. 2012).

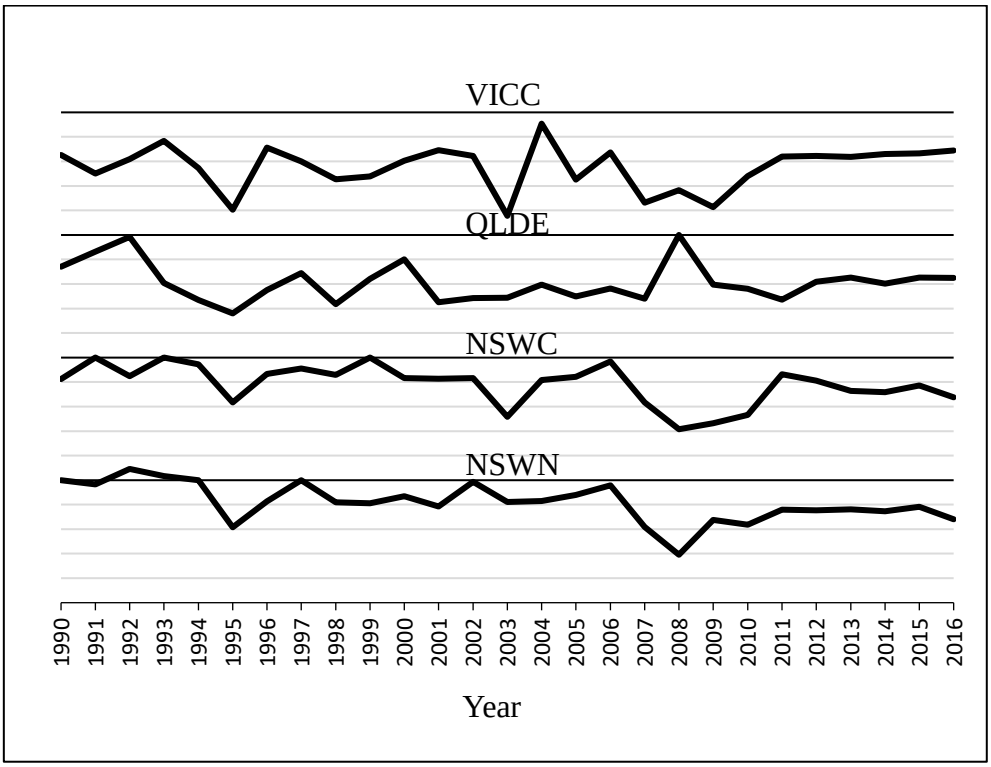

Figure 6.17 Scale and mix efficiency in high AARFRs

The minimum and maximum output-oriented scale-mix efficiency scores in medium AARFRs ranged between 28 percent in 1995 in QLDD and 100 percent in NSWR (1990, 1993, 2006 and 2011) and WANE (1991, 1994, 2000 and 2004). In addition, QLDD and WACS did not achieve 100 percent over the sample study period (Figure 6.18; Table D.6 in Appendix D). QLDD saw more reduction and was more inefficient than WACS. Farmers in QLDD experienced problems related to their residual output-oriented scale efficiency (Figure 6.13) owing to various issues such as soil quality degradation (DAFF 2014) despite recording 100 percent output-oriented technical efficiency (CRS) and output-oriented technical efficiency (VRS) (Figure 6.1) for several years. This could reflect negatively on their output-oriented scale-mix efficiency scores.

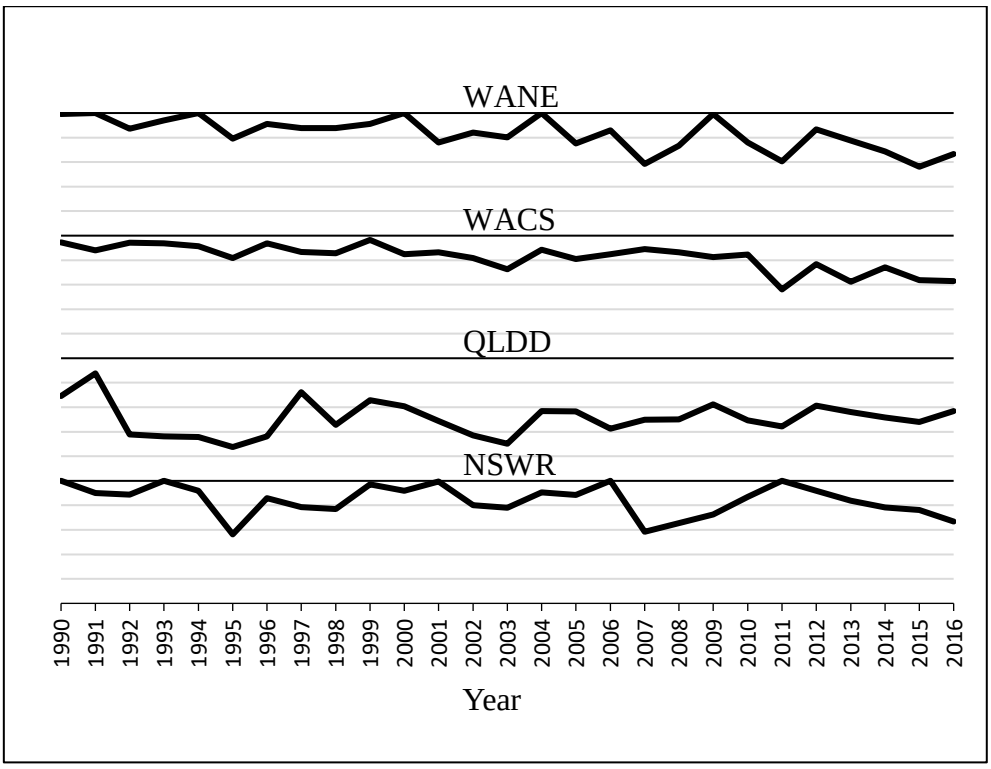

Figure 6.18 Scale and mix efficiency in medium AARFRs

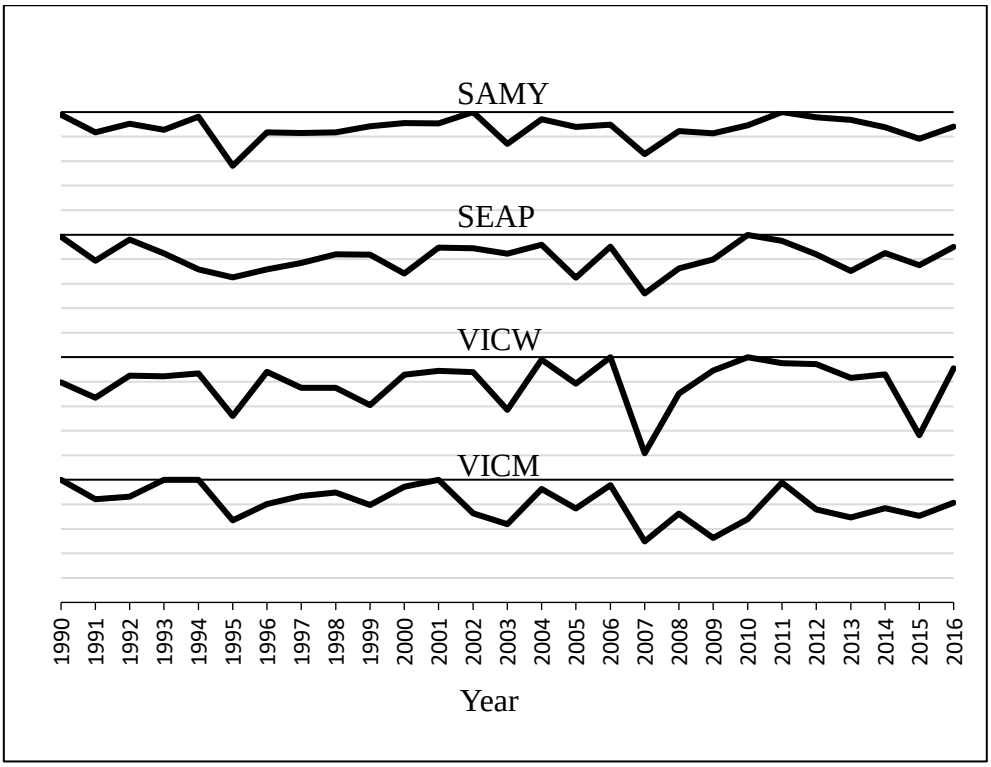

Figure 6.19 Scale and mix efficiency in low AARFRs

In low AARFRs, output-oriented scale-mix efficiency scores ranged between a minimum of 22 percent in 2007 in VICW and a maximum of 100 percent in VICM (1990, 1993–1994 and 2001); VICW (2006); SAEP (2010) and SAMY (2002 and 2011) (Figure 6.19; Table D.6 in Appendix D). Trends of output-oriented scale-mix efficiency scores for the various farm regions in low AARFRs exhibited high variabilities over the study period, and there were considerable declines in output-oriented scale-mix efficiency during the drought years (1995, 2002–2003 and 2007–2008; Figure 6.19).

In all AARFRs, a maximum average output-oriented scale-mix efficiency of 88 percent and a minimum of 54 percent were recorded in 1990 and 2007, respectively (Table D.6, Appendix D). Considerable fluctuations and drops were observed in all AARFRs (Figure 6.20), with output-oriented scale-mix efficiency scores decreasing drastically during years of severe drought (1995, 2003 and 2007). Generally, the output-oriented scale-mix efficiency of all AARFRs in the Wheat Belt regions of Australia was less than 100 percent throughout the study period. This could imply that farmers experienced many challenges such as environmental changes, which negatively impacted soil and plant health. Thus, a lack of incentive for farmers to benefit from economies of scale and scope was expected.

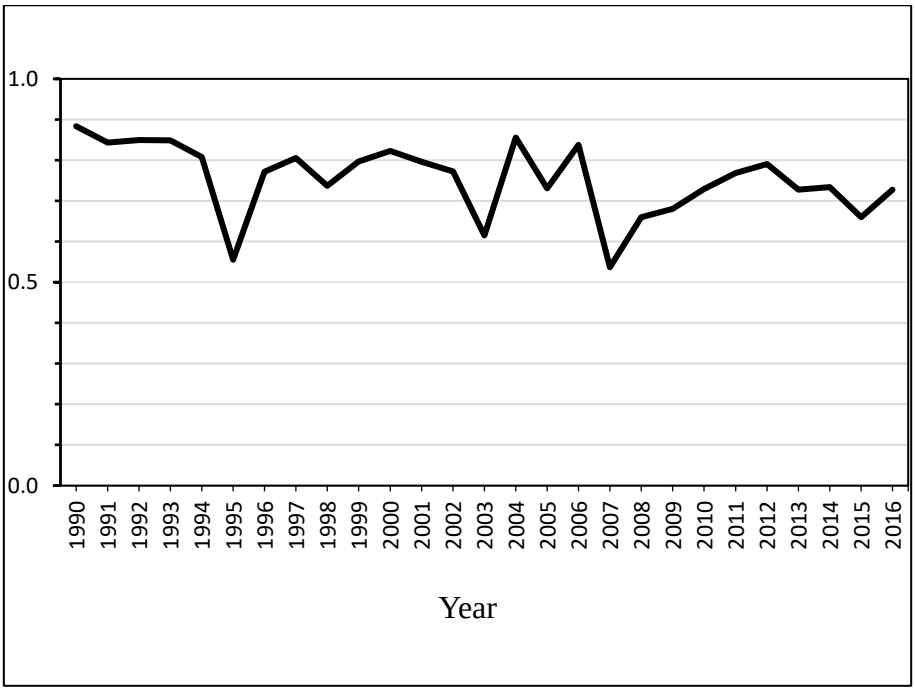

Figure 6.20 Scale and mix efficiency in all AARFRs

6.3.6 Technical and scale-mix efficiency

6.3.6.1 Average technical and scale-mix efficiency for all farm regions

Average technical and scale-mix efficiency, estimated for all 12 farm regions over the 27-year study period are presented in Table 6.7. O'Donnell, Fallah-Fini and Triantis (2017) stated that technical and scale-mix efficiency, measures how successful a farm manager and/or his spouse are in achieving the maximum possible productivity without constraints in the selection of inputs and/or outputs.

Average technical and scale-mix efficiency, in the high AARFRs was lowest (52 percent) in VICC and highest (69 percent) in NSWN, which implies farmers can improve their technical and scale-mix efficiency, by 31 to 48 percent to obtain the maximum TFP related to the optimal scale of operations (adjusting the output mix and/or the input mix) with existing technology. Thus, farm managers failed to capture the maximum TFP during the 27-year period under study. This is because farm managers or their spouses did not use, on average, the existing technology and varied their output and/or input mixes efficiently.

Table 6.7 Average TSME for all farm regions over 1990–2016

Farm region (DMUs)	TSME
High AARFRs	
NSWN	0.69
NSWC	0.65
QLDE	0.59
VICC	0.52
Medium AARFRs	
NSWR	0.74
QLDD	0.48
WACS	0.77
WANE	0.77
Low AARFRs	
VICM	0.69
VICW	0.71
SAEP	0.74
SAMY	0.77
All AARFRs	0.68

In medium AARFRs, average technical and scale-mix efficiency, ranged between a minimum of 48 percent in QLDD and a maximum of 77 percent in WACS and WANE. Therefore, farm managers/spouses in medium AARFRs could increase their technical and scale-mix efficiency, by 23 to 52 percent to achieve the maximised TFP by obtaining advantages of the altering of output mix and/or input mix with the use of existing technology. This suggests that farm managers in these farm regions were also unsuccessful in solving different optimisation issues, i.e. they were inefficient regarding the average technical and scale-mix efficiency over the study period.

In low AARFRs, average technical and scale-mix efficiency was between 69 percent in VICM and 77 percent in SAMY. This reveals that there is room for farm managers/spouses in low AARFRs to improve their technical and scale-mix efficiency, by 23 to 31 percent to reach maximum TFP if they have free options related to the outputs and inputs with the use of available technology. These results indicate that farm managers or their spouse did not use their existing technologies and also did not vary their output mix and/or input mix (the scale of operations) optimally.

Average technical and scale-mix efficiency, of all AARFRs was 68 percent over 1990 to 2016, which suggests that farm managers/spouses were inefficient with respect to technical and scale-mix efficiency. Generally, the reason for this inefficiency might be because the farm managers could not successfully solve problems related to the different optimisation processes. However, QLDD was the most inefficient with regards to technical and scale-mix efficiency. This finding was not surprising because the average output-oriented scale-mix efficiency of QLDD (51 percent) was the lowest (Table 6.6).

6.3.6.2 Score of technical and scale-mix efficiency

Figures 6.21 to 6.24 and Table D.7 in Appendix D present technical and scale-mix efficiency scores in all farm regions for each level of rainfall. Starting with the high AARFRs, the lowest and highest TSME scores were 11 percent in 1995 in NSWC and 100 percent in 1990, 1994 and 1997 in NSWN; 1991, 1993 and 1999 in NSWC; and 2008 in QLDE (Figure 6.21 and Table D.7, Appendix D). Therefore, there is a significant gap among farm regions in the high AARFRs, which might explain the failure of farm managers to achieve maximum possible productivity except for only in a few years. This variation may be due to variability in the change in rainfall rates (Table 6.1) or the change in the availability of inputs and outputs or their mixing. It may also affect the optimum utilisation of available technology by farm owners.

All technical and scale-mix efficiency scores declined most in either or both of 1995 and 2003 (Figure 6.21). Furthermore, since TSME = $OTE_{VRS} \times$ OSME, a similar trend was observed between technical and scale-mix efficiency and output-oriented scale-mix efficiency for VICC and QLDE (Figure 6.17 and Figure 6.21) over the study period. This implies that farm managers in VICC and QLDE might have used the existing technology efficiently in most years. They could not capture the full effect of economies of scale and/or scope via inputs and/or outputs mixes as shown in Figure 6.21. However, maximum output-oriented technical efficiency (VRS) was achieved in 11 out of 27 years in both NSWN and NSWC, whereas maximum output-oriented scale-mix efficiency was achieved in 5 and 3 out of 27 years in NSWN and NSWC, respectively. Therefore, these farm regions only slightly made optimum use of the existing technology, and possibly failed to reach economies of scale and/or scope.

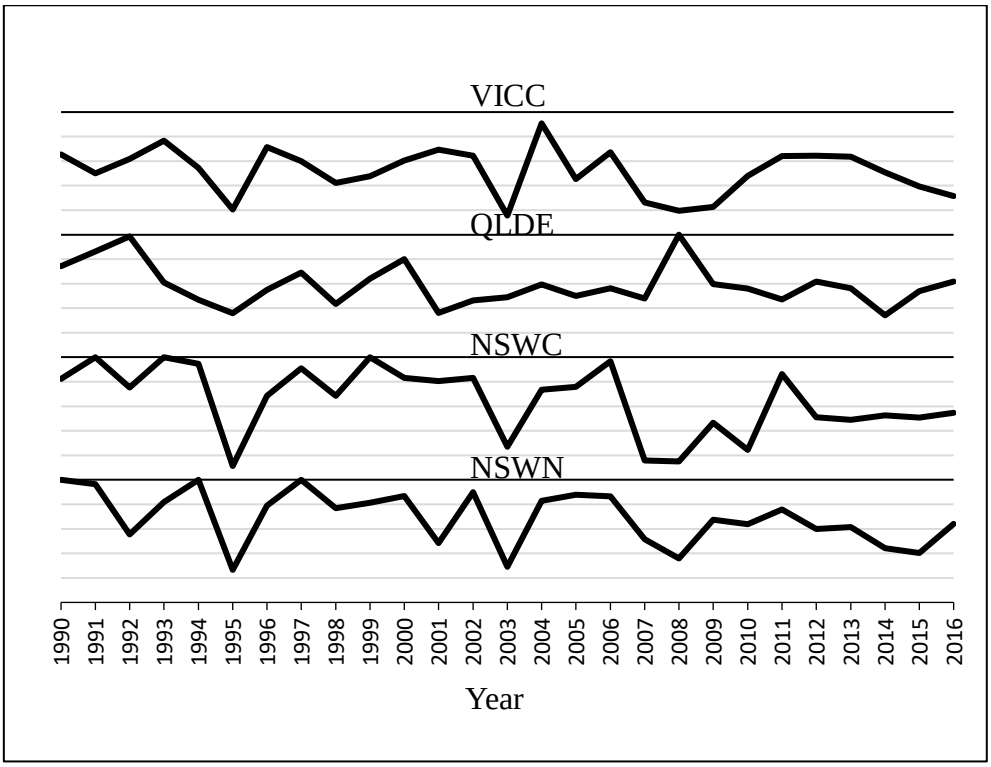

Figure 6.21 Technical and scale-mix efficiency in high AARFRs

For medium AARFRs, technical and scale-mix efficiency scores ranged from 17 percent in NSWR in 2008 to 100 percent in 1990, 1993, 2006 and 2011 in NSWR and in 1991, 1994, 2000 and 2004 in WANE (Figure 6.22; Table D.7, Appendix D). Measures of technical and scale-mix efficiency over the study period indicated a decline in efficiency; however, this did not generally mention that there was no improvement in efficiency for individual AARFRs in some years. This implies that farmers of these farm regions might be able to improve their technical and scale-mix efficiency by changing the output and input mixes.

Figure 6.22 reveals that NSWR had the lowest technical and scale-mix efficiency score (17 percent) during 2008. This might be due to the inability of farm managers to reach the maximum TFP by altering the scale of operations (changing the output and/or input mixes). Farm managers and/or their spouses were able to use the available technology optimally; however, they did not capture scale and mix efficiency by changing the scale of operations in the farms to obtain maximum TFP.

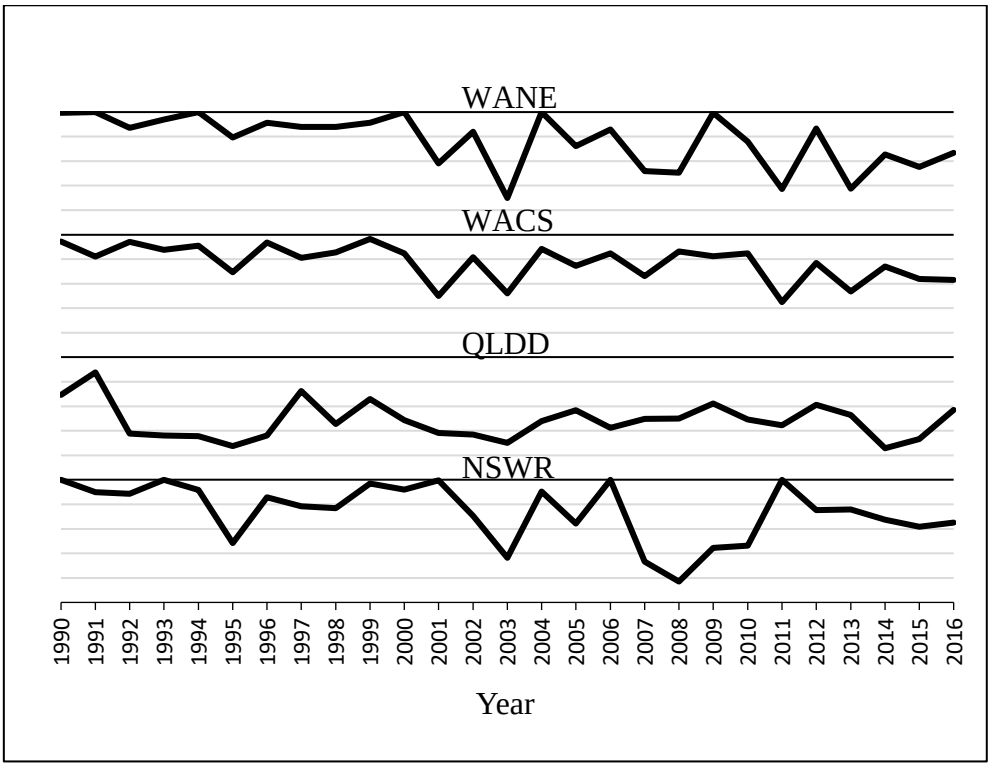

Figure 6.22 Technical and scale-mix efficiency in medium AARFRs

For example, it was shown that output-oriented scale-mix efficiency (Figure 6.18) and technical and scale-mix efficiency (Figure 6.22) for QLDD followed a similar trend from 1990 until 2012. This confirmed that output-oriented scale-mix efficiency had less effect on technical and scale-mix efficiency than that of output-oriented technical efficiency (VRS). This is because QLDD was fully efficient for 21 out of 27 years in respect to output-oriented technical efficiency (VRS). Again, there was a relative decrease in technical and scale-mix efficiency scores for the four farm regions in 1995 and 2003, which was likely due to environmental, economic or social reasons.

In low AARFRs, technical and scale-mix efficiency scores varied between a minimum of 13 percent in 2003 in VICW and a maximum of 100 percent in only four years (1990, 1993–1994 and 2001) in VICM; two years (2006 and 2010) in VICW; one year (2010) in SAEP and two years (2002 and 2011) in SAMY (Figure 6.23; Table D.7, Appendix D). Failure to achieve full efficiency in many years may be explained by poor performance (inefficiency) of farm managers in these regions in solving the problems and challenges related to achieving the maximum possible productivity. An examination of Figures 6.3, 6.19 and 6.23 reveals that technical and scale-mix efficiency was directly affected by output-oriented technical efficiency

(VRS). This could be attributed to the inability of farm managers to capture the full scale of operations by changing the output and input mixes. This may be due to the sensitivity of these regions to environmental or socioeconomic changes as they are located in low rainfall regions. Therefore, there was no or less influence of scale-mix efficiency (less efficient) on technical and scale-mix efficiency in low AARFRs (Figure 6.23).

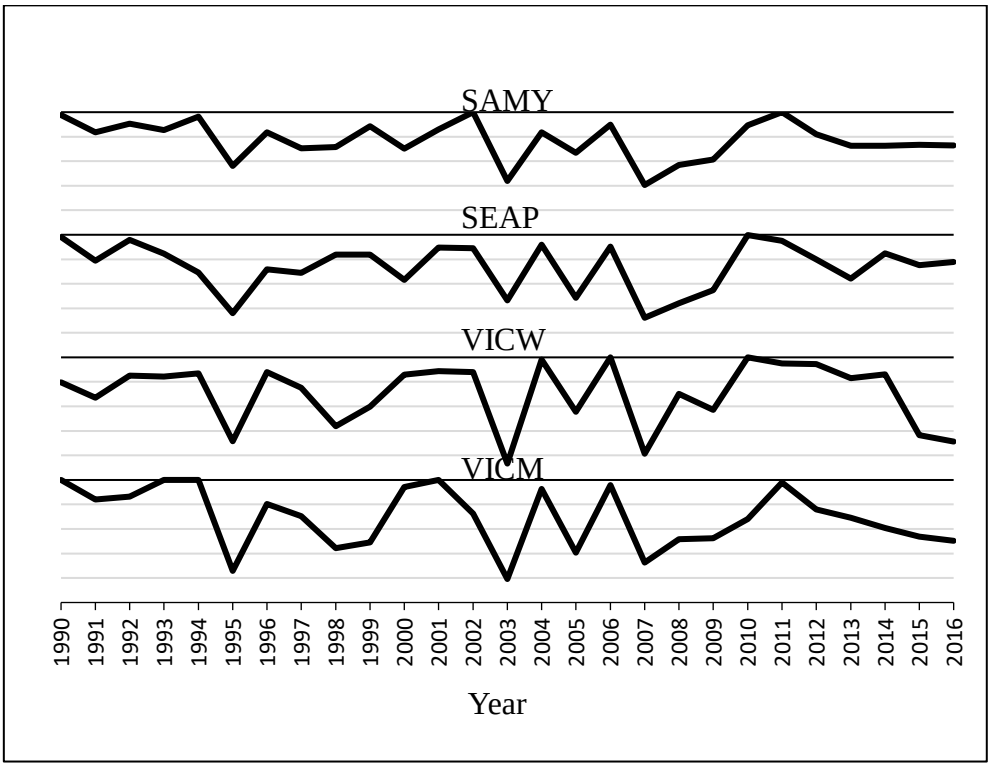

Figure 6.23 Technical and scale-mix efficiency in low AARFRs

Finally, technical and scale-mix efficiency scores of all AARFRs ranged between a minimum of 33 percent in 2003 and a maximum of 88 percent in 1990 (Figure 6.24; Table D.7, Appendix D). Therefore, the farms in all farm regions were operating inefficiently with regards to technical and scale-mix efficiency for the past three decades. These results were expected, looking at results for the three AARFRs discussed above. Figure 6.24 also shows the considerable drop in technical and scale-mix efficiency in the three main drought years (1995, 2002–2003 and 2007–2008) in the Australian Wheat Belt regions. These shortfalls in the efficiency of technical and scale-mix efficiency could be attributed to a number of reasons, namely conditions beyond the control of the farm manager such as the deterioration of environmental conditions (decreased rainfall), poor use of available technology and poor mixing of inputs and/or outputs by the farm manager. There were also wide variations in

technical and scale-mix efficiency score in all AARFRs over the study period, which confirms what has been explained above.

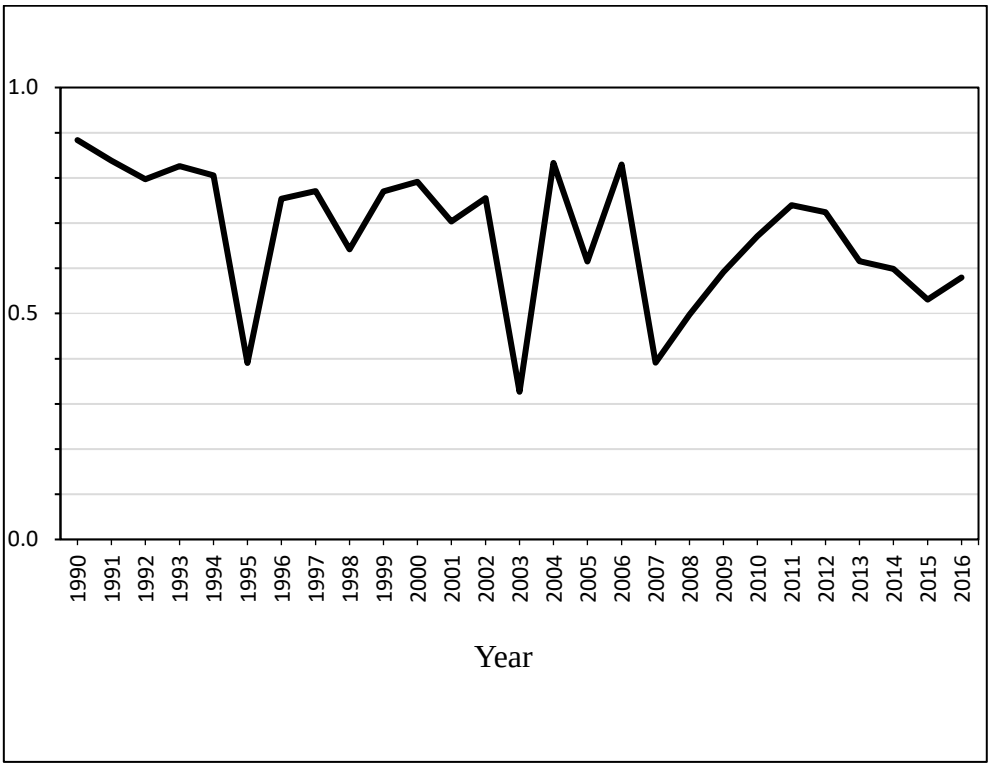

Figure 6.24 Technical and scale-mix efficiency in all AARFRs

6.3.7 Environmental efficiency

6.3.7.1 Average environmental efficiency for all farm regions

O'Donnell (2016) stated that the production environment variables such as rainfall influence the output-input combinations as well as the production possibilities that are set. This variable is beyond the control of farmers and is involved in the farm production process; therefore, any significant change in rainfall level could lead to a change in crop output.

The average rainfall efficiency was 88, 89 and 94 percent in the high, medium and low AARFRs, respectively (Table 6.8). Thus, farmers in these AARFRs could improve their respective environmental (rainfall) efficiency by 12, 11 and 6 percent via the implementation of a long-term plan for adapting to drought and the adoption of modern technology during the cultivation of wheat and non-wheat crops. Furthermore, the average rainfall efficiency in all AARFRs was 90 percent; therefore, farmers in the Wheat Belt regions of Australia must improve their rainfall efficiency by 10 percent to obtain a maximum rainfall efficiency.

However, average rainfall efficiency farms in low AARFRs was the highest at 94 percent. This might be achieved by farm managers paying more attention to rainfall change. According to Hughes, Lawson and Valle (2017), increasing farmers' awareness of the adoption of modern technology and adaptation to reduced rainfall levels can be reflected in increased farm productivity. For example, increasing nitrogen in sandy soils in VICM, which was located in the low AARFRs, led to an increase in crop yield and income (Grain Growers 2016).

Table 6.8 Average EEr for all farm regions over 1990–2016

AARFRs	**EEr**
High AARFRs	0.88
Medium AARFRs	0.89
Low AARFRs	0.94
All AARFRs	0.90

6.3.7.2 Environmental efficiency Score

Variations in rainfall efficiency in all AARFRs over the study period are presented in Figure 6.25 and Table D.8, Appendix D. In high AARFRs, rainfall efficiency scores ranged between a minimum of 68 percent in 1993 and a maximum of 100 percent in 2008–2016 (9 out of 27 years). This could support the view that farm managers did not consider adapting to rainfall change during the farming seasons despite a decline in rainfall quantity. This is because they might have relied on the fact that they are located in regions where the rainfall was adequate. The four farm regions being fully efficient from 2008 to 2016 (Figure 6.25) could indicate that farm managers and/or their spouses might have improved their management performance and used modern technology to find appropriate solutions to the various challenges associated with the production process.

The rainfall efficiency scores in the medium AARFRs varied from 67 percent in 1990 to 100 percent in 2000 (Figure 6.25). Thus, farmers were less efficient with respect to rainfall efficiency for many years and they might have failed to reach full efficiency because they did not appropriately match up production resources to the rainfall level.

In low AARFRs, the rainfall efficiency scores ranged between 75 percent in 2008 and 2009 and 100 percent in 1990 to 1999 and 2001 to 2007 (Figure 6.25). Rainfall efficiency in low AARFRs was 100 percent in most years, which might be because farmers developed long-term strategies to introduce modern technology in their agricultural inputs and adopted management strategies that were adapted to the low rainfall level. Additionally, farm managers might have adopted the strategy of mixing crop output (wheat and non-wheat crops) efficiently to boost productivity and profitability in the face of low rainfall level as evidenced in Figure 6.11.

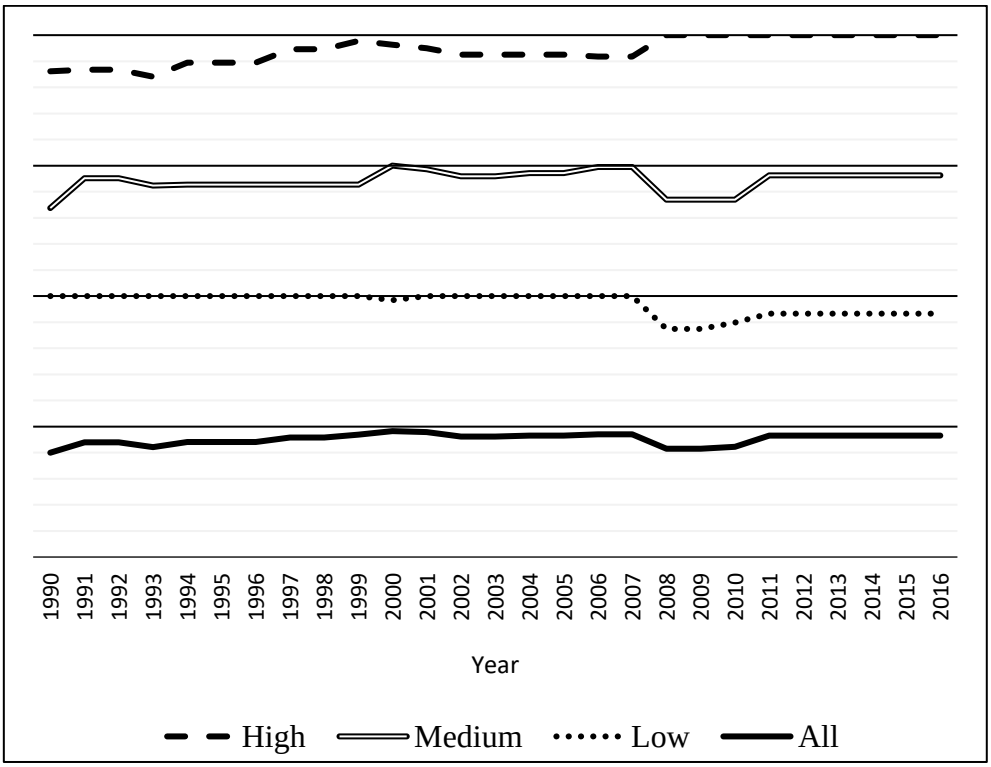

Figure 6.25 Rainfall efficiency in Farm regions

The average rainfall efficiency score for all AARFRs ranged between 80 percent in 1990 and 97 percent in 2000 (Figure 6.25; Table D.8, Appendix D). Thus, farmers in the Wheat Belt regions of Australia generally did not achieve full efficiency regarding the use of rainfall. These farmers can get closer to 100 percent rainfall efficiency by continuing to adopt modern technologies for soil and water management and optimum utilisation of other production inputs. Figure 6.25 indicates a gradual increase in rainfall efficiency since 1990. This was likely due to the commitment and awareness of farm managers in adapting to rainfall changes over the period in addition to using modern technology to support and solve the problems faced during the production process through successful management.

In general, there are a number of climatic factors that can affect rainfall efficiency. For example, a farm region with high rainfall might have a low soil infiltration rate. This makes it important for farmers to critically consider soil moisture content. Thus, farmers should choose the best type of crop to cultivate considering the average rainfall level in their geographical region.

6.4 Second Stage Regression Analysis Using Tobit Model

Tables 6.9 and 6.10 present results from the second stage regression analysis of the Tobit model introduced by Tobin (1958), and the double bootstrap corrected model proposed by Simar and Wilson (2007) respectively. Truncated regression analysis in the double bootstrap analysis was used as a bias-corrected test. The significance of the effects of the explanatory variables on the efficiency indicators was established based on the stated level of significance. Both the Tobit model and the double bootstrap corrected model produced similar estimations of the efficiency indicators. This showed that the Tobit model was robust for estimating the effects of the explanatory variables on the performance of the farm regions and was therefore effective for such estimations.

Furthermore, Tables F.1 and F.2 in Appendix F present the outcomes of the random effects Tobit model and lag model. These results were used for further confirmation of the robustness of the result of the Tobit model. Slight differences were observed between the coefficient values of the explanatory variables estimated with the random effect Tobit, lag and standard Tobit models. However, comparison of the results of the three models in Table F.3, Appendix F shows that over 90% of the coefficients of the Tobit model had the same signs (positive and negative) with the random effect Tobit and lag models and a greater number of coefficients were simultaneously significant for all three models. In addition, logSigma-Mu in Table F.1, Appendix F, which indicates standard deviation and population mean, reveals that the amount of variation or dispersion of dataset values were significant. This is because the data used was found to be normally distributed and hence the models were unbiased.

Specifically, statistical results of the four models reveal significant relationship between the following efficiency indicators and explanatory variables:

- Output-oriented technical efficiency (CRS and VRS), and off-farm work of spouse of farm manager, capital-labour ratio and land-labour ratio;
- Output-oriented mix efficiency and age of spouse of farm manager;
- Residual output-oriented scale efficiency, and off-farm work of spouse of farm manager and capital-labour ratio;
- Output-oriented scale-mix efficiency, and off-farm work of spouse of farm manager and capital-labour ratio;
- Technical and scale-mix efficiency, and off-farm work of farm manager, off-farm work of spouse of farm manager, capital-labour ratio and land-labour ratio;
- Rainfall efficiency, and age of farm manager, age of spouse of farm manager, capital-labour ratio and land-labour ratio.

These results are well representative of the real situation of the Australian agricultural sector in recent decades and are also economically meaningful. Further details related to these explanatory variables are discussed in Sections 6.4.1, 6.4.5 and 6.4.6 of this chapter. Based on these results, it could be said that the eight efficiency indicators considered in this study can be said to be unbiased predictive models. Using a log likelihood test, the best model with the highest log likelihood was the output-oriented mix efficiency model in Tables 6.9, 6.10 and F.1, Appendix F, with this model able to best explain the influence of the explanatory variables on the performance of farm regions. These further confirm that estimations with the Tobit model were unbiased and consistent. Similar results were found for the second stage regression analysis of the effects of temperature variation on efficiency in Chapter 7.

Table 6.9 Results of Tobit models: Determinants of efficiency indicators

	Dependent variables							
	OTE_{CRS}	**OTE_{VRS}**	**OSE**	**OME**	**ROSE**	**OSME**	**TSME**	**EEr**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.821***	0.837***	0.973***	0.912***	1.097***	1.018***	0.918***	1.184***
	(0.181)	(0.178)	(0.100)	(0.071)	(0.173)	(0.174)	(0.183)	(0.097)
Independent variables								
Age of farm manager (ev_1)	-0.001	0.0001	-0.001	-0.005	-0.014	-0.018*	-0.016	-0.026***
	(0.010)	(0.010)	(0.005)	(0.004)	(0.009)	(0.009)	(0.010)	(0.005)
Age of spouse of farm	0.004	0.003	0.001	0.007*	0.009	0.014	0.014	0.020***
manager (ev_2)	(0.010)	(0.010)	(0.005)	(0.004)	(0.009)	(0.010)	(0.010)	(0.005)
Off-farm work of farm	-0.003	-0.0002	-0.002	0.002	-0.008**	-0.006*	-0.006*	-0.001
manager (ev_3)	(0.003)	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)
Off-farm work of spouse	-0.005*	-0.006*	0.0004	-0.002	0.014***	0.013***	0.008**	-0.0004
of a farm manager (ev_4)	(0.003)	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)
Capital-labour ratio (ev_5)	0.005***	0.004***	0.001**	0.0004	0.005***	0.005***	0.008***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.001)
Land-labour ratio (ev_6)	-0.515***	-0.469***	-0.082	-0.034	-0.290**	-0.304**	-0.589***	0.127*
	(0.127)	(0.124)	(0.070)	(0.050)	(0.121)	(0.122)	(0.128)	(0.067)
Year effect	yes	Yes	yes	yes	yes	yes	yes	yes
Observations	324	324	324	324	324	324	324	324
Log likelihood	162.311	168.889	355.226	466.697	177.458	175.217	159.559	366.349
Wald test (df = 32)	266.851***	183.157***	103.762***	88.971***	197.136***	230.990***	440.502***	135.399***

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

Table 6.10 Results of bootstrap truncated regression (algorithm #2)

	Dependent variables							
	OTE_{CRS}	**OTE_{VRS}**	**OSE**	**OME**	**ROSE**	**OSME**	**TSME**	**EEr**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.821***	0.837***	0.973***	0.912***	1.097***	1.019***	0.992***	1.184***
	-0.181	-0.178	-0.1	-0.071	-0.173	-0.174	-0.185	-0.097
Independent variables								
Age of farm manager (ev_1)	-0.001	0.0001	-0.001	-0.005	-0.014	-0.018*	-0.016	-0.026***
	(0.010)	(0.010)	(0.005)	(0.004)	(0.009)	(0.009)	(0.010)	(0.005)
Age of spouse of farm	0.004	0.003	0.001	0.007*	0.009	0.014	0.015	0.020***
manager (ev_2)	(0.010)	(0.010)	(0.005)	(0.004)	(0.009)	(0.010)	(0.010)	(0.005)
Off-farm work of farm	-0.003	-0.0002	-0.002	0.002	-0.008**	-0.006*	-0.006*	-0.001
manager (ev_3)	(0.003)	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)
Off-farm work of spouse of	-0.005*	-0.006*	0.0004	-0.002	0.014***	0.013***	0.008**	-0.0004
farm manager (ev_4)	(0.003)	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)
Capital-labour ratio (ev_5)	0.005***	0.004***	0.001**	0.0004	0.005***	0.005***	0.008***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	0.001
Land-labour ratio (ev_6)	-0.516***	-0.469***	-0.082	-0.034	-0.290**	-0.304**	-0.592***	0.127*
	(0.127)	(0.124)	(0.070)	(0.049)	(0.121)	(0.122)	(0.129)	0.067
Year effect	yes	yes	yes	yes	yes	yes	yes	yes
Observations	324	324	324	324	324	324	324	324
Sigma	0.147***	0.144***	0.081***	0.057***	0.140***	0.141***	0.149***	0.078***
	(0.006)	(0.006)	(0.003)	(0.002)	(0.005)	(0.006)	(0.006)	(0.003)
Log likelihood	162.311	168.889	355.226	466.7	177.458	175.217	160.26	366.349

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

6.4.1 Age of farm manager

Table 6.9 is a summary of the results of the second stage analysis of efficiency determinants based on the given independent variables. Farm managers were aged between 41 and 64 years old, with an average of approximately 54 years. The results revealed a statistically significant effect of the age of farm manager on output-oriented scale-mix efficiency and rainfall efficiency. In contrast, age of farm manager had a non-significant effect on output-oriented technical efficiency (CRS), output-oriented technical efficiency (VRS), output-oriented scale efficiency, output-oriented mix efficiency, residual output-oriented scale efficiency and technical and scale-mix efficiency. The coefficient for age of farm manager was positive; however, it was not significant at any level with respect to output-oriented technical efficiency (VRS). This could indicate that age of farm manager had an insignificant effect on output-oriented technical efficiency (VRS) because of the small difference in age of the sampled farm managers.

The National Farmers' Federation (2008) argued that the migration of young farmers from rural areas to cities to study or for a change of lifestyle might have a negative impact on rural development and the proportion of the working population. The number of young farmers in rural areas has decreased by 68 percent in recent decades (Barr 2014). Therefore, it could be that older farmers are less efficient (negative impact) and less open to accepting new technologies compared to young farmers. Tipi et al. (2009) showed that older farmers are unlikely or slower to accept new technologies than young farmers in Turkey.

The outcomes imply that a 1-year increase in a farm manager's age resulted in an approximate 1.8 and 2.6 percent reduction in output-oriented scale-mix efficiency and rainfall efficiency models at p-values < 0.1 and 0.01, respectively. Therefore, there were diseconomies of scale and scope (less efficient) or rainfall inefficiency associated with wheat and non-wheat crop production under older farm managers. Previous researchers (Battese & Coelli 1995; Bozoğlu & Ceyhan 2007; Tipi et al. 2009) have found that old age shows a negative relationship with technical efficiency. The results from the present study showed a strong significant and negative effect of age of farm manager on rainfall efficiency. This slowness in the adoption and application of modern technology required for adapting to environmental changes and improving efficiency in general and rainfall efficiency in particular over the past three decades

could be attributed to the older age of the farm managers. Therefore, no change or small change in the strategy of the farm manager, i.e. continuing to use traditional methods, might have adversely affected rainfall efficiency.

6.4.2 Age of spouse of farm manager

There was a significantly positive relationship between the age of spouse of farm manager and the output-oriented mix efficiency and rainfall efficiency models. An increase in the age of spouse of farm manager by one year resulted in an approximately 0.7 and 2 percent increase in output-oriented mix efficiency and rainfall efficiency at p-values < 0.1 and 0.01, respectively. In contrast, a positive but insignificant relationship was observed between the age of spouse of farm manager and output-oriented technical efficiency (CRS), output-oriented technical efficiency (VRS), output-oriented scale efficiency, residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency. The ages of the sampled spouses of farm managers ranged from 40 to 62 years, with an average of approximately 52 years.

The age of farm managers' spouses had a non-significant impact on output-oriented technical efficiency (CRS), output-oriented technical efficiency (VRS), output-oriented scale efficiency, residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency. Therefore, these efficiency indicators are not sensitive to the age of the spouse of farm managers. Additionally, there was a significantly positive relationship between the age of spouse of farm manager and output-oriented mix efficiency and rainfall efficiency. The relatively old age of the spouses of farm managers could imply that they had obtained enough farming experience, with which they were able to assist farm managers in decision making concerning the proportions of crops to mix (OME). The strongly positive and significant impact of the age of the spouse of farm managers on rainfall efficiency was also likely attributable to the collective positive contributions of output-oriented technical efficiency (CRS), output-oriented technical efficiency (VRS), output-oriented scale efficiency, residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency (although individually insignificant) and the significant contribution of output-oriented mix efficiency.

6.4.3 Off-farm work of farm manager

Table 6.9 shows that there was a significantly negative relationship between off-farm work of farm manager and residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency. A 1 hour per week increase in off-farm work of farm manager led to a decrease in residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency by 0.8, 0.6 and 0.6 percent at p-values < 0.05, 0.1 and 0.1, respectively. Coelli, Rahman and Thirtle (2002) showed that farmers who had the least number of off-farm hours and a greater interest in agricultural inputs were more efficient. In Australian agriculture, the farm manager, who is also mostly the owner, is usually the leader of the farming family (Barr 2014). The farm manager, therefore, has the foremost responsibility of decision making at all stages of the production process such as soil preparation, sowing, crop protection, harvesting, and the purchase and determination of the specific quantities of farm inputs.

Findings on the relationship between off-farm work and technical efficiency from the present study are consistent with those of Coelli, Rahman and Thirtle (2002), Tipi et al. (2009) and Chang, Dong and MacPhail (2011). These researchers observed a significantly negative impact of off-farm work on technical efficiency, whereas findings reported by Yang, J. et al. (2016) stated that off-farm work did not have any negative impact on technical efficiency in grain production. In contrast, the relationship between off-farm work and output-oriented mix efficiency in the present study were insignificant and positive.

6.4.4 Off-farm work of spouse of farm manager

Regression coefficients of the number of hours used for off-farm work by spouse of farm manager revealed a significantly positive relationship with residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency models. Residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency increased by 1.4, 1.3 and 0.8 percent (at p-values < 0.01, 0.01 and 0.05), respectively, with an increase of 1 hour per week in off-farm work of farm managers' spouses. According to Alston (2013), Australian women in agricultural areas engage in off-farm work as a strategy to earn more income. Barr (2014) also stated that farmers' spouses may not be involved in farm management in Australian agriculture. Income received by the spouses

of farm managers from off-farm work could serve as financial support to farm managers in offsetting family expenses (Productivity Commission 2005). This frees up farming capital, which could then be used, for instance, in the purchase of more advanced production inputs that could improve production. On the other hand, coefficients of the number of hours used for off-farm work by spouse of farm manager revealed a significantly negative relationship with output-oriented technical efficiency (CRS) and output-oriented technical efficiency (VRS). These indicators declined by 0.5 and 0.6 percent, respectively, at p-value < 0.1 with an increase of 1 hour per week in off-farm work of farm managers' spouses. This implies that more hours per week of on-farm work of spouses are required to increase outputs and/or re-mix crop output ratios with the same level of inputs.

The result shows a positive but non-significant impact of off-farm work of spouses on output-oriented scale efficiency. This suggests slight support of off-farm work of the spouses of farm managers for their scale of production. Furthermore, it could imply that off-farm work of farm managers' spouses was the main determining factor for residual output-oriented scale efficiency (1.4 percent) of farms in the study area. This might be explained by, as pointed out earlier, the support offered by farm managers' spouses in decision making concerning changing output and input mixes to improve output-oriented scale efficiency, which could include a residual effect.

6.4.5 Capital-labour ratio

The results in Table 6.9 show a positive relationship between capital-labour ratio ($/hour) and output-oriented technical efficiency (CRS), output-oriented technical efficiency (VRS), output-oriented scale efficiency, residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency and a negative relationship between the capital-labour ratio and EE. The coefficient of the capital-labour ratio was positive and significant at 0.05 and 0.01 significance levels. Therefore, a $1/hour higher capital-labour ratio implies an approximate 0.5, 0.4, 0.1, 0.5, 0.5 and 0.8 percent higher output-oriented technical efficiency (CRS), output-oriented technical efficiency (VRS), output-oriented scale efficiency, residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency, respectively.

Growth in labour productivity requires an increase in the amount of capital, both physically and qualitatively. In other words, an increase in the capital-labour ratio may lead to an increase in labour productivity and, consequently, an increase in profit and quality of output because of lower unit costs. In particular, Australian broadacre farmers, over the past 40 years, have reduced their total input by approximately 1 percent per year (Xia, Zhao & Valle 2017). This suggests that farm managers and/or their spouses, over time, could use modern technology to improve their management practices to reduce their input costs (e.g. fertiliser, chemicals and fuel).

For technical efficiency, this finding agrees with that reported by Mathijs and Vranken (2000) who stated that a greater capital-labour ratio leads to higher technical efficiency. The technical efficiency result obtained in the present study was not consistent with that reported by Latruffe et al. (2004) who found a positive relationship between the capital-land ratio and inefficiency of crop farms in Poland. This might be due to the use of different farming systems and sample sizes.

It was observed that the capital-labour ratio was a strong determinant of technical and scale-mix efficiency (0.8 percent). This might be due to the expansion of the capital-labour ratio by farm managers to maximise TFP and their ability to use existing technology and alter the scale of operations efficiently. As productivity is an indicator of underlying farm business efficiency, so it is important to reveal that increase in the mix of inputs used in production has led to increases in the capital-labour ratio of 12.7 times between 1948 to 1949 and 2013 to 2014 (Sheng & Jackson 2015).

A strong significance (at p-value < 0.01) and negative relationship was observed between the capital-labour ratio and EEs. This could be because a unit increase in the capital-labour ratio resulted in an approximately 0.2 percent reduction in rainfall efficiency. This is likely attributable to imbalances between traditional inputs and the prevailing rainfall situation. For instance, a higher level of inputs should be balanced with a higher quantity of water use, which is mostly obtained from rainfall.

6.4.6 Land-labour ratio

Result presented in Table 6.9 reveal that the land-labour ratio (ha/hour) has a negative and significant impact on the different indicators of efficiency at varying levels of significance. Specifically, coefficients of the land-labour ratio variable could reduce output-oriented technical efficiency (CRS), output-oriented technical efficiency (VRS), residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency, respectively, by approximately 51.5, 46.9, 29, 30.4 and 58.9 percent with a unit growth in land-labour ratio. In contrast, the regression coefficient showed a statistically significant and positive impact of the land-labour ratio on the rainfall efficiency at the 0.1 level of significance. Therefore, a unit increase in the land-labour ratio could lead to an approximately 12.7 percent improvement in rainfall efficiency. This suggests that investment in land size could lead to improvement in rainfall efficiency in dryland farm regions. These results might be because broadacre farming in the Wheat Belt regions of Australia heavily depends on rainfall (dryland), labour cost is high and farm size (land area) is large. ABARES (2016a) stated that the total number of farm employees fell from 390,000 in 1972 to 110,000 in 2015. Therefore, there is a lack of labour resource required for such a massive land area, resulting in a negative impact of the land-labour ratio on efficiency. Contrary to the findings of the present study, Latruffe et al. (2004) argued that an increase in the land-labour ratio leads to an increase in technical efficiency.

Therefore, the land-labour ratio was a major contributing factor for technical and scale-mix efficiency (58.9 percent). As mentioned previously, increasing the farm land area without a corresponding increase in labour and technology use may lead to poor productivity and efficiency. In other words, the farm manager, due to uncalculated expansion, might not be able to control mixing outputs and/or mixing inputs optimally. This will lead to reduction in the change of the scale of operation.

6.5 Conclusion

In this chapter, a standard two-stage DEA approach was used to examine the effect of rainfall variation on efficiency and its determinants. Tobit regression was used to examine the effects of socioeconomic variables on eight efficiency indicators (scores) and the robustness of the results was checked using truncated regression and double bootstrap methods. The first stage

analysis revealed that of all the 12 farm regions, farms in QLDD, QLDE and WANE recorded the highest output-oriented technical efficiency (CRS), output-oriented technical efficiency (VRS) and output-oriented scale efficiency, respectively, whereas farms in NSWC recorded the lowest output-oriented technical efficiency (CRS) and output-oriented technical efficiency (VRS), and farms in VICC recorded the lowest output-oriented scale efficiency. It was also found that the capital-labour ratio had a positive and significant influence on the six efficiency indicators.

CHAPTER 7: EFFECT OF TEMPERATURE VARIATION ON EFFICIENCY AND ITS DETERMINANTS

7.1 Introduction

This chapter presents the empirical results of an analysis of temperature variation on efficiency and its determinants. All analysis processes in the study of temperature variations were similar to the analyses previously conducted for rainfall variations. All inputs, outputs and farm-specific factors used in these analyses are presented in Table 7.1.

The chapter is organised in several sections. Section 7.2 presents the descriptive statistics of the input and output variables that were used to estimate the different indicators of efficiency and also the independent variables in the Tobit regression and double bootstrap with truncated regression estimations of temperature analysis. Section 7.3 presents the empirical results and provides a discussion of the first stage analysis of efficiency scores of temperature variation. Section 7.4 reports the results and discussion for the second stage analysis. Conclusions are presented in Section 7.5.

7.2 Descriptive Statistics of First Stage Analysis and Second Stage Analysis of Temperature Data

The descriptive statistics of the inputs and outputs that were used to measure the different types of efficiency scores (dependent variables) and explanatory variables (independent variables) are presented in Table 7.1. The independent variables were age of farm manager, age of spouse of farm manager, off-farm work of farm manager, off-farm work of spouse of farm manager, capital-labour ratio and land-labour ratio, whereas, the dependent variables were output-oriented technical efficiency (CRS), output-oriented technical efficiency (VRS), output-oriented scale efficiency, output-oriented mix efficiency, residual output-oriented scale efficiency, output-oriented scale-mix efficiency, technical and scale-mix efficiency, and environmental efficiency (temperature efficiency= EEt). All variables were explained in detail in Chapter 4.

Table 7.1 Summary statistics of variables used in the models from1990 to 2016 in different AARTRs

(a) High AATFRs

Variable	Unit	N	Mean	St. Dev.	Min	Max
Output						
Wheat crop (q_1)	Tonnes	108	488.22	346.27	30	1,638
Non-wheat crops (q_2)	Tonnes	108	384.83	372.78	21	1,707
Input						
Land area (x_1)	Hectare	108	550.79	398.02	171	1,825
Chemical (x_2)	kg	108	284.64	213.94	27.92	1,100.38
Fertiliser (x_3)	kg	108	318.67	327.39	23.57	1,385.91
Fuel (x_4)	litre	108	20,350.39	6,057.37	10,411.77	38,387.81
Labour (x_5)	hour/year	108	2,464.70	241.14	1,800.00	2,976.00
Temperature input (z_1)	^{0}C	108	15.24	0.86	13.18	16.7
Farm-specific factors						
-Age of farm manager (**ev_1**)	year	54.89	3.59	47	64	54.89
- Age of spouse of farm manager(**ev_2**)	year	51.98	3.72	44	62	51.98
- Off-farm work of farm manager (**ev_3**)	hrs/wk	2.97	2.76	0	19	2.97
- Off-farm work of spouse of farm manager (**ev_4**)	hrs/wk	5.84	3.36	1	14	5.84
-Capital-labour ratio (**ev_5**)	$/hr	40.26	27.43	9.81	137.2	40.26
-Land-labour ratio (**ev_6**)	hectare/hr	0.22	0.15	0.08	0.73	0.22

(b) Medium AATFRs

Variable	Unit	N	Mean	St. Dev.	Min	Max
Output						
Wheat crop (q_1)	Tonnes	108	782.16	783.06	4	3,144
Non-wheat crops (q_2)	Tonnes	108	496.68	296.21	52	1,539
Input						
Land area (x_1)	Hectare	108	872.41	780.55	85	3,092
Chemical (x_2)	kg	108	374.4	314.1	35.6	1,510.33
Fertiliser (x_3)	kg	108	485.45	386.41	84.81	1,545.69
Fuel (x_4)	litre	108	21,991.13	9,676.46	8,121.22	47,946.68
Labour (x_5)	hrs/year	108	2,444.57	332.32	1,824.00	3,264.00
Temperature input (z_1)	^{0}C	108	13.42	0.62	12.01	15.23
Farm-specific factors						
-Age of farm manager (**ev_1**)	year	108	53.55	4.54	41	63
- Age of spouse of farm manager(**ev_2**)	year	108	50.77	4.39	40	61
- Off-farm work of farm manager (**ev_3**)	hrs/wk	108	2.6	3.14	0	18
- Off-farm work of spouse of farm manager (**ev_4**)	hrs/wk	108	5.24	3.24	0	14
-Capital-labour ratio (**ev_5**)	$/hr	108	52.03	34.14	12.71	181.74
-Land-labour ratio (**ev_6**)	hectare/hr	108	0.34	0.29	0.04	1.31

(c) Low AATFRs

Variable	**Unit**	N	Mean	St. Dev.	Min	Max
Output						
Wheat crop (q_1)	Tonnes	108	385.44	281.29	30	1,592
Non-wheat crops (q_2)	Tonnes	108	408.99	239.32	39	926
Input						
Land area (x_1)	Hectare	108	490.01	285.01	92	1,350
Chemical (x_2)	kg	108	246.56	145.38	39.12	690.74
Fertiliser (x_3)	kg	108	259.78	105.15	67.57	617.44
Fuel (x_4)	litre	108	16,073.46	5,806.95	5,783.30	39,126.78
Labour (x_5)	hour/year	108	2,143.86	229.6	1,560.00	2,904.00
Temperature input (z_1)	^{0}C	108	11.16	1.1	9.16	13.3
Farm-specific factors						
-Age of farm manager (**ev_1**)	year	108	54.51	3.67	46	62
- Age of spouse of farm manager(**ev_2**)	year	108	51.99	3.65	43	59
- Off-farm work of farm manager (**ev_3**)	hrs/wk	108	3.9	2.14	0	9
- Off-farm work of spouse of farm manager (**ev_4**)	hrs/wk	108	6.69	3.67	0	16
-Capital-labour ratio (**ev_5**)	$/hr	108	38.23	16.96	9.63	86.34
-Land-labour ratio (**ev_6**)	hectare/hr	108	0.22	0.12	0.05	0.57

(d) All AATFRs

Variable	Unit	N	Mean	St. Dev.	Min	Max
Output						
Wheat crop (q_1)	Tonnes	324	551.94	545.35	4	3,144
Non-wheat crops (q_2)	Tonnes	324	430.17	310.47	21	1,707
Input						
Land area (x_1)	Hectare	324	637.73	556.29	85	3,092
Chemical (x_2)	kg	324	301.87	240.27	27.92	1,510.33
Fertiliser (x_3)	kg	324	354.64	312.72	23.57	1,545.69
Fuel (x_4)	litre	324	19,471.66	7,783.66	5,783.30	47,946.68
Labour (x_5)	hour/year	324	2,351.04	308.07	1,560.00	3,264.00
Temperature input (z_1)	^{0}C	324	13.27	1.89	9.16	16.7
Farm-specific factors						
-Age of farm manager (**ev_1**)	year	324	54.31	3.99	41	64
- Age of spouse of farm manager(**ev_2**)	year	324	51.58	3.97	40	62
- Off-farm work of farm manager (**ev_3**)	hrs/wk	324	3.16	2.76	0	19
- Off-farm work of spouse of farm manager (**ev_4**)	hrs/wk	324	5.93	3.47	0	16
-Capital-labour ratio (**ev_5**)	$/hr	324	43.51	27.71	9.63	181.74
-Land-labour ratio (**ev_6**)	hectare/hr	324	0.26	0.21	0.04	1.31

7.3 Empirical First Stage Results and Discussion of Temperature Analysis

7.3.1 Technical efficiency

7.3.1.1 Average OTE for all farm regions

Averages of overall and pure technical efficiency estimated from the DEA approach under high, medium, low and all AATFRs are presented in Table 7.2. The average output-oriented technical efficiency (CRS) of all farm regions in the three AATFRs under study over 27 years are displayed in Table 7.2. Results for farms in high AATFRs showed variation between a minimum of 79 percent in NSWC and a maximum of 95 percent in QLDD (Table 7.2). Therefore, farmers in high AATFRs could improve their outputs by 5 to 21 percent without increasing their input. In the medium AATFRs, average output-oriented technical efficiency (CRS) ranged between 86 percent in NSWR and 97 percent in QLDE. Therefore, farms in medium AATFRs could improve their outputs (wheat and non-wheat) by approximately 3 to 14 percent without having to increase inputs (Table 7.2). The minimum output-oriented technical efficiency (CRS) for farms in the low AATFRs was estimated to be 80 percent in VICM and the maximum output-oriented technical efficiency (CRS) was 86 percent in both VICC and SAMY (Table 7.2). This implies a possible increase of 14 to 20 percent in output at the same level of input.

Table 7.2 Average OTE_{CRS} and OTE_{VRS} for all farm regions over 1990-2016

Farm region (DMUs)	**OTE_{CRS}**	**OTE_{VRS}**
High AATFRs		
NSWN	0.85	0.95
NSWC	0.79	0.82
QLDD	0.95	0.97
WACS	0.94	0.96
Medium AATFRs		
NSWR	0.86	0.89
QLDE	0.97	0.98
SAEP	0.88	0.89
WANE	0.91	0.92
Low AATFRs		
VICM	0.80	0.82
VICW	0.81	0.92
VICC	0.86	0.92
SAMY	0.86	0.92
All ATFRs	0.87	0.91

For high AATFRs, output-oriented technical efficiency (VRS) ranged between a minimum of 82 percent in NSWC and a maximum of 97 percent in QLDD. Therefore, farmers in high AATFRs could increase their output by 3 to 18 percent using a similar level of inputs.

Average output-oriented technical efficiency (VRS) in the medium AATFRs varied between 89 percent in NSWR and SAEP and 98 percent in QLDE. This suggests a possible improvement of approximately 2 to 11 percent in outputs of these farm regions without any change in input levels. Mean output-oriented technical efficiency (VRS) for farms in low AATFRs ranged between 82 percent in VICM and 92 percent in VICW, VICC and SAMY. This implies a possible increase of 8 to 18 percent in output at the same level of input. The mean output-oriented technical efficiency (CRS) and output-oriented technical efficiency (VRS) of all AATFRs were 87 and 91 percent, respectively. This implies that, in general, farmers could have improved their output by 9 and 13 percent, respectively, with the same amount of input.

These findings imply that farms in the 12 farm regions were less efficient with respect to output-oriented technical efficiency (CRS) and output-oriented technical efficiency (VRS). Farms in QLDE were the most efficient whereas farms in NSWC were the least efficient. Farms in low AATFRs were mostly inefficient regarding output-oriented technical efficiency (CRS) and output-oriented technical efficiency (VRS). This suggests that temperature variation in the Wheat Belt regions of Australia may have a negative effect on crop outputs (Hughes et al. 2011). For example, wheat, which was the dominant crop in the study area, had the least output in the low AATFRs, whereas the medium AATFRs was the highest (Table 7.2). Farm managers have the chance to reach the best performance of the production frontier if they are able to adapt to temperature change by increasing their use of technology in the storage and transport of water and the preservation of soil moisture in areas with low rainfall.

7.3.1.2 Technical efficiencies scores

Output-oriented technical efficiency (CRS) and output-oriented technical efficiency (VRS) scores are presented in [3]Figures 7.1 to 7.4 and Table E.1, Appendix E. In the high AATFRs, the lowest and highest output-oriented technical efficiency (CRS) scores were, respectively, 25

[3] All thick horizontal axes in Figures 7.1 to 7.25 represent 100 percent efficiency line.

percent in NSWC in 2007 and 100 percent in the four farm regions in different years (Figure 7.1; Table E.1, Appendix E). QLDD recorded the highest count of fully efficient years, i.e. 22 out of 27 years (1990–1999, 2002–2012 and 2016) (Table E.1, Appendix E). Despite the high temperature in this farm region, the farmers were able to conserve soil moisture through the use of best-practice management on land and water; thus, the improvement in the productivity and efficiency in QLDD (DAFF 2014). Hughes, Lawson and Valle (2017) also found that some parts of QLD have experienced improvement in productivity since 2000–2001 due to favourable temperatures. Moreover, all four farm regions recorded 100 percent efficiency in 1990–1991, 1993–1994, 1999 and 2009 (Figures 7.1; Table E.1, Appendix E).

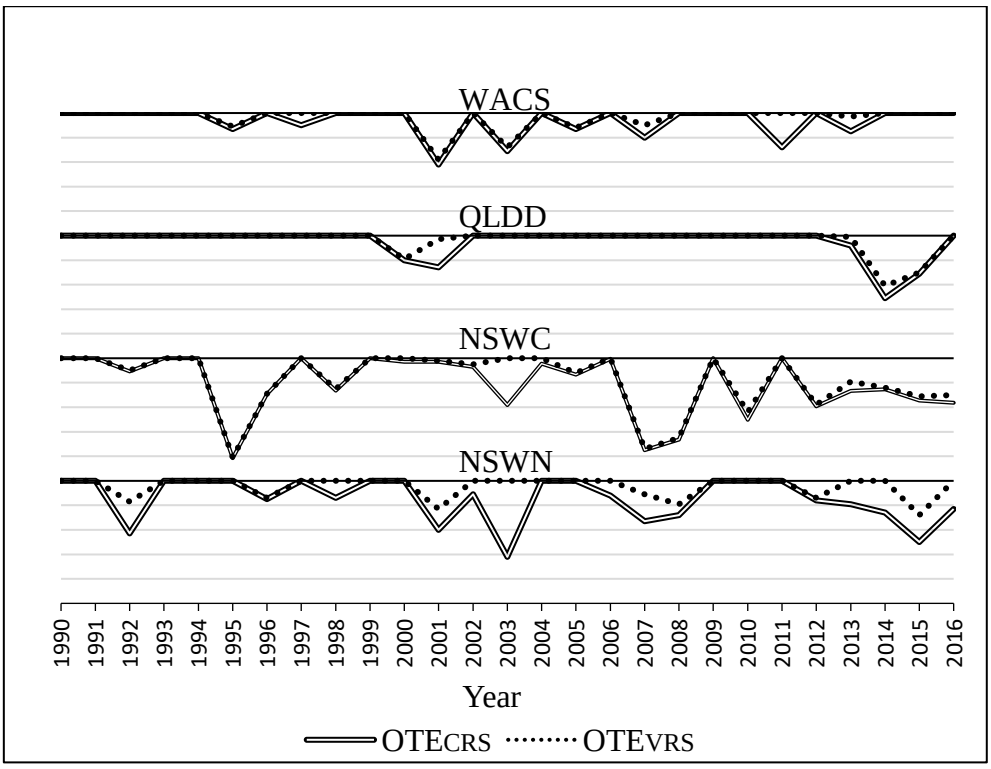

Figure 7.1 Overall and pure technical efficiency in high AATFRs

The output-oriented technical efficiency (CRS) scores in the medium AATFRs ranged from 25 percent in NSWR in 2008 to 100 percent in different farm regions and years (Figure 7.2; Table E.1, Appendix E). QLDE had the highest number of 100 percent (20 out of 27 years). Furthermore, it was observed that full efficiency was achieved in all four farm regions in 1990, 1992–1993, 1996, 1998–1999, 2004 and 2006. Therefore, the farmers in the medium AATFRs achieved higher possible productivity than farmers in other farm regions likely through the efficient control of production input quantities.

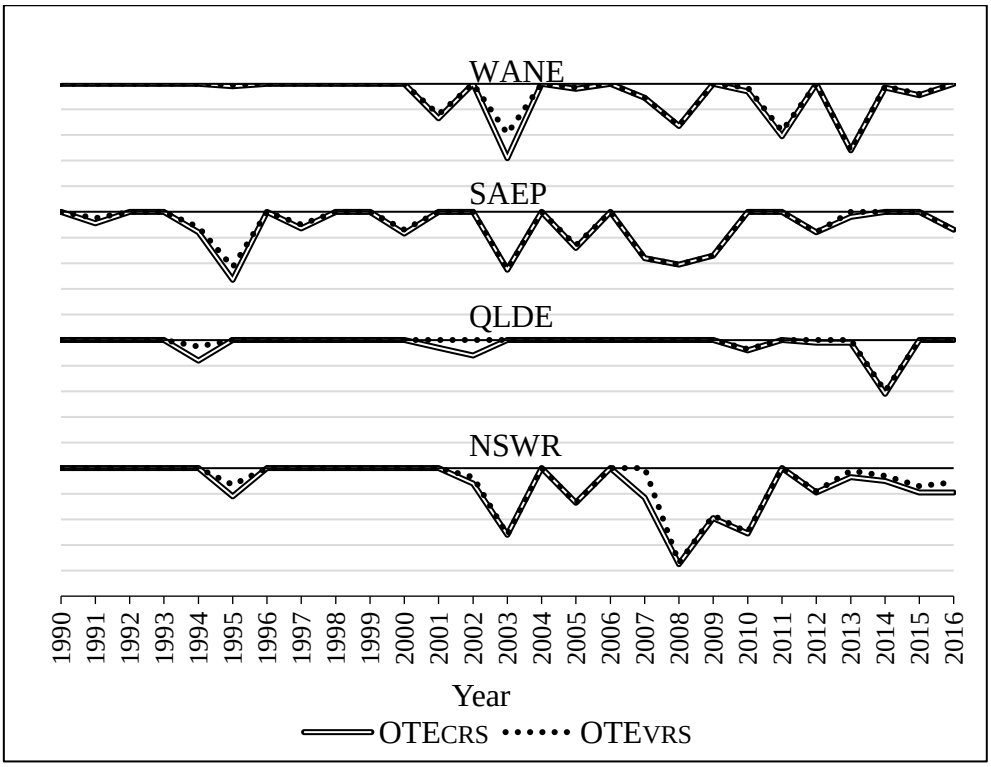

Figure 7.2 Overall and pure technical efficiency in medium AATFRs

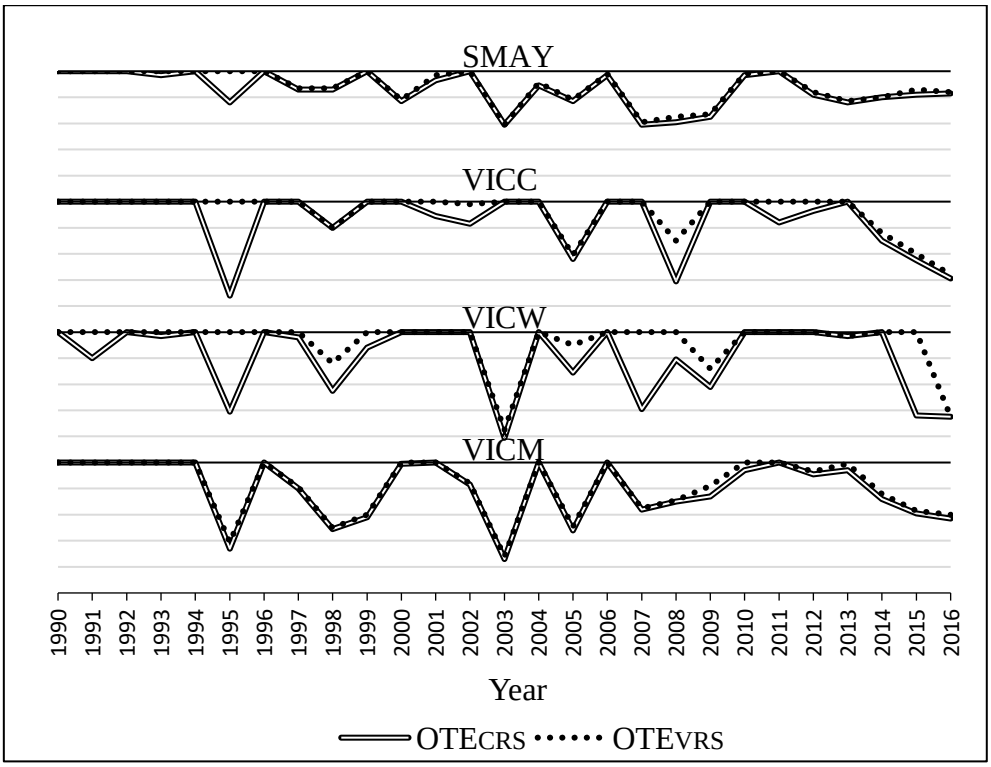

Figure 7.3 Overall and pure technical efficiency in low AATFRs

In low AATFRs, output-oriented technical efficiency (CRS) scores ranged between a minimum of 19 percent in 2003 in VICW and a maximum of 100 percent in different farm regions and years (Figure 7.3; Table E.1, Appendix E). Farm regions in VICC recorded 100 percent efficiency in 16 out of 27 years. Additionally, full efficiency was achieved in all four farm regions in 1990, 1992–1994 and 1996. Therefore, farmers in the low AATFRs were inefficient with respect to output-oriented technical efficiency (CRS) during the sample period. This could be due to high sensitivity of these farm regions to low temperature. Therefore, it may be useful for farmers to increase the use of technology in their agricultural operations to improve their overall efficiency.

The minimum and maximum output-oriented technical efficiency (VRS) scores in high AATFRs were 26 percent in NSWC in 2007 and 100 percent in all four farm regions, respectively, over the sample study period. In addition, NSWC achieve 100 percent efficiency in 1990–1991, 1993–1994, 1999–2000, 2003–2004, 2006, 2009 and 2011. Figure 7.1 shows that NSWC saw more reduction and inefficiency than the other three farm regions. This likely reveals that NSWC experienced a decrease in output due to the lack of sufficient moisture in the soil over the study period. Since this farm region shows high sensitivity to high temperature, it is particularly important to encourage farm managers to use technologies specific to the situation in their farm region.

Furthermore, in medium AATFRs, the lowest and highest output-oriented technical efficiency (VRS) scores were, respectively, 26 percent in NSWR in 2008 and 100 percent in all farm regions in different years (Figure 7.2; Table E.2, Appendix E). Additionally, it was observed that farm regions in QLDE recorded full efficiency in 24 out of 27 years in medium AATFRs (Table E.2, Appendix E). This confirms that these farm regions captured the best-practice production frontier due to favourable soil moisture and medium temperature level.

In the low AATFRs, output-oriented technical efficiency (VRS) scores ranged between a minimum of 25 percent in 2003 in VICW and a maximum of 100 percent in various farm regions and years. In 21 out of 27 years, farms in VICW achieved 100 percent output-oriented technical efficiency (VRS) (Table E.2, Appendix E). Therefore, farmers in this farm region have probably adapted to low temperature by changing the timing or location of their cropping activities.

The trend of output-oriented technical efficiency (CRS) and output-oriented technical efficiency (VRS) in all AATFRs showed the most fluctuation and lowest values over the study period (Figure 7.4). This reveals that there was significant variation in output quantity. Additionally, output-oriented technical efficiency (CRS) and output-oriented technical efficiency (VRS) dropped significantly in 1995, 2003, 2007 and 2008. Temperature change, change of evaporation rates and drought conditions most adversely affected crop productivity during these years (ABS 2012a; Che et al. 2012; Hughes et al. 2016; Steffen 2015).

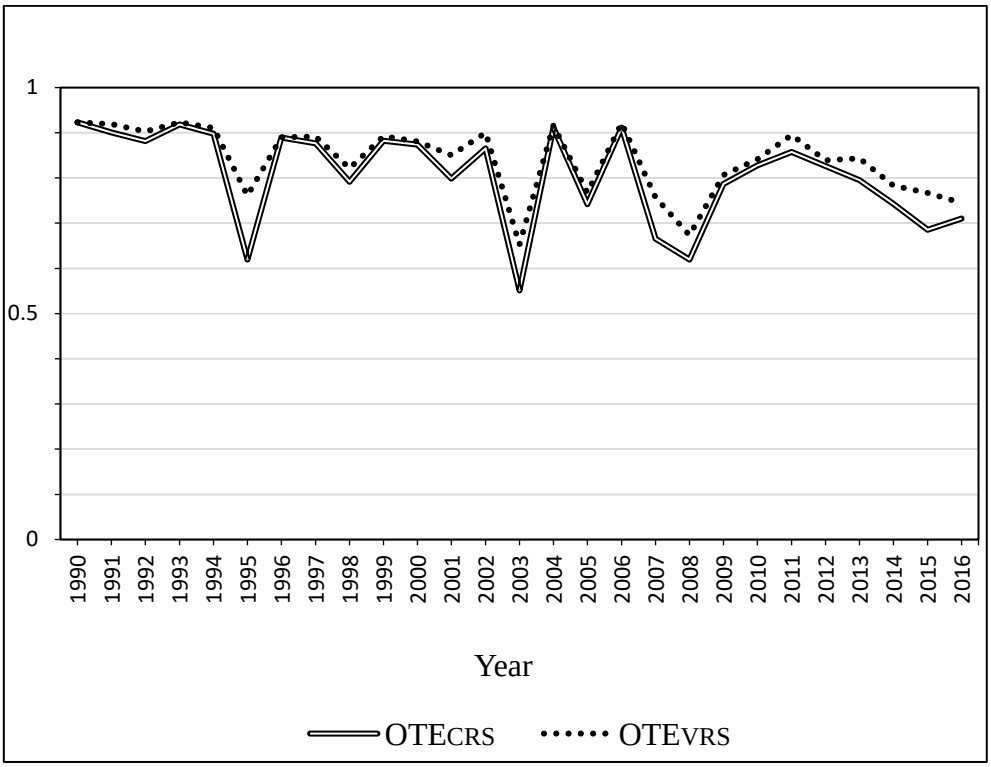

Figure 7.4 Overall and pure technical efficiency in all AATFRs

7.3.2 Scale efficiency

7.3.2.1 Average scale efficiency for all farm regions

For farms in high AATFRs, output-oriented scale efficiency ranged between a minimum of 89 percent in NSWN and a maximum of 98 percent in QLDD. Therefore, farmers in the high AATFRs, on average, could increase their scale efficiency by 2 to 11 percent by changing the production scale (Table 7.3). Mean output-oriented scale efficiency for farms in the medium AATFRs ranged between 97 percent in NSWR and 99 percent in QLDE and SAEP. On

average, this suggests a possible improvement of approximately 1 to 3 percent to obtain full scale efficiency by slight modification of farm size. In the low AATFRs, the average output-oriented scale efficiency of farms in VICW was the lowest (87 percent) whereas that of farms within SAMY was the highest (98 percent) (Table 7.3). Therefore, farms in low AATFRs could improve their output-oriented scale efficiency by 2 to 13 percent to reach the optimal scale (where OTE_{CRS} equals OTE_{VRS}) by adjusting the production scale.

Table 7.3 Average of OSE for all farm regions over 1990-2016

Farm region (DMUs)	**OSE**
High AATFRs	
NSWN	0.89
NSWC	0.96
QLDD	0.98
WACS	0.97
Medium AATFRs	
NSWR	0.97
QLDE	0.99
SAEP	0.99
WANE	0.98
Low AATFRs	
VICM	0.97
VICW	0.87
VICC	0.93
SAMY	0.98
All AATFRs	0.96

In all AATFRs, the average output-oriented scale efficiency was approximately 96 percent. Therefore, farmers in the Wheat Belt regions of Australia could improve their output-oriented scale efficiency by 4 percent by changing farm size. Overall, the highest average output-oriented scale efficiency was observed in QLDE and SAEP and the lowest was observed in VICW.

Although there were differences in study area and sample size, the average output-oriented scale efficiency of the present study was consistent with that of previous studies. Coelli, Rahman and Thirtle (2002) found a scale efficiency of 95 percent in Bangladesh rice cultivation, which was a similar result to the average of high AATFRs analysis in the present research. In addition, Tipi et al. (2009) also found that scale efficiency was 98 percent in the

Marmara region, Turkey. Moreover, the result in low AATFRs in the present study was similar to that of Abatania, Hailu and Mugera (2012) in a study of crop production in northern Ghana. Farms in medium AATFRs had the highest output-oriented scale efficiency (closest to 100 percent) because they were able expand their farm sizes appropriately to suit their temperature conditions (Table 7.1).

7.3.2.2 Scale efficiency Scores

Figures 7.5 to 7.8 and Table E.3 in Appendix E present variations in output-oriented scale efficiency scores over the study period (1990 to 2016) in each farm region under all AATFRs and the three levels of temperature (high, medium, and low AATFRs).

Estimates of output-oriented scale efficiency for farm regions in high AATFRs showed minimum and maximum scores of approximately 38 percent in 2003 in NSWN and 100 percent in all four farm regions over the study period, respectively (Table E.3, Appendix E). Furthermore, since output-oriented scale efficiency= OTE_{CRS}/OTE_{VRS}, a similar trend was observed among output-oriented technical efficiency (CRS), output-oriented technical efficiency (VRS) and output-oriented scale efficiency for QLDD (Figure 7.1 and Figure 7.5) over the study period. In addition, the trend of output-oriented scale efficiency for NSWN showed most fluctuation over the 27 years (Figure 7.5). The major type of soil found in NSWN is red soil (chromosols), which is low in soil organic carbon and therefore has poor soil structure. Additionally, soil carbon content is significantly affected by temperature change and other environmental factors (McLeod et al. 2013). This farm region (NSWN) is located in high AATFRs; therefore, crop production declined or at least varied from year-to-year.

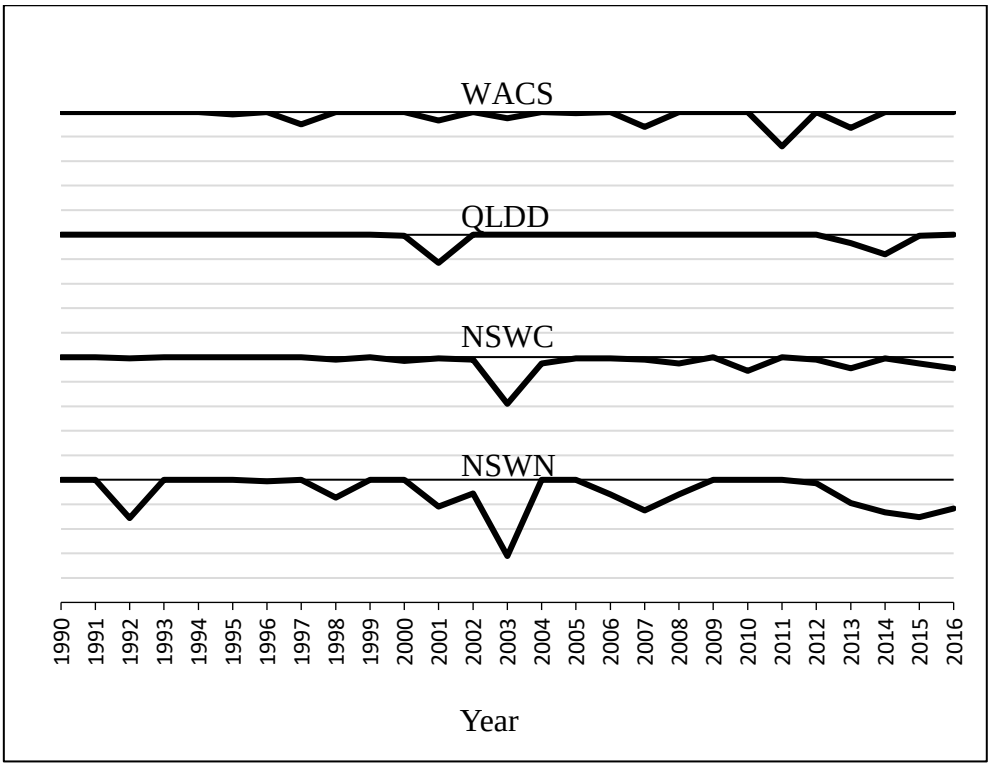

Figure 7.5 Scale efficiency in high AATFRs

The output-oriented scale efficiency scores of farms in the medium AATFRs ranged between 68 percent in 2003 in WANE and 100 percent in the four farm regions over the study period (Figure 7.6; Table E.3, Appendix E). QLDE recorded 100 percent efficiency in most years (20 out of 27 years) (Table E.3, Appendix E). This is because output-oriented technical efficiency (CRS) and output-oriented technical efficiency (VRS) of the farm region of QLDE were also the highest in the medium AATFRs. Crop area (wheat and non-wheat crop) was also highest in the medium AATFRs among the three temperature levels (Table 7.1). This confirms that it is possible for farm managers to increase their output-oriented scale efficiency by expanding their farm size.

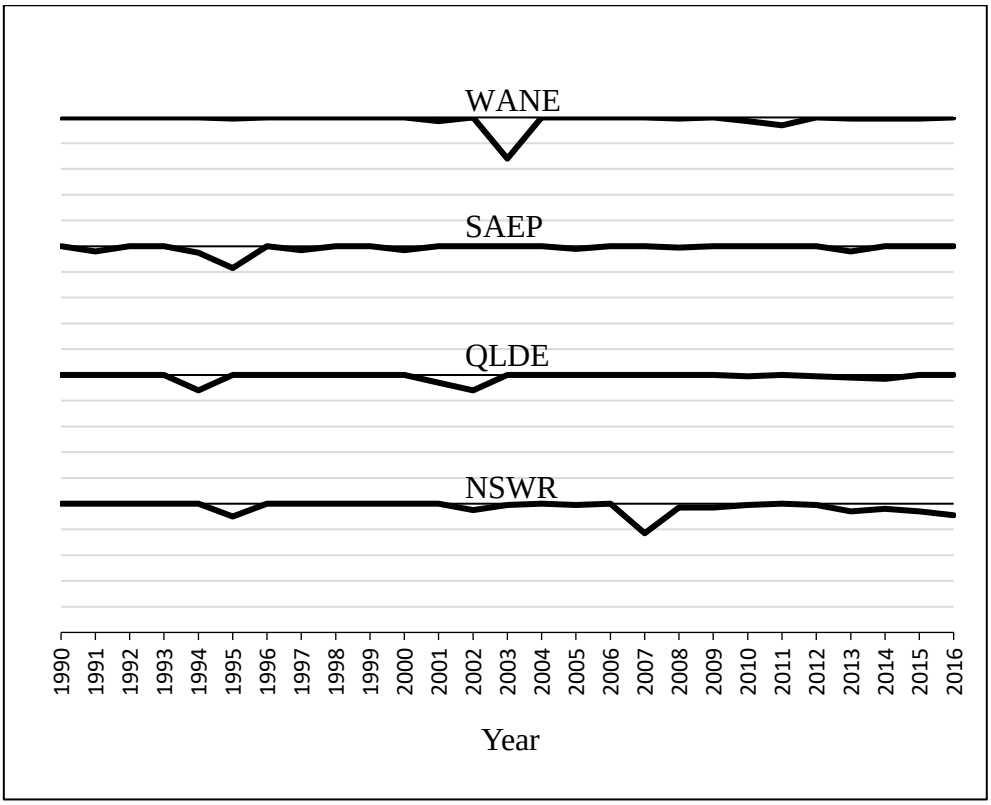

Figure 7.6 Scale efficiency in medium AATFRs

Output-oriented scale efficiency estimated for farm regions within low AATFRs ranged from approximately 36 percent in 2015 in VICW to 100 percent in all four farm regions in some years (Figure 7.7). VICC farm regions recorded 100 percent efficiency in 16 out of 27 years (Table E.3, Appendix E). In general, all farm regions experienced a decline in output-oriented scale efficiency in 1995 with the greatest decreases occurring in VICW and VICC. Although these farm regions are located in low AATFRs, drought conditions (i.e. low rainfall) might be one of the reasons that did not encourage farmers to expand their farm size. Evapotranspiration becomes worse when there is low rainfall, even under low temperature conditions. Additionally, it could be that farms located in VICW and VICC are more sensitive to low temperature than other farm regions.

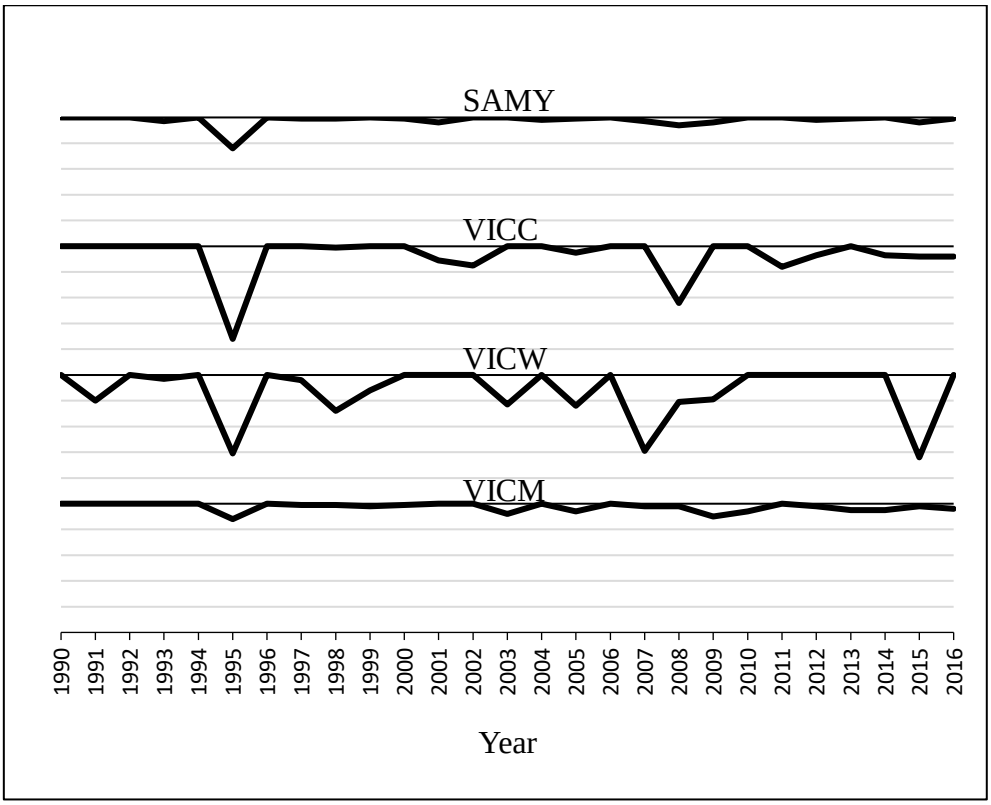

Figure 7.7 Scale efficiency in low AATFRs

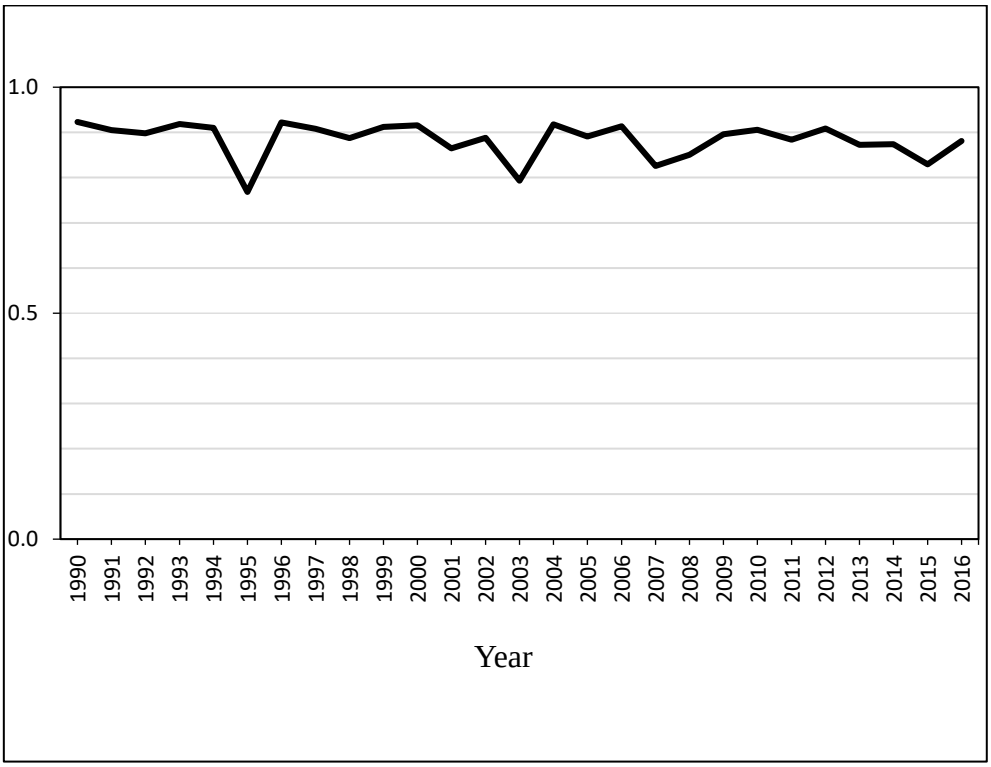

Figure 7.8 Scale efficiency in all AATFRs

Figure 7.8 shows scale efficiency (88 percent OSE) in all AATFRs. Average output-oriented scale efficiency was lowest (77 percent) in 1995 due to the drought. The scale inefficiency could be attributed to the inability of farmers to optimally expand their farm sizes for both wheat and non-wheat groups. Farmers in medium AATFRs were close to achieving full output-oriented scale efficiency because the mean of the land area of farms in medium AATFRs was the largest (872.41 ha) in comparison to high and low AATFRs (Table 7.1).

7.3.3 Mix efficiency

7.3.3.1 Average mix efficiency for all farm regions

Average mix efficiency of the farm regions under study are presented in Table 7.4. In high AATFRs, the average output-oriented mix efficiency was the lowest (95 percent) in NSWC and the highest (99 percent) in QLDD, which implies farms in high AATFRs could improve their output-oriented mix efficiency by 1 to 5 percent without having to change inputs if they were adjusting their mix of wheat and non-wheat output. In medium AATFRs, the average output-oriented mix efficiency ranged between 96 percent in NSWR and 97 percent in QLDE, SAEP and WANE. Therefore, farms in the high AATFRs could improve their output-oriented mix efficiency by 3 to 4 percent with the given amount of input by changing the proportion of output mix (wheat and non-wheat).

Table 7.4 Average OME for all farm regions over 1990–2016

Farm region (DMUs)	OME
High AATFRs	
NSWN	0.97
NSWC	0.95
QLDD	0.99
WACS	0.98
Medium AATFRs	
NSWR	0.96
QLDE	0.97
SAEP	0.97
WANE	0.97
Low AATFRs	
VICM	0.96
VICW	0.99
VICC	0.99
SAMY	0.99
All AATFRs	0.97

For low AATFRs, the output-oriented mix efficiency ranged between a minimum of 96 percent in VICM and a maximum of 99 percent in VICW, VICC and SAMY. Therefore, farmers could improve their output-oriented mix efficiency by 1 to 4 percent without increasing their amounts of input by a re-mix of crop output ratios. This confirms that these farm regions were very close to the optimal mix of crop outputs.

The average output-oriented mix efficiency in all AATFRs was approximately 97 percent. This suggests that output-oriented mix efficiency in the 12 farm regions in Australian Wheat Belt may be optimised by increasing output-oriented mix efficiency by only 3 percent by mixing wheat and non-wheat crops more efficiently.

7.3.3.2 Mix efficiency Scores

Figures 7.9 to 7.12 and Table E.4 in Appendix E present mix efficiency scores. In the high AATFRs, the lowest and highest output-oriented mix efficiency scores were, respectively, 63 percent in NSWC in 2008 and 100 percent in the four farm regions in different years (Figure 7.9; Table E.4, Appendix E). The lowest frequency of full output-oriented mix efficiency was observed in NSWC in the years 1990–1991, 1993–1994, 1996–1997, 1999, 2003–2004, 2006 and 2011. QLDD recorded the highest number of years (24 out of 27 years) with full efficiency in mixing different proportions of crop products. Furthermore, trends of output-oriented mix efficiency scores for the farm region of NSWC in high AATFRs showed high variabilities over the sample period compared to QLDD (Figure 7.9).

The output-oriented mix efficiency of three farm regions (QLDD, NSWC and NSWN) dropped slightly in 2001. DAFF (2014) and McLeod et al. (2013) stated that these farm regions may have experienced issues associated with soil health from season to season, which likely had a significant influence on crop output mix in 2001.

The output-oriented mix efficiency scores in the medium AATFRs ranged from 66 percent in NSWR in 2008 and 100 percent in the four regions in different years. Over the 27 years, farms were fully efficient with respect to output-oriented mix efficiency in 16 years in NSWR, SAEP and WANE and 21 years in QLDE (Figure 7.10; Table E.4, Appendix E). Thus, farmers in QLDE performed well in mixing wheat and non-wheat crops appropriately for the prevailing temperature. Figure 7.10 shows that all farm regions in medium AATFRs had different trends

over the study period. This suggests that the farm regions followed different plans in mixing their crop outputs.

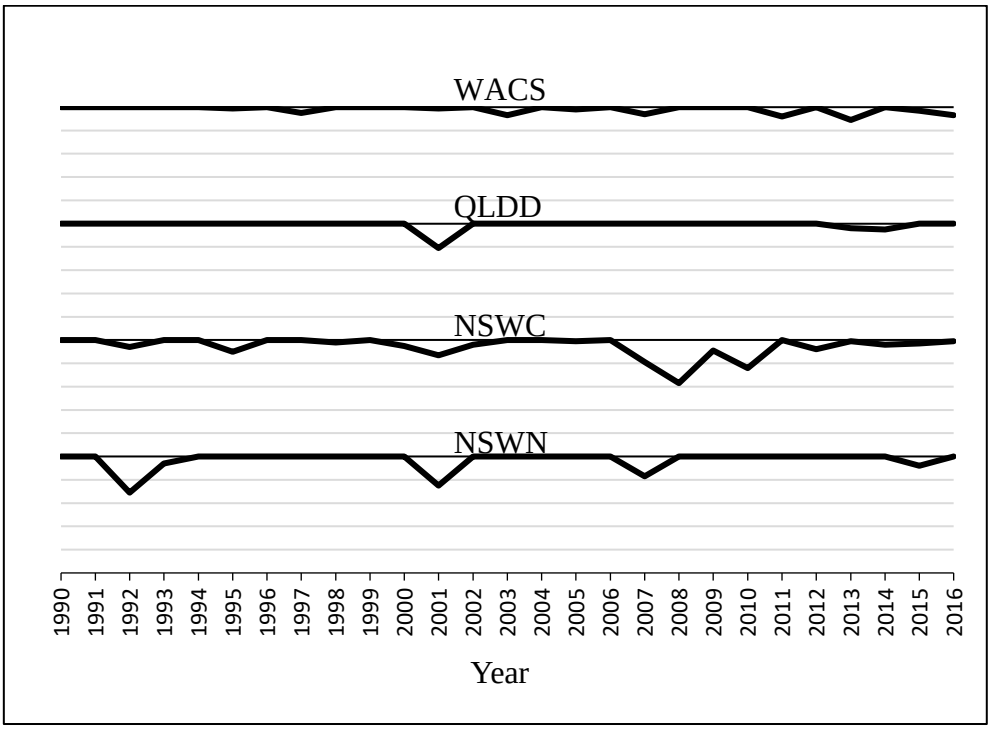

Figure 7.9 Mix efficiency in high AATFRs

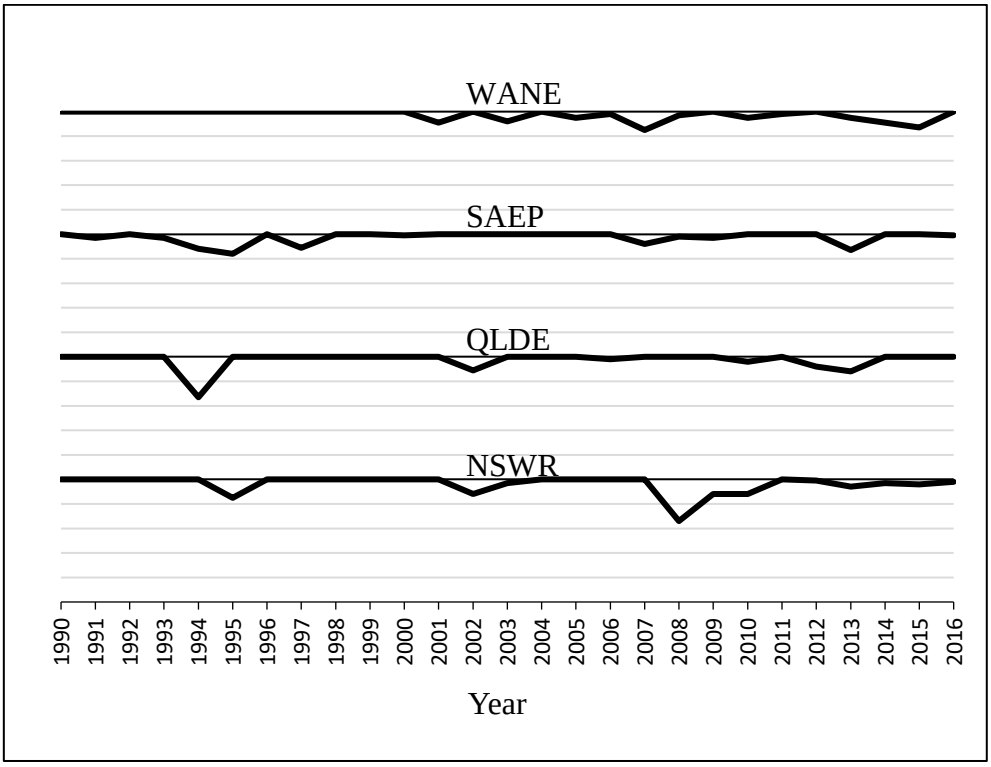

Figure 7.10 Mix efficiency in medium AATFRs

The output-oriented mix efficiency estimated for farm regions within low AATFRs ranged from approximately 83 percent in 2007 and 2013 in VICM to 100 percent in all four farm regions in varying years (Figure 7.11). VICW recorded 100 percent efficiency in 21 out of 27 years (Table E.4, Appendix E). Figure 7.11 indicates that although VICW, VICC and SAMY had varying numbers of years with full efficiency, they were most stable in the low AATFRs over the study period. This might be a reflection of farmers in these regions being able to achieve an optimal mix of crop cultivation during most of the sample period by adapting to low temperature using modern technology in their farming activities. Furthermore, farmers in the low AATFRs recorded the highest crop yields of 1.62 t/ha (Table 7.1) because they experienced increase in crop prices (Figure A.1c, Appendix A), which likely encouraged them to increase production.

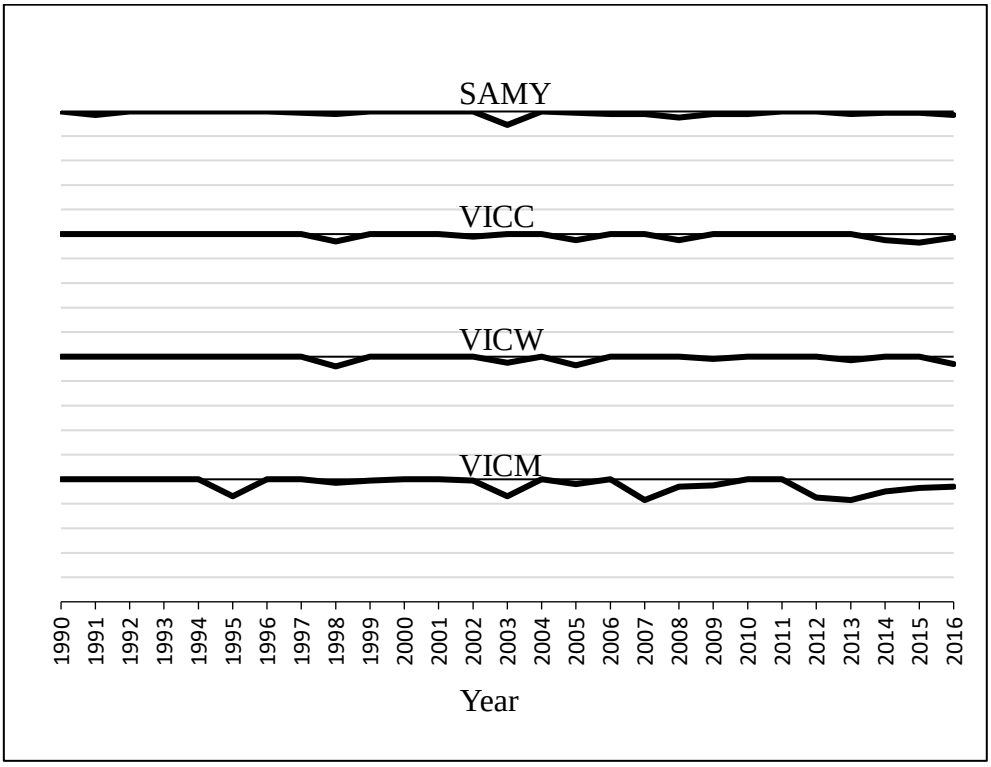

Figure 7.11 Mix efficiency in low AATFRs

In all AATFRs, output-oriented mix efficiency scores ranged between a minimum of 92 percent in 2008 and a maximum of 100 percent in 1990–1991, 1996, 1999–2000, 2004 and 2006 (Table E.4, Appendix E). Generally, it was observed that farmers of the 12 farm regions did not achieve full mix efficiency in many years during the sample period (Figure 7.12). However,

there is still potential to achieve 100 percent mix efficiency by considering temperature change and its influence on the soil moisture when mixing crop outputs.

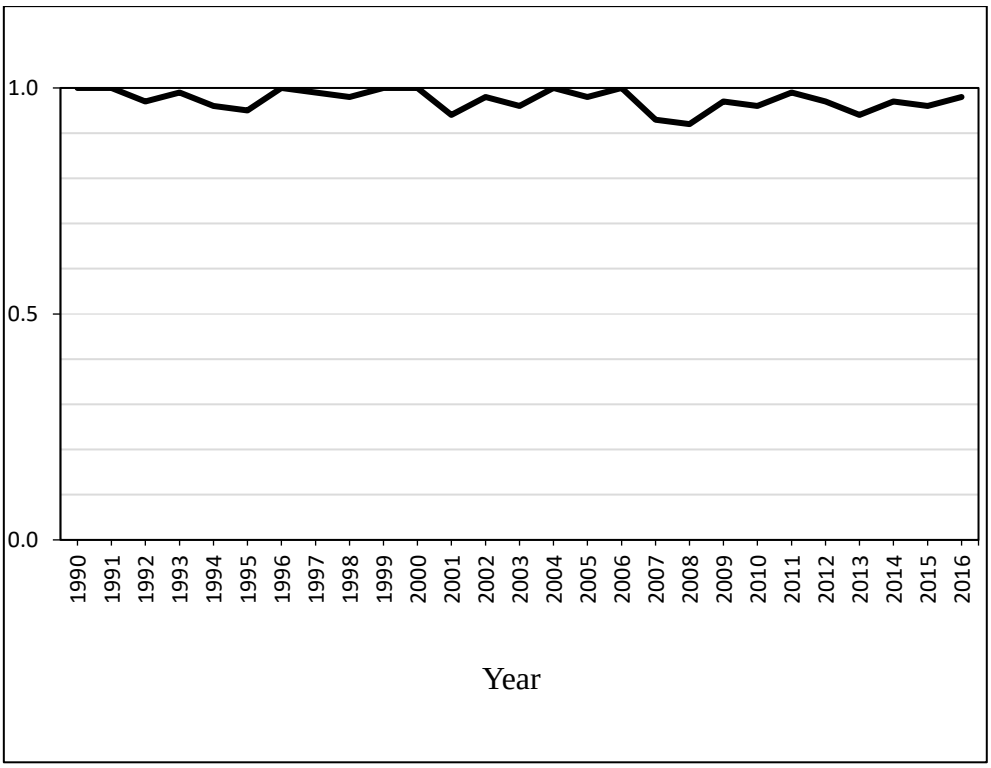

Figure 7.12 Mix efficiency in all AATFRs

7.3.4 Residual output-oriented scale efficiency

7.3.4.1 Average residual output-oriented scale efficiency for all farm regions

Residual output-oriented scale efficiency is a measure of scale efficiency and may contain a residual mix effect (O'Donnell 2010). Table 7.5 presents average residual output-oriented scale efficiency of all farm regions under study from 1990 to 2016. In the high AATFRs, average residual output-oriented scale efficiency ranged between a minimum of 54 percent in QLDD and a maximum of 87 percent in WACS. Therefore, farms in high AATFRs could improve their residual output-oriented scale efficiency by 13 to 46 percent to obtain the best scale and residual effects by changing output and input mixes (Table 7.5). Low residual output-oriented scale efficiency recorded in high AATFRs could imply that farmers did not capture the benefit

(residual) of change in the input/output mix over the study period. Average residual output-oriented scale efficiency, in medium AATFRs, varied between 57 percent in QLDE and 84 percent in SAEP. Farms in medium AATFRs can, therefore, improve their residual output-oriented scale efficiency by 16 to 43 percent by changing output and input mixes with existing technology (Table 7.5).

Table 7.5 Average ROSE for all farm regions over 1990–2016

Farm region (DMUs)	ROSE
High AATFRs	
NSWN	0.79
NSWC	0.86
QLDD	0.54
WACS	0.87
Medium AATFRs	
NSWR	0.80
QLDE	0.57
SAEP	0.84
WANE	0.79
Low AATFRs	
VICM	0.87
VICW	0.77
VICC	0.54
SAMY	0.89
All AATFRs	0.76

Mean residual output-oriented scale efficiency for farms in low AATFRs ranged between 89 percent in SAMY and 54 percent in VICC. Therefore, farmers within low AATFRs could increase their residual output-oriented scale efficiency by 11 to 46 percent to obtain the optimal scale and residual effects when they appropriately change their output and input mixes. Generally, farm regions in low and high AATFRs have a better chance of obtaining full efficiency when they have the flexibility to change the input and output mix during the production process to obtain the remaining (residual) benefit. The average residual output-oriented scale efficiency of both low and high AATFRs was 77 percent, which was greater than the medium AATFRs (75 percent).

The mean residual output-oriented scale efficiency of all AATFRs was 76 percent. Therefore, all farmers in the Wheat Belt regions of Australia could improve their average residual output-oriented scale efficiency by 24 percent when they are able to capture the positive scale and

residual effects. Farmers in SAMY were the most efficient regarding residual output-oriented scale efficiency, whereas farmers in QLDD and VICC were the least efficient.

7.3.4.2 Residual output-oriented scale efficiency Scores

Figures 7.13 to 7.16 and Table E.5 in Appendix E present the results of differences in residual output-oriented scale efficiency scores over the sample period. The residual output-oriented scale efficiency scores in the high AATFRs ranged between 27 percent in NSWN and NSWC in 1995 and 2003, respectively, to 100 percent in all four farm regions but only during a few years of the study period (Figure 7.13; Table E.5, Appendix E). All four farm regions in high AATFRs experienced a decline in residual output-oriented scale efficiency. Additionally, Table E.5 in Appendix E shows that farmers in NSWN, NSWC and WACS achieved full efficiency in 4 out of 27 years, whereas farmers in QLDD were fully efficient in only 1 out of 27 years. Farmers in QLDD faced problems with the soil moisture from time to time (DAFF 2014). Moreover, the residual output-oriented scale efficiency of all farm regions in the high AATFRs fluctuated dramatically over the study period (Figure 7.13). This evidence could confirm that farmers did not capture residual advantages via the process of changing the input/output mix. Residual output-oriented scale efficiency scores dropped in 1995 and 2003 in NSWN, NSWC and QLDD relatively (Figure 7.13). These shortfalls in residual output-oriented scale efficiency could be attributed to conditions beyond the control of farmers, such as high temperature and decreased rainfall (Che et al. 2012), which led to a deterioration of soil moisture.

For medium AATFRs, the residual output-oriented scale efficiency scores ranged from 33 percent in 2007 and 2001 in NSWR and QLDE, respectively, to 100 percent in NSWR in 2006; QLDE in 2008; SAEP in 1990, 1993, 1994 and 1997; and WANE in 1994, 2000 and 2004 (Figure 7.14; Table E.5, Appendix E). Farms in NSWR and QLDE achieved 100 percent residual output-oriented scale efficiency only in 2006 and 2008, respectively (Figure 7.14).

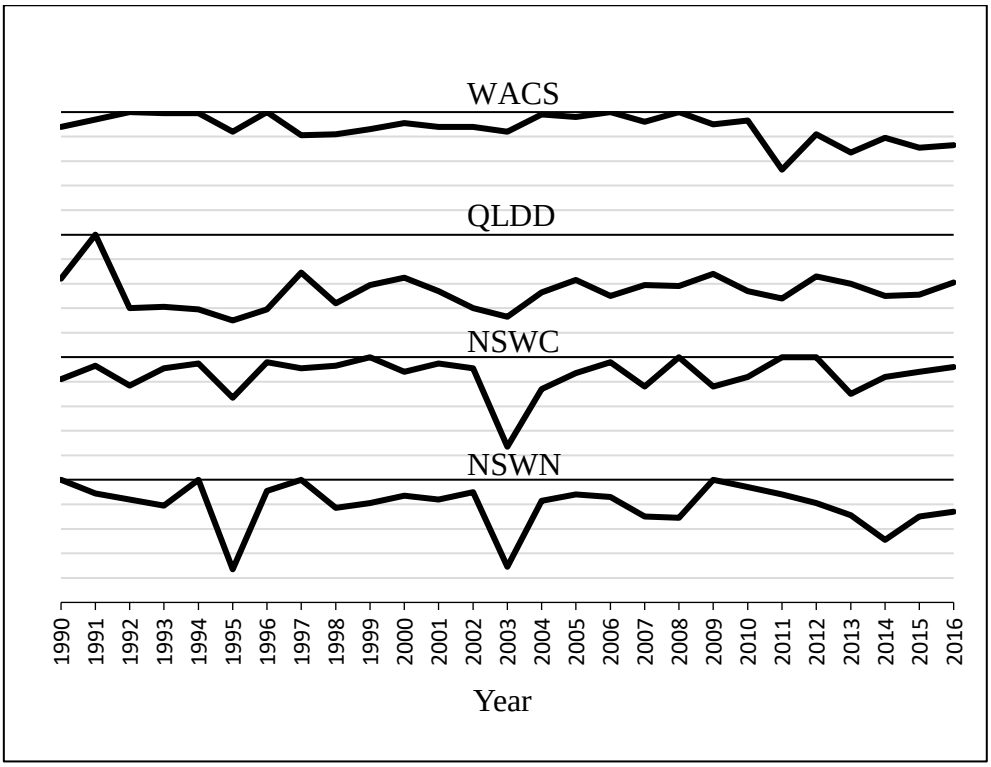

Figure 7.13 Residual output-oriented scale efficiency in high AATFRs

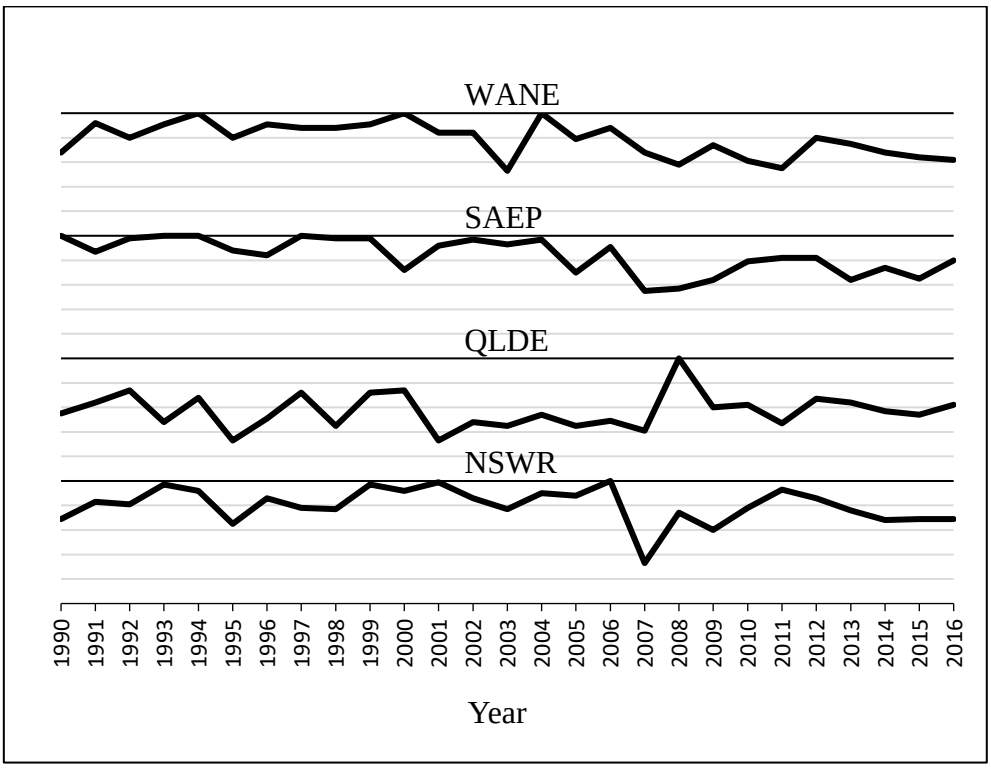

Figure 7.14 Residual output-oriented scale efficiency in medium AATFRs

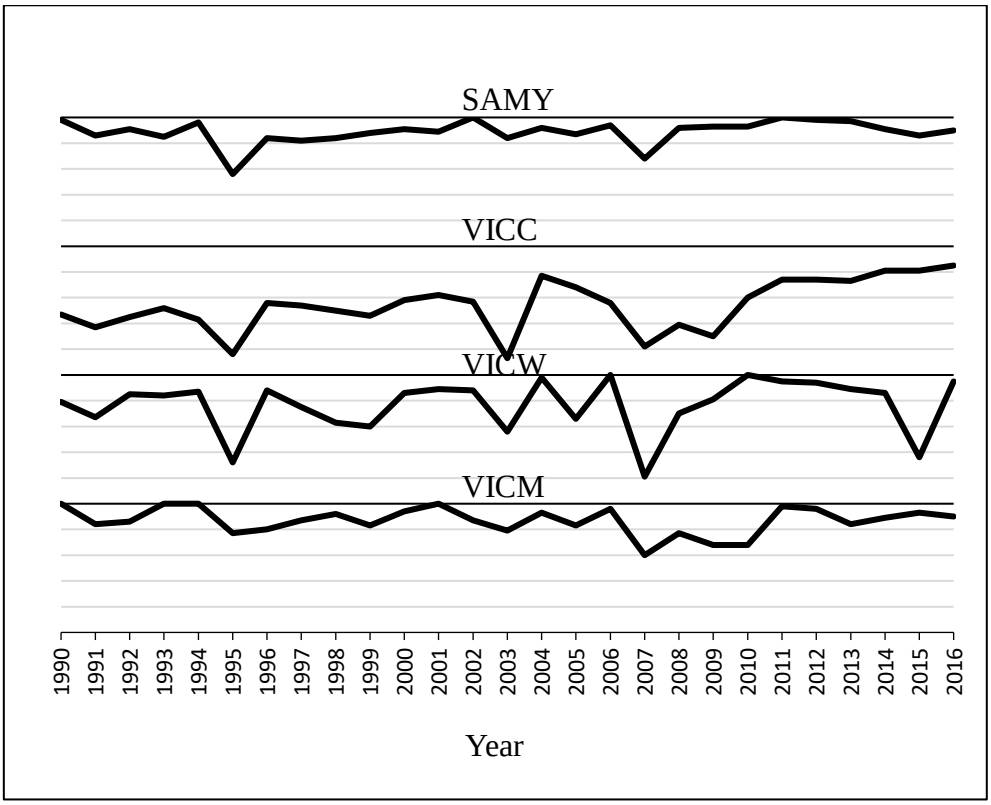

Figure 7.15 Residual output-oriented scale efficiency in low AATFRs

The lowest score of residual output-oriented scale efficiency (13 percent in 2003) in the low AATFRs was recorded in VICC, whereas the highest score (100 percent) was recorded in the three other farm regions (Figure 7.15; Table E.5, Appendix E). Furthermore, although farms in VICC had higher scale effect scores, residual output-oriented scale efficiency was not 100 percent in any year over the study period (Figure 7.15). This could suggest that farmers captured the advantage of scale effect but were not able to capture the residual mix effect. Besides, the residual output-oriented scale efficiency of all farm regions in low AATFRs reduced in 1995, 2003 and 2007. This could be due to drought during those years (ABS 2012a; Che et al. 2012; Hughes et al. 2016; Steffen 2015) which may have affected the distribution of resources and productivity.

A maximum residual output-oriented scale efficiency of 84 percent (in 2004, 2006 and 2012) and a minimum of 55 percent (in 1995 and 2007) were found in all AATFRs (Table E.5, Appendix E). Residual output-oriented scale efficiency was less than 85 percent in all AATFRs throughout the study period. This implies that the Wheat Belt regions of Australia were inefficient regrading residual output-oriented scale efficiency during the last three decades. In addition, all AATFRs experienced drastic decline (around 55 percent) in residual

output-oriented scale efficiency scores in 1995, 2003 and 2007, which might have been due to the adverse impact of temperature change especially on soil moisture because of the unpredictable nature of climatic conditions.

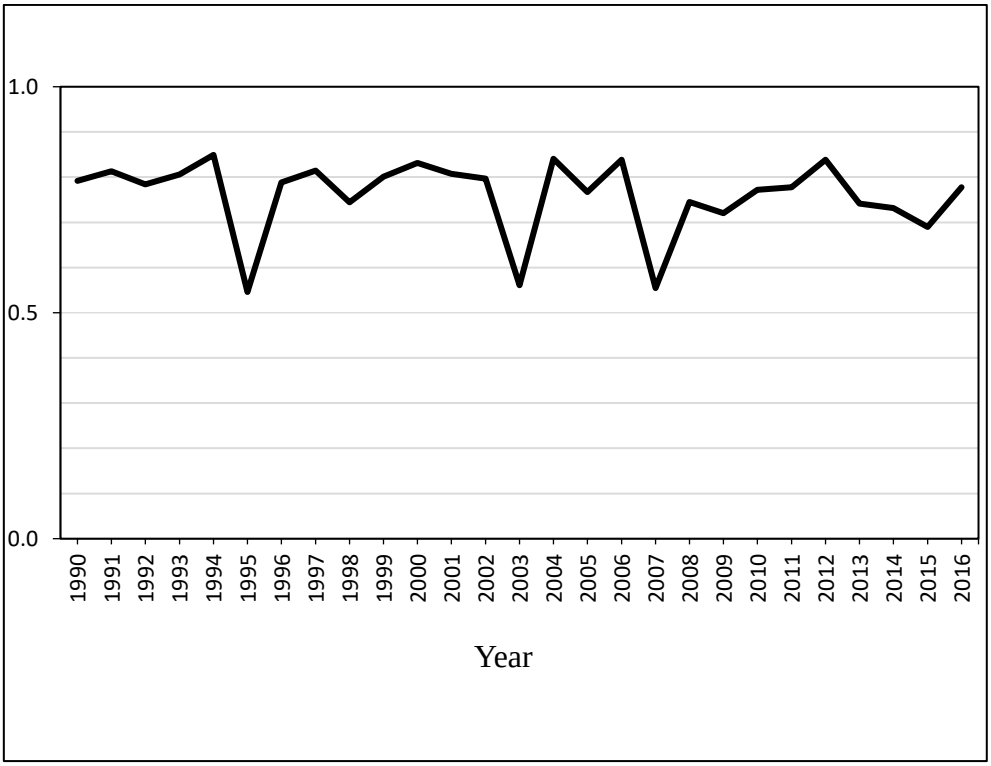

Figure 7.16 Residual output-oriented scale efficiency in all AATFRs

7.3.5 Scale and mix efficiency

7.3.5.1 Average scale and mix efficiency for all farm regions

Average output-oriented scale-mix efficiency estimated for all 12 farm regions over the 27-year study period are presented in Table 7.7. According to O'Donnell (2012c, 2016), output-oriented scale-mix efficiency measures the improvements in productivity related to the economies of scale and scope. In high AATFRs, output-oriented scale-mix efficiency, on average, ranged between a minimum of 53 percent in QLDD and a maximum of 86 percent in WACS. Therefore, farmers could improve their output-oriented scale-mix efficiency by 14 to 47 percent by changing the farm size and mix of the wheat and non-wheat ratio.

In medium AATFRs, average output-oriented scale-mix efficiency ranged between 56 percent in QLDE and 82 percent in SAEP. Therefore, farmers in medium AATFRs could improve their

output-oriented scale-mix efficiency by 18 to 44 percent to capture the optimal economies of scale and scope by altering their output mixes and farm size.

Average output-oriented scale-mix efficiency in the low AATFRs was lowest (53 percent) in VICC and highest (87 percent) in SAMY. Farm regions in the low AATFRs could improve their output-oriented scale-mix efficiency by 13 to 47 percent by adjusting the production scale and proportion of output mix (i.e. wheat and non-wheat).

Table 7.6 Average OSME for all farm regions over 1990–2016

Farm region (DMUs)	**OSME**
High AATFRs	
NSWN	0.77
NSWC	0.81
QLDD	0.53
WACS	0.86
Medium AATFRs	
NSWR	0.77
QLDE	0.56
SAEP	0.82
WANE	0.77
Low AATFRs	
VICM	0.83
VICW	0.76
VICC	0.53
SAMY	0.87
All AATFRs	0.74

Average output-oriented scale-mix efficiency of all AATFRs was 74 percent over the period 1990 to 2016, which suggests that farm managers were inefficient with respect to output-oriented scale-mix efficiency. Therefore, they could have faced problems in capturing the economies of scale and scope. Seasonal temperature variability can occur across farm regions and can have negative effect on economies of scale and scope when farmers change their output mixes. Over 27 years, the average of output-oriented scale-mix efficiency for high, medium and low AATFRs was 0.74, 0.73 and 75 percent, respectively (Table 7.6). Therefore, farmers in low AATFRs had the highest output-oriented scale-mix efficiency.

7.3.5.2 Scale and mix efficiency Scores

Figures 7.17 to 7.20 and Table E.6 in Appendix E present the output-oriented scale-mix efficiency scores in all farm regions for each temperature level. Output-oriented scale-mix efficiency was estimated by multiplying output-oriented mix efficiency and residual output-oriented scale efficiency. For high AATFRs, the output-oriented scale-mix efficiency scores ranged from 27 percent in 1995 and 2003 in NSWN and NSWC, respectively, to 100 percent in NSWN in 1990, 1994, 1997 and 2009; NSWC in 1999 and 2011; QLDD in 1991; and WACS in 1992, 1996, 2006 and 2008. QLDD farms did not achieve full output-oriented scale-mix efficiency in only one year (1991). This could suggest that the soils for the farms in QLDD are sensitive to environmental change, such as temperature change. Recall that farmers in QLDD experienced problems related to their residual output-oriented scale efficiency (Figure 7.13) despite recording 100 percent output-oriented technical efficiency (CRS) and output-oriented technical efficiency (VRS) (Figure 7.1) in many years. According to DAFF (2014), farmers in QLDD are faced with soil degradation and loss of crop land due to worsening of environmental changes. Additionally, the output-oriented scale-mix efficiency scores were highly variable over the study period in general. These scores were relatively low in 1995, 2003 and 2007. Che et al. (2012) stated that 1995, 2002–2003 and 2007–2008 were drought years (i.e. low rainfall level).

The output-oriented scale-mix efficiency scores in the medium AATFRs varied between the lowest of 33 percent in NSWR (2007) and QLDE (1995 and 2001) and full efficiency in NSWR (2006); QLDE (2008); SAEP (1990) and WANE (1994, 2000 and 2004) (Figure 7.18; Table E.6, Appendix E). Output-oriented scale-mix efficiency was low and dramatically fluctuated in the medium AATFRs from 1990 to 2016.

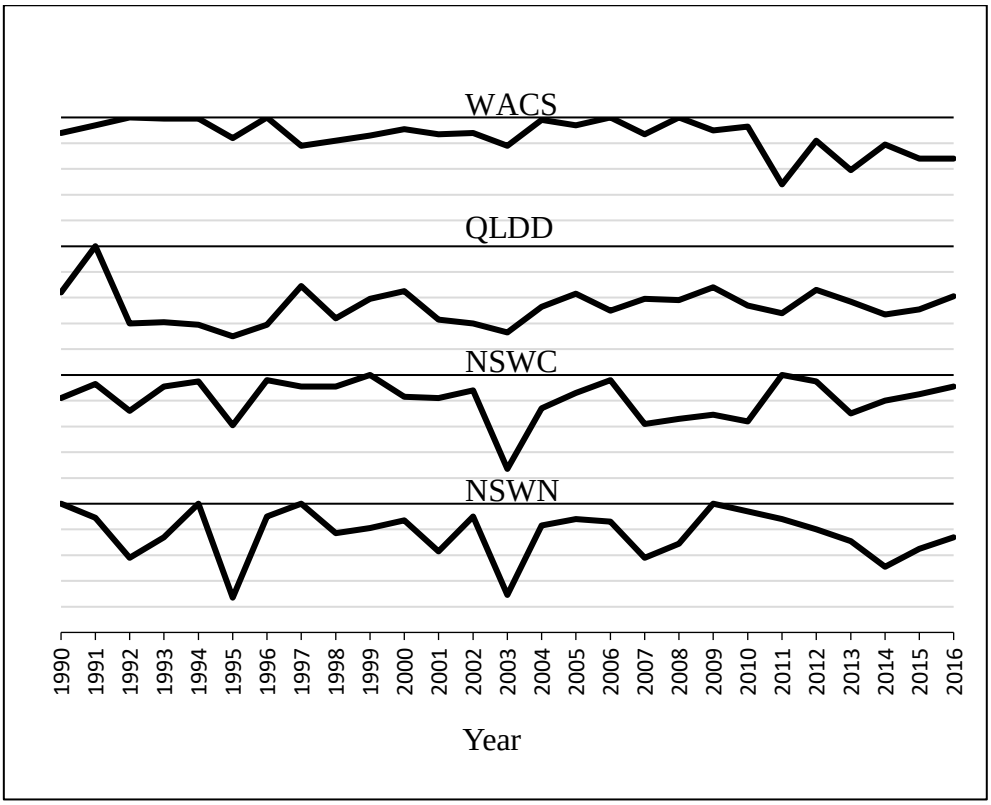

Figure 7.17 Scale and mix efficiency in high AATFRs

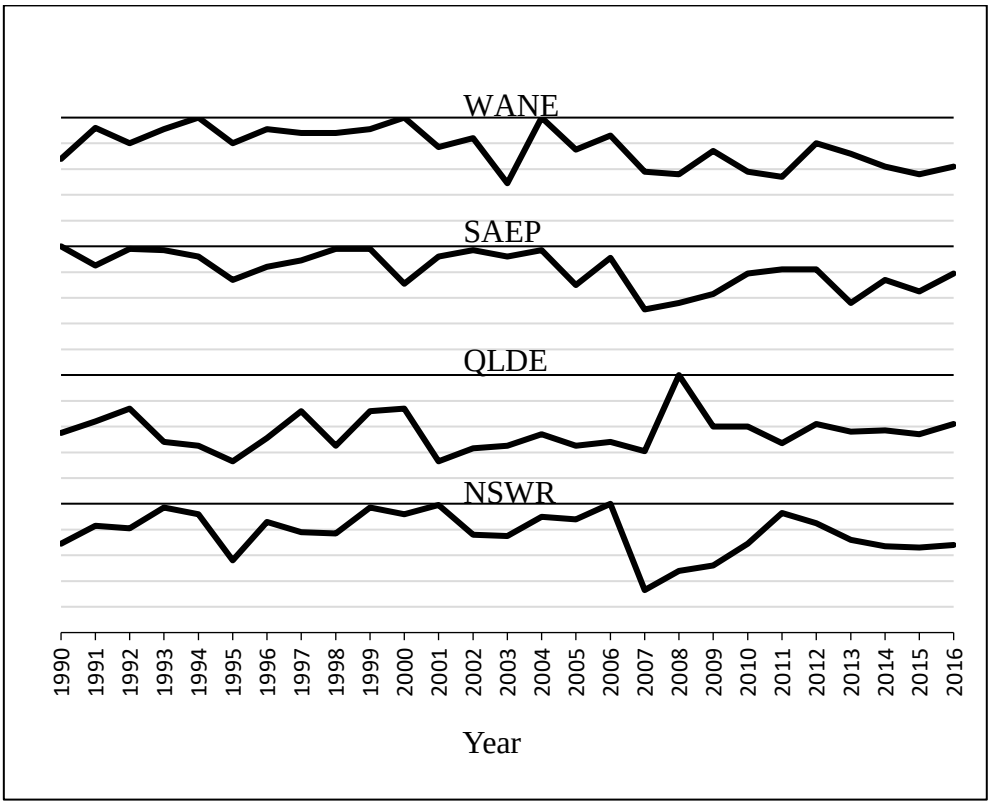

Figure 7.18 Scale and mix efficiency in medium AATFRs

In low AATFRs, output-oriented scale-mix efficiency scores ranged between a minimum of 13 percent in VICC (2003) and a maximum of 100 percent in VICM (1990, 1993–1994 and 2001); VICW (2006 and 2010) and SAMY (2002 and 2011) (Figure 7.19; Table E.6, Appendix E). Throughout the study period, the highest output-oriented scale-mix efficiency achieved by farmers in VICC was 77 percent (Figure 7.19; Table E.6 in Appendix E). This could have happened because farmers in VICC were inefficient with respect to residual output-oriented scale efficiency over the study period (Figure 7.15). Additionally, the output-oriented scale-mix efficiency of farms located in low AATFRs declined during 1995, 2003 and 2007.

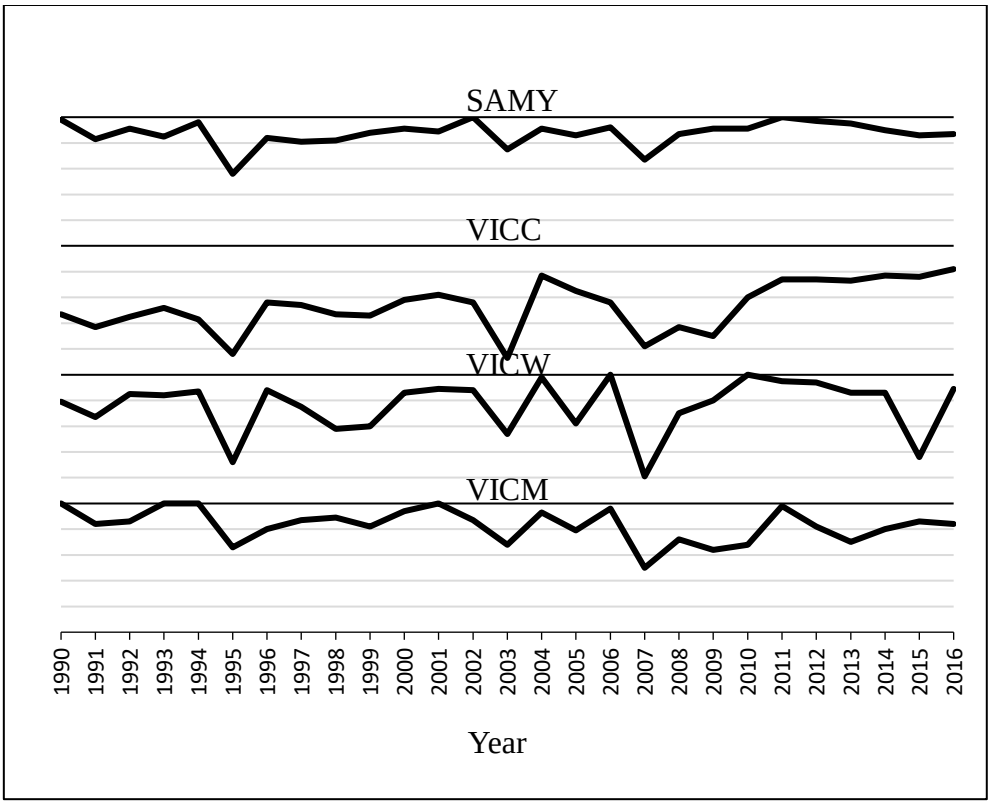

Figure 7.19 Scale and mix efficiency in low AATFRs

Figure 7.20 shows that output-oriented scale-mix efficiency scores of all AARFRs ranged between 51 percent in 1995 and 2007 and 84 percent in 2004. Because of prior explanation, output-oriented scale-mix efficiency of all farm regions fell in 1995, 2003 and 2007.

Recall that OSME = OME × ROSE (or OSME = TSME/ OTE_{VRS}). Output-oriented scale-mix efficiency in the high, medium and low AATFRs was 100 percent in similar years as those of residual output-oriented scale efficiency . Therefore, output-oriented scale-mix efficiency was more influenced by residual output-oriented scale efficiency than it was by output-oriented mix

efficiency. Thus, to improve output-oriented scale-mix efficiency (economies of scale and scope of production) farmers must pay more attention to increasing residual output-oriented scale efficiency.

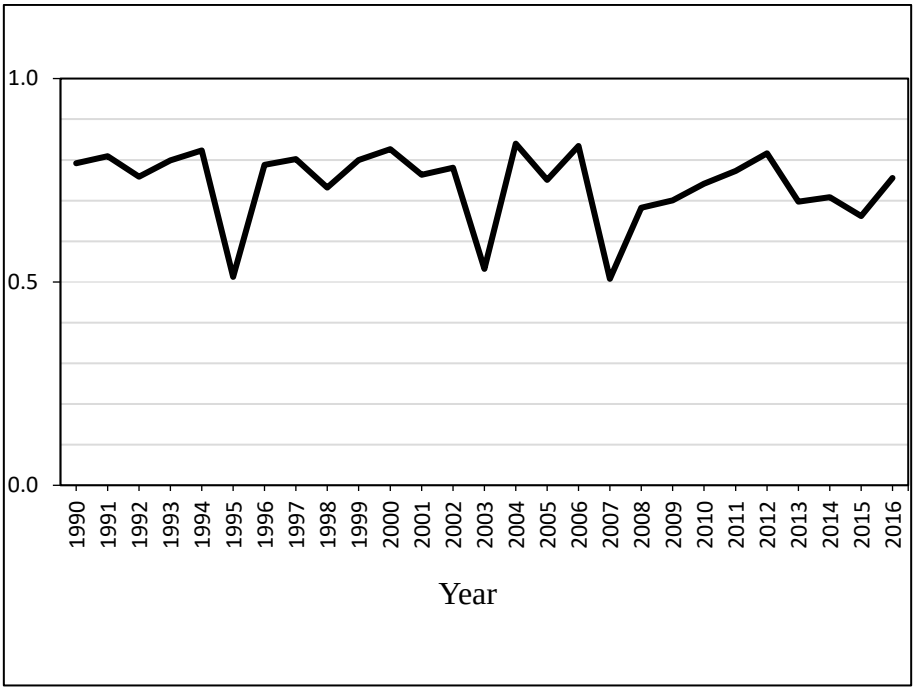

Figure 7.20 Scale and mix efficiency in all AATFRs

7.3.6 Technical and scale-mix efficiency

7.3.6.1 Average technical and scale-mix efficiency for all farm regions

Table 7.7 presents the average technical and scale-mix efficiency of all farm regions under study from 1990 to 2016. Average technical and scale-mix efficiency, in the high AATFRs, varied between 52 percent in QLDD and 83 percent in WACS. Therefore, there is opportunity for farm managers in high AARFRs to improve their technical and scale-mix efficiency by 17 to 48 percent to reach maximum TFP when they have free options related to outputs and inputs with the use of the available technology.

In the medium AATFRs, average technical and scale-mix efficiency ranged between a minimum of 54 percent in QLDE and a maximum of 74 percent in SAEP. Therefore, farmers could improve their technical and scale-mix efficiency by 26 to 46 percent to obtain the maximum TFP related to the optimal scale of operations (adjusting output mix and/or input

mix) with existing technology. Thus, farm managers did not use their existing technologies and also did not vary their output mix and/or input mix (scale of operations) optimally.

Table 7.7 Average TSME for all farm regions over 1990–2016

Farm region (DMUs)	TSME
High AATFRs	
NSWN	0.74
NSWC	0.68
QLDD	0.52
WACS	0.83
Medium AATFRs	
NSWR	0.70
QLDE	0.54
SAEP	0.74
WANE	0.72
Low AATFRs	
VICM	0.69
VICW	0.71
VICC	0.48
SAMY	0.77
All AATFRs	0.68

Mean technical and scale-mix efficiency for farms in the low AATFRs ranged between 48 percent in VICC and 77 percent in SAMY. Therefore, farm managers in the low AATFRs could increase their technical and scale-mix efficiency by 23 to 52 percent to reach the maximum TFP by obtaining advantages of changing the output mix and/or input mix by using the existing technology. Farm managers in low AATFRs were also unsuccessful in solving different optimisation issues.

The mean technical and scale-mix efficiency of all AATFRs was 68 percent; therefore, all farmers in the Wheat Belt regions of Australia could improve their technical and scale-mix efficiency by 32 percent when they able to capture maximum TFP related to changing the output mix and/or input mix with existing technology. Thus, in general, farm managers were not able to solve problems related to the different optimisation processes to reach maximum TFP.

7.3.6.2 Technical and scale-mix efficiency Score

Figures 7.21 to 7.24 present variations in technical and scale-mix efficiency of all farm regions from 1990 to 2016. The minimum and maximum technical and scale-mix efficiency scores in

high AATFRs were 11 percent in 1995 in NSWC and 100 percent in NSWN (1990, 1994, 1997 and 2009); NSWC (1999 and 2011); QLDD (1991) and WACS (1992, 1996, 2006 and 2008), respectively (Figure 7.21; Table E.7, Appendix E). Figure 7.21 shows that technical and scale-mix efficiency scores in NSWN and NSWC dropped in 1995 and 2003, which were drought years. The large variation in technical and scale-mix efficiency scores may be due to (1) conditions beyond the control of farm managers, such as high temperature variation (Table 7.1) in high AATFRs and (2) failure of farm managers, such as differences in the mix of inputs and/or outputs.

This suggests that farm managers may have used existing technology efficiently in most years; however, they experienced diseconomies of scale and/or scope in many years due to poor mixing of inputs and/or outputs. Because TSME = OTE_{VRS} × OSME, a similar trend was observed between technical and scale-mix efficiency and output-oriented scale-mix efficiency for NSWN, WACS and QLDD (Figure 7.17 and Figure 7.21) in high AATFRs over the study period. This is because these farm regions achieved 100 percent output-oriented technical efficiency (VRS) in 20, 21 and 22 years and 100 percent output-oriented scale-mix efficiency in only 4, 4 and 1 out of 27 years, respectively (Figure 7.17).

In medium AATFRs, the lowest and highest technical and scale-mix efficiency scores were, respectively, 13 percent in NSWR in 2008 and 100 percent in all farm regions in 2006 in NSWR; 2008 in QLDE; 1990 in SAEP and 1994, 2000 and 2004 in WANE (Figure 7.17; Table E.7, Appendix E). Therefore, farm managers in medium AATFRs were inefficient with respect to technical and scale-mix efficiency in most of the years under study. Farm managers could improve their technical and scale-mix efficiency if they altered the mixing of inputs and/or outputs optimally. Although the lowest technical and scale-mix efficiency score was observed in 2008 in NSWR, the technical and scale-mix efficiency of QLDE declined the greatest among the four farm regions.

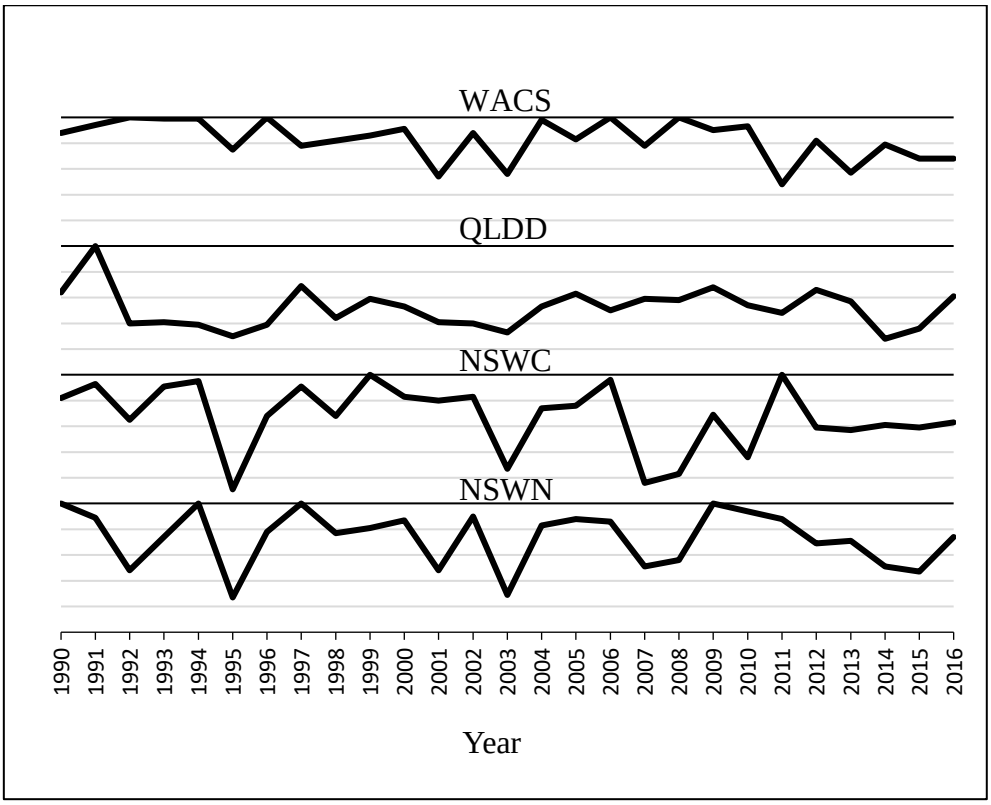

Figure 7.21 Technical and scale-mix efficiency in high AATFRs

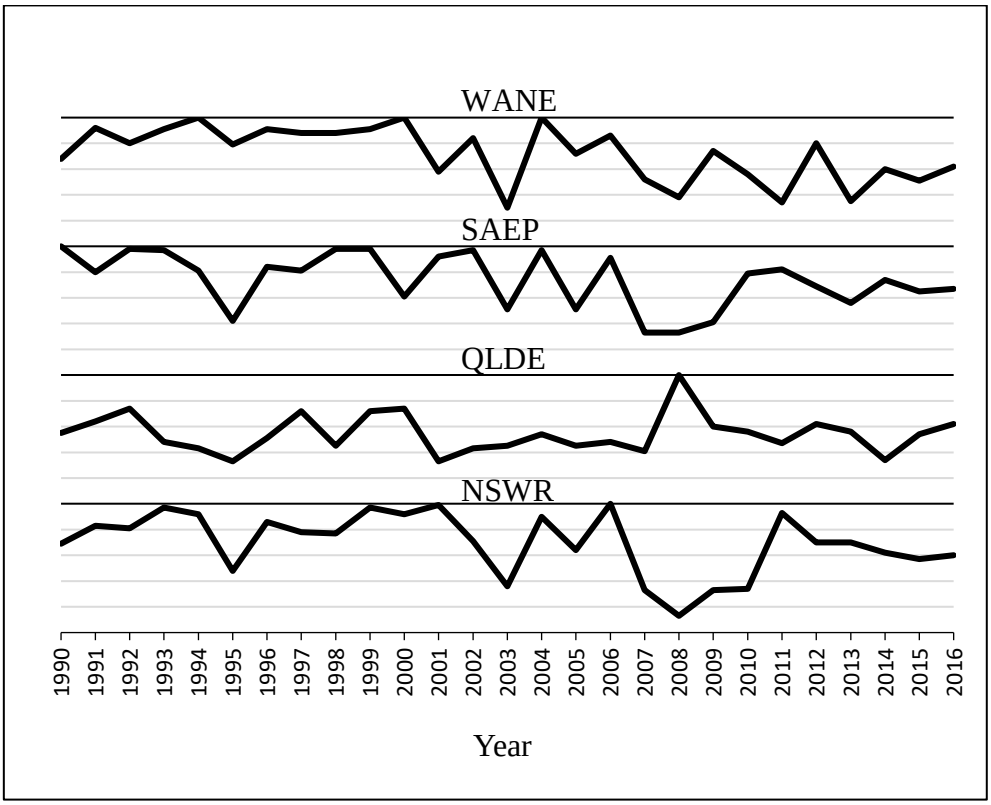

Figure 7.22 Technical and scale-mix efficiency in medium AATFRs

A similar trend was observed between the output-oriented scale-mix efficiency (Figure 7.18) and technical and scale-mix efficiency (Figure 7.22) of farms in NSWR and QLDE from 1990 to 2001. This was because output-oriented technical efficiency (VRS) was 100 percent in 15 and 24 out of 27 years, whereas output-oriented scale-mix efficiency was 100 percent in only 2006 and 2008, respectively. This shows that the technical and scale-mix efficiency of these two farm regions was influenced more by technical and scale-mix efficiency than output-oriented technical efficiency (VRS). The similarity in the trend between output-oriented scale-mix efficiency and technical and scale-mix efficiency of farms in QLDE could be because of farm managers not being able to obtain economies of scale and/or scope in medium AATFRs. However, they did achieve the best production frontier in many years (24 out of 27years).

Similar to other efficiency indicators, technical and scale-mix efficiency scores of all farm regions dropped in 1995 and 2003 due to drought. The lowest score of technical and scale-mix efficiency (13 percent in 2003) in the low AARFRs was recorded in VICW and VICC. A technical and scale-mix efficiency score of 100 percent was recorded in VICM in 1990, 1993–1994 and 2001; VICW in 2006 and 2010 and SAMY in 2002 and 2011 (Figure 7.23; Table E.7, Appendix E). VICC did not record any full efficiency in any year. Therefore, farm managers were inefficient regarding technical and scale-mix efficiency in the low AATFRs.

Figures 7.3, 7.19 and 7.23 show that output-oriented scale-mix efficiency directly affected technical and scale-mix efficiency, since TSME = $OTE_{VRS} \times OSME$, because output-oriented technical efficiency (VRS) was 100 percent in many years in low AATFRs. For example, it was observed that the output-oriented scale-mix efficiency trends of VICW and VICC were similar (Figure 7.19) to that of technical and scale-mix efficiency (Figure 7.23) in low AARFRs. This could suggest that farm managers were unable to capture the full scale of operations by changing output and input mixes. One of the reasons could be that these regions were sensitive to low temperature condition during crop growth.

The technical and scale-mix efficiency scores of all AATFRs ranged between 33 percent in 2003 and 83 percent in 2004 and 2006 (Figure 7.24). Therefore, all farm regions were inefficient regarding technical and scale-mix efficiency. In addition, Figure 7.24 also shows that technical and scale-mix efficiency dropped drastically in 1995, 2003 and 2007 in Australian Wheat Belt regions. These drops could be attributed to the poor use of available technology and also the inefficient mixing of inputs and/or outputs in some farms.

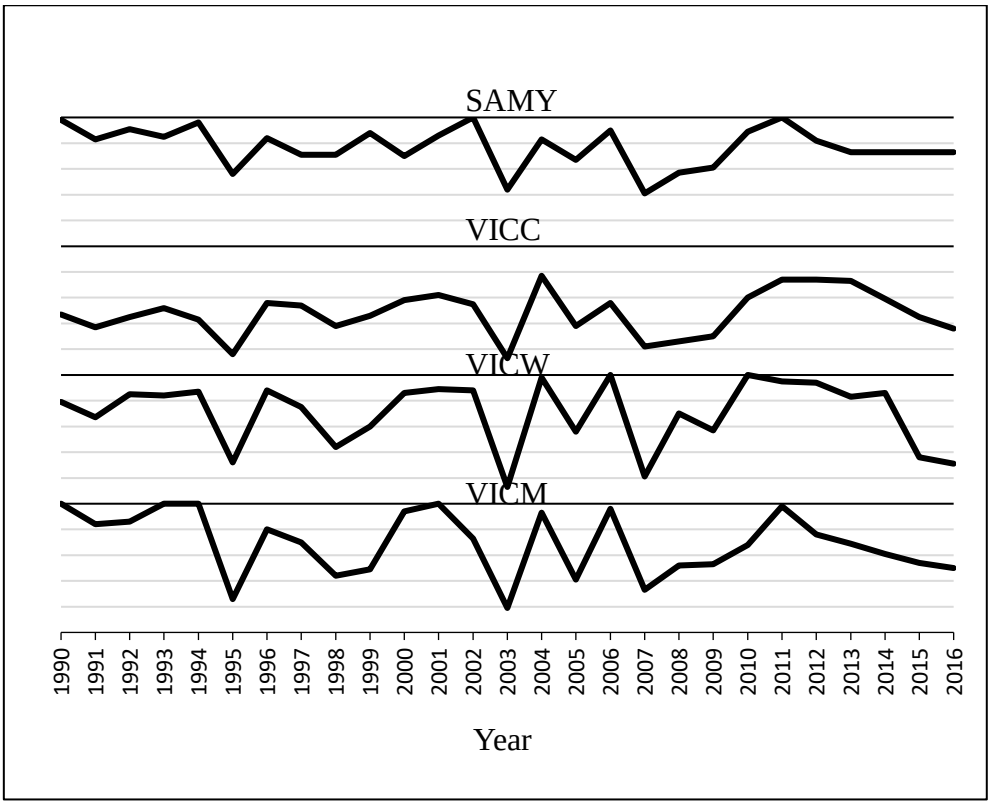

Figure 7.23 Technical and scale-mix efficiency in low AATFRs

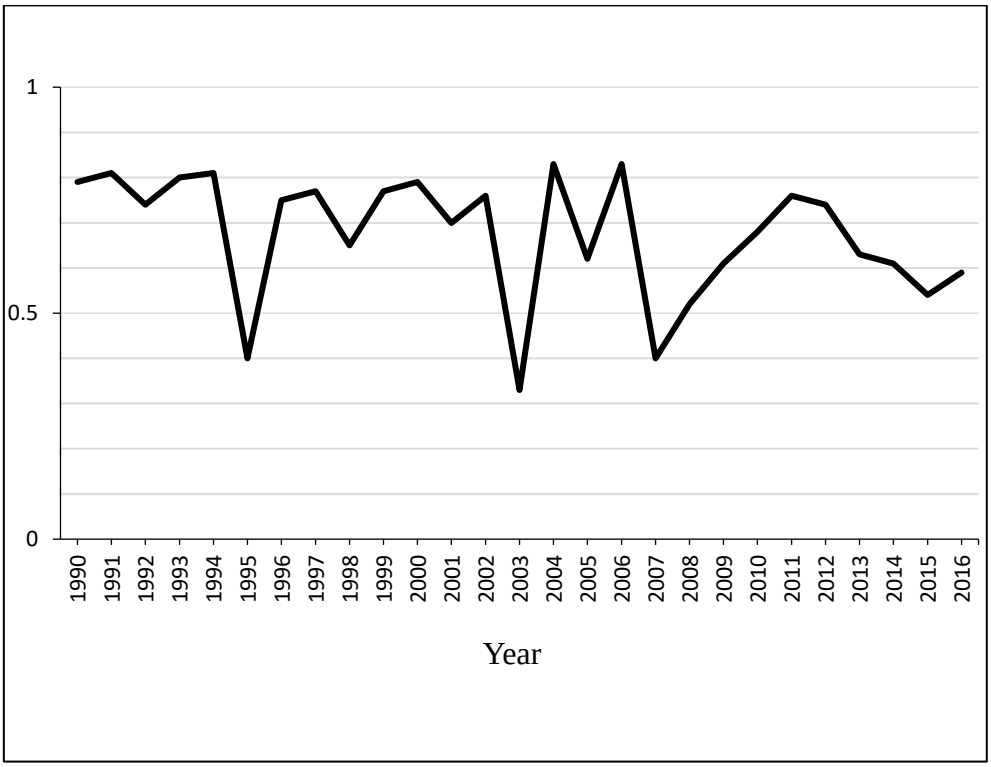

Figure 7.24 Technical and scale-mix efficiency in all AATFRs

7.3.7 Environmental efficiency

7.3.7.1 Average environmental efficiency for all farm regions

Production environment variables such as temperature have an impact on output/input combinations as well as on the production possibilities set (O'Donnell 2016). This variable is included in the farm production process. Thus, any variation in temperature change could affect crop output because of the impact of temperature on the rate of evapotranspiration of the plant.

Table 7.8 Average EEt for all farm regions over 1990–2016

AATFRs	EEt
High AATFRs	0.83
Medium AATFRs	0.95
Low AATFRs	0.94
All AATFRs	0.91

The average temperature efficiency was 83, 95 and 94 percent in the high, medium and low AATFRs, respectively. Therefore, farmers in these AATFRs could improve their respective temperature efficiency by 17, 5 and 6 percent by the implementation of a long-term plan for adapting to temperature change and the adoption of modern technology in the cultivation of wheat and non-wheat crops. Average temperature efficiency was maximum (95 percent) in medium AATFRs. This was likely due to the combined effect of medium temperature and favourable rainfall, for example in WA, which resulted in an increase in wheat productivity (Van Ittersum, Howden & Asseng 2003). This also implies that farmers in medium AATFRs might have considered temperature change in the farming process via the adoption of approaches that help conserve moisture in the root zone and moisture of plant.

7.3.7.2 Environmental efficiency Scores

Figure 7.25 and Table E.8 in Appendix E present the variations in temperature efficiency in all AARFRs over 1990–2016. In high AATFRs, the lowest and highest temperature efficiency scores were, respectively, 64 percent in NSWN in 2008 and 96 percent in 1999 in the four farm regions (Figure 7.25; Table E.8, Appendix E). Therefore, farmers did not achieve full efficiency within the study period. This could be because farmers were unable to reduce the rate of evapotranspiration (from soil and vegetation) due to high temperatures that were beyond their control.

As can be seen in Figure 7.25, trends of temperature efficiency scores for the various farm regions in high AATFRs exhibited low variabilities over the study period. The minimum and maximum temperature efficiency scores in the medium AATFRs were 86 percent in 1994–1999 and 100 percent in 2000 and 2008–2016, respectively. Therefore, farms in medium AATFRs achieved full efficiency in 10 out of 27 years (Figure 7.25). Achieving full efficiency continuously after 2007 indicates a successful change in farming policy by farmers to improve temperature efficiency (Figure 7.25).

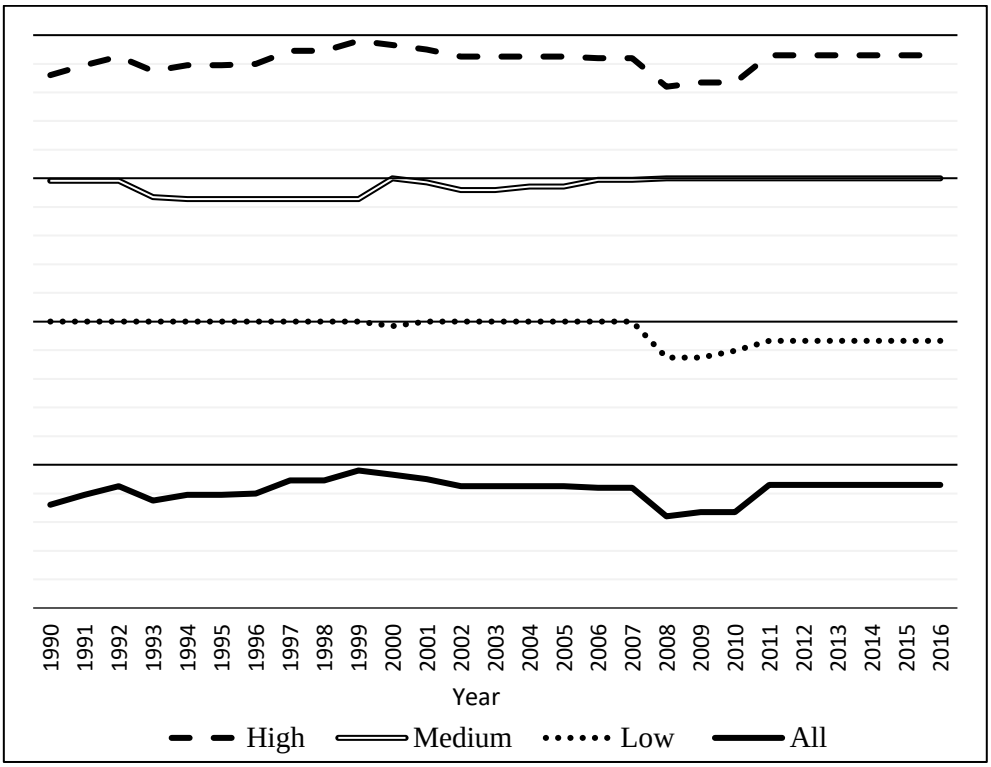

Figure 7.25 Temperature efficiency in farm regions

Temperature efficiency scores in rainfall and temperature analysis produced similar estimations in low AATFRs/AARFRs. Temperature efficiency scores ranged between 75 percent in 2008 and 2009 and 100 percent in 1990 to 1999 and 2001 to 2007 (Figure 7.25) in low AATFRs. This could suggest that both rainfall and temperature have similar sensitivity and impact on crop production and efficiency associated with temperature efficiency in low AATFRs.

Figure 7.25 and Table E.8 in Appendix E show that average temperature efficiency scores for all AATFRs varied between 80 percent in 2008 and 97 percent in 2000. This is because no farm region recorded 100 percent temperature efficiency throughout the 27 years under study.

Change in the evapotranspiration rate depends on change in temperature, assuming all other climatic factors are held constant. According to Charlesworth (2005), continuous monitoring of soil moisture content helps farmers make informed decisions to ensure that irrigation is applied in a timely manner. This reflects in reduced crop water stress, maximising crop production and reducing operating costs through the effective use of labour, energy, and water. Additionally, the difference between maximum and minimum temperatures (Table 7.1) in the three AATFRs might have influenced the variations in temperature efficiency in the farm regions.

7.4 Second Stage Regression Analysis Using Tobit Model

Tables 7.9 and 7.10 present results of second stage regression analysis using the Tobit model and double bootstrap analysis with truncated regression respectively. These two approaches produced similar estimations of the efficiency indicators. Also, Tables F.4 and F.5 in Appendix F present the results of random effects Tobit model and lagged model. By comparing the results of the double bootstrap, random effects Tobit and lag models to that of the standard Tobit model (Table F.6, Appendix F), a similar observation as explained in Section 6.4 of Chapter 6 (Table F.3, Appendix F) was made.

Specifically, statistical results of the four models indicate significant relationship between the following efficiency indicators and the respective explanatory variables:

- Output-oriented technical efficiency (CRS and VRS), and off-farm work of spouse of farm manager, capital-labour ratio and land-labour ratio;
- Output-oriented mix efficiency, and age of farm manager, age of spouse of farm manager and land-labour ratio;
- Residual output-oriented scale efficiency, and off-farm work of farm manager, off-farm work of spouse of farm manager and capital-labour ratio;
- Output-oriented scale-mix efficiency, and age of farm manager, off-farm work of spouse of farm manager and capital-labour ratio;
- Technical and scale-mix efficiency, and age of farm manager, off-farm work of farm manager, capital-labour ratio and land-labour ratio;
- Rainfall efficiency, and land-labour ratio.

These results are economically meaningful and well representative of the real situation of the Australian agricultural sector in recent decades. Further details related to these explanatory variables are discussed in Sections 7.4.1, 7.4.5 and 7.4.6 of this chapter. Furthermore, results of the log likelihood test in Tables 7.9, 7.10 and F.4 in Appendix F show that the output-oriented mix efficiency model had the highest log likelihood ratio; therefore, it is the best model for explaining the variations in the performance of farm regions.

Table 7.9 Results of Tobit models: Determinants of efficiency indicators

	Dependent variables							
	OTE_{CRS}	**OTE_{VRS}**	**OSE**	**OME**	**ROSE**	**OSME**	**TSME**	**EEt**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.840***	0.847***	0.984***	1.044***	1.271***	1.299***	1.136***	0.812***
	(0.183)	(0.169)	(0.113)	(0.062)	(0.194)	(0.191)	(0.196)	(0.100)
Independent variables								
Age of farm manager (ev_1)	-0.003	-0.006	0.003	-0.010***	-0.019*	-0.027***	-0.028***	-0.005
	(0.010)	(0.009)	(0.006)	(0.003)	(0.010)	(0.010)	(0.011)	(0.005)
Age of spouse of farm manager (ev_2)	0.006	0.010	-0.003	0.010***	0.009	0.017	0.022**	0.007
	(0.010)	(0.009)	(0.006)	(0.003)	(0.011)	(0.010)	(0.011)	(0.005)
Off-farm work of farm manager (ev_3)	-0.001	0.001	-0.002	0.001	-0.009***	-0.008**	-0.008**	0.003
	(0.003)	(0.003)	(0.002)	(0.001)	(0.004)	(0.003)	(0.004)	(0.002)
Off-farm work of spouse of farm manager (ev_4)	-0.008**	-0.006**	-0.002	-0.003**	0.014***	0.012***	0.007**	0.001
	(0.003)	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)
Capital-labour ratio (ev_5)	0.005***	0.005***	0.001	0.001	0.004***	0.005***	0.008***	-0.001**
	(0.001)	(0.001)	(0.001)	(0.0003)	(0.001)	(0.001)	(0.001)	(0.001)
Land-labour ratio (ev_6)	-0.560***	-0.558***	-0.029	-0.089**	-0.260*	-0.327**	-0.687***	0.222***
	(0.128)	(0.118)	(0.079)	(0.044)	(0.136)	(0.134)	(0.137)	(0.070)
Year effect	yes	yes	yes	yes	yes	yes	yes	yes
Observations	324	324	324	324	324	324	324	324
Log likelihood	158.877	185.028	314.332	508.157	140.343	144.728	137.898	354.671
Wald test (df = 32)	216.998***	149.426***	74.994***	77.458***	179.070***	204.061***	350.632***	99.982***

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

Table 7.10 Results of bootstrap truncated regression (algorithm #2)

	Dependent variables							
	OTE_{CRS}	**OTE_{VRS}**	**OSE**	**OME**	**ROSE**	**OSME**	**TSME**	**EEt**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.838***	0.847***	0.984***	1.044***	1.272***	1.301***	1.144***	0.812***
	(0.183)	(0.169)	(0.113)	(0.062)	(0.194)	(0.192)	(0.198)	(0.100)
Independent variables								
Age of farm manager (ev_1)	-0.003	-0.006	0.003	-0.010***	-0.019*	-0.027***	-0.029***	-0.005
	(0.010)	(0.009)	(0.006)	0.003	(0.010)	(0.010)	(0.011)	(0.005)
Age of spouse of farm	0.006	0.010	-0.003	0.010***	0.009	0.017	0.022**	0.007
manager (ev_2)	(0.010)	0.009	(0.006)	(0.003)	(0.011)	(0.010)	(0.011)	(0.005)
Off-farm work of farm	-0.001	0.001	-0.002	0.001	-0.009***	-0.008**	-0.008**	0.003
manager (ev_3)	(0.003)	0.003	(0.002)	(0.001)	(0.004)	(0.003)	(0.004)	(0.002)
Off-farm work of spouse of	-0.008**	-0.006**	-0.002	-0.003**	0.014***	0.012***	0.007**	0.001
farm manager (ev_4)	(0.003)	0.003	(0.002)	(0.001)	(0.003)	(0.003)	(0.004)	(0.002)
Capital-labour ratio (ev_5)	0.005***	0.005***	0.001	0.001	0.004***	0.005***	0.008***	-0.001**
	(0.001)	(0.001)	(0.001)	(0.0003)	(0.001)	(0.001)	(0.001)	(0.001)
Land-labour ratio (ev_6)	-0.560***	-0.558***	-0.029	-0.089**	-0.260*	-0.328**	-0.692***	0.222***
	(0.128)	0.118	(0.079)	(0.044)	(0.136)	(0.134)	(0.138)	(0.070)
Year effect	yes	yes	yes	yes	yes	yes	yes	yes
Observations	324	324	324	324	324	324	324	324
Sigma	0.148***	0.137***	0.092***	0.050***	0.157***	0.155***	0.159***	0.081***
	(0.006)	(0.005)	0.004	(0.002)	(0.006)	(0.006)	(0.006)	(0.003)
Log likelihood	158.88	185.03	314.33	508.16	140.38	144.79	138.88	354.67

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

7.4.1 Age of farm manager

A summary of results of the second stage analysis of efficiency determinants based on the given independent variables is presented in Table 7.9. A positive but insignificant relationship was observed between age of farm manager and output-oriented scale efficiency. In contrast, age of farm manager had a significantly negative impact on output-oriented mix efficiency, residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency. An increase in the age of farm manager by 1 year resulted in an approximately 1, 1.9, 2.7 and 2.8 percent decrease in output-oriented mix efficiency, residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency at p-values < 0.01, 0.1, 0.01, and 0.01, respectively. In particular, the migration of young Australians from rural to urban areas to study or to change their lifestyle has a negative impact on farming development and creates low productivity due to the low level of employment in rural regions (National Farmers' Federation 2008).

The average age of farm managers in this study was approximately 54 years. The House of Representatives Standing Committee on Agriculture and Industry (2016) stated that the average age of Australian farmers is 52 years. The average age of farm managers in this study was 14 years higher than that in other sectors. This may present serious limitations to the use of modern technologies (such as computing, robotics and sensing) as their adoption in farming operations is more difficult for older farmers. Barr (2014) also confirmed that the number of young farmers has decreased by 68 percent in recent decades in Australia. Therefore, it could be that this increase in older farmers had a negative impact on the efficiency indicators. The main determining factor of the age of farm manager for the technical and scale-mix efficiency (−2.8 percent) of farms could support the justifications above. Therefore, farm managers or their spouses did not use existing and/or modern technology and varied their mixes of output and/or input efficiently. The result of the age of farm manager and technical efficiency was consistent with the results of previous studies (Battese & Coelli 1995; Bozoğlu & Ceyhan 2007; Tipi et al. 2009). They also found that a negative relationship between older farmers and technical efficiency.

7.4.2 Age of spouse of farm manager

There was a significantly positive relationship between the age of spouse of farm manager and output-oriented mix efficiency and technical and scale-mix efficiency (Table 6.9). A 1-year increase in the age of spouse of farm manager resulted in an approximately 1 and 2.2 percent increase in output-oriented mix efficiency and technical and scale-mix efficiency at p-values < 0.01 and 0.05, respectively. The average age of the sampled spouses of farm managers was approximately 52 years. Therefore, the spouses of farm managers might have a lot of experience to assist farm managers in the proportions of crops to mix (OME). Additionally, spouses might play a significant role in encouraging the adoption of emerging technologies such as digital technologies (Hay & Pearce 2014). The findings showed positive but non-significant relationships between the age of spouse of farm manager and other efficiency indicators except for output-oriented scale efficiency. Although these indicators might be less sensitive to the age of the spouse of farm managers, they could support the farming performance to improve technical and scale-mix efficiency.

7.4.3 Off-farm work of farm manager

Regression coefficients of the number of hours used for off-farm work by the farm manager revealed a significantly negative relationship with residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency. Residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency decreased by 0.9, 0.8 and 0.8 percent (at p-values < 0.01, 0.05 and 0.05), respectively, with an increase of 1 hour per week in off-farm work of farm managers. Farm managers are more efficient when they allocate less hours to off-farm work (Coelli, Rahman & Thirtle 2002). Furthermore, according to Barr (2014), farm managers (owners) are usually the leaders of farming families in Australian agriculture. Therefore, the farm manager has the responsibility of decision making at all stages of the production process, including use of existing technology and determination of specific quantities of farm inputs. Thus, any hour per week of off-farm work significantly affects residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency. On the other hand, the relationship between off-farm work and output-oriented technical efficiency (VRS), output-oriented mix efficiency and temperature efficiency was positive but non-significant.

The findings of Coelli, Rahman and Thirtle (2002), Tipi et al. (2009) and Chang, Dong and MacPhail (2011) on the relationship between the off-farm work of farm managers and technical efficiency are similar to that found in the present study. They found that off-farm work has a significantly negative influence on technical efficiency.

7.4.4 Off-farm work of spouse of farm manager

The results in Table 7.9 shows a significant and negative relationship between off-farm work of spouse of farm manager and output-oriented technical efficiency (CRS), output-oriented technical efficiency (VRS) and output-oriented mix efficiency. A 1 hour per week increase in off-farm work by a spouse of a farm manager led to a decrease in output-oriented technical efficiency (CRS), Output-oriented technical efficiency (VRS) and output-oriented mix efficiency by 0.8, 0.6 and 0.3 percent at p-values < 0.05, respectively. Therefore, increasing the number of hours per week used by spouses of farm managers in on-farm work will increase outputs of wheat and non-wheat crops. A key livelihood strategy largely used by female partners of farm managers in Australian agriculture is to become employed in off-farm work (Alston 2013). According to Palmer (2012), most farmers/farm managers are men (72 percent). According to Barr (2014), farm managers' spouses may not be involved in the farm management in Australian agriculture. Thus, it is not surprising that off-farm work of these spouses impacted negatively on output-oriented technical efficiency (CRS), output-oriented technical efficiency (VRS) and output-oriented mix efficiency.

In contrast, significant and positive relationships were observed between off-farm work of spouse of farm manager and residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency. An hour per week increase in the off-farm work of spouse of farm manager resulted in approximately 1.4, 1.2 and 0.7 percent higher residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency at p-values < 0.01, 0.01 and 0.05, respectively. Productivity Commission (2005) and Palmer (2012) stated that the income received by the spouses of farm managers from off-farm work could serve as financial support to farm managers in offsetting family expenses. Furthermore, this income could be used also in the purchase of more advanced production inputs that could improve production. In contrast, the relationship between off-farm work and temperature efficiency was non-significant and positive.

It appears that off-farm work of farm manager's spouse was a major contributing factor to the increase (1.4 percent) in the residual output-oriented scale efficiency of farms in the study area. Farmers in the farm regions have a better chance of obtaining full efficiency because they have the flexibility of changing the input and output mixes during the production process to obtain the remaining (residual) benefit. A positive and significant relationship between the off-farm work of the spouse and technical and scale-mix efficiency supports this view.

7.4.5 Capital-labour ratio

Result presented in Table 7.9 reveal that the capital-labour ratio ($/hour) had a positive and significant impact on output-oriented technical efficiency (CRS), output-oriented technical efficiency (VRS), residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency at varying levels of significance. Specifically, regression coefficients showed an approximately 0.5, 0.5, 0.4, 0.5 and 0.8 percent increase in output-oriented technical efficiency (CRS), output-oriented technical efficiency (VRS), residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency, respectively, with a unit growth in the capital-labour ratio.

To increase labour productivity requires an increase in the level of capital (e.g. fertiliser, chemicals and fuel). This could lead to an increase in profit, and quantity and quality of output levels due to lower unit cost. Xia, Zhao and Valle (2017) stated that Australian broadacre farmers have experienced a decline in total input by approximately 1 percent per year over the last four decades. This positive and significant relationship between the capital-labour ratio and output-oriented technical efficiency (CRS), output-oriented technical efficiency (VRS), residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency could imply that farm managers might be using modern technology to help reduce input costs associated with fertiliser, chemicals and fuel use. Mathijs and Vranken (2000) also found that higher capital-labour ratio leads to higher technical efficiency.

On the other hand, coefficients of the capital-labour ratio revealed a significantly negative relationship with temperature efficiency. A unit increase in the capital-labour ratio could lead to a decrease in temperature efficiency by 0.1 at a p-value < 0.01. Favourable irrigation water or rainwater and temperature are required at each stage of the crop production process to facilitate the efficient interaction between crops and inputs such as fertiliser and chemicals.

From 1990 to 2015, rainfall declined by 2.76 mm per year while maximum daily temperatures rose by 0.04 °C per year (Hochman, Gobbett & Horan 2017). This could lead to high evaporation rates and frequency of droughts. Therefore, an increase in the capital-labour ratio with higher temperatures might have led to a reduction in temperature efficiency (EEt) due to the lack of adequate labour to manage such an increased input.

7.4.6 Land-labour ratio

The results in Table 7.9 show a significant and negative relationship between land-labour ratio (ha/hour) and output-oriented technical efficiency (CRS), output-oriented technical efficiency (VRS), output-oriented mix efficiency, residual output-oriented scale efficiency, output-oriented scale-mix efficiency and technical and scale-mix efficiency. Therefore, a unit rise in the land-labour ratio may lead to a decrease in these efficiency indicators by 56, 55.8, 8.9, 26, 32.7 and 68.7 percent, respectively, at varying levels of significance. This finding could suggest that, in Australia, the cost of farming is relatively high due to the low labour availability in rural regions. The total number of farm employees has decreased from 390,000 in 1972 to 110,000 in 2015 (ABARES 2016a). Increasing farm sizes in the face of a declining labour force likely impacted negatively on productivity and efficiency. The highest regression coefficient was recorded between the land-labour ratio and technical and scale-mix efficiency. Technical and scale-mix efficiency measures how well farm managers can solve variety optimisation problems in the farm regions (O'Donnell, Fallah-Fini & Triantis 2017). This could confirm that farm managers did not consider expansion of the farm land area and the limited availability of labour. Thus, they were not able to manage and control mixing outputs and/or mixing inputs and using existing technology optimally.

On the other hand, the coefficient for land-labour ratio shows a statistically significant and positive effect on temperature efficiency. A unit increase in the land-labour ratio resulted in approximately 22.2 percent increase in temperature efficiency at p-values < 0.01. This is likely due to improvement in farm management and technology, which imply lower labour requirement as well as increased farm land area. This progressive improvement over 27 years could be the driving force for the improvement observed in temperature efficiency and could confirm that favourable temperature assists annual cropping growth in Australian Wheat Belt regions.

7.5 Conclusion

The same approaches used in Chapter 6 were employed in this chapter to investigate the impact of temperature variation on efficiency and its determinants. The first stage analysis revealed that of all the 12 farm regions, farms in QLDE recorded the highest average output-oriented technical efficiency (CRS) and average output-oriented technical efficiency (VRS). Farms in QLDE and SAEP recorded the highest average output-oriented scale efficiency. On the other hand, farms in NSWC recorded the lowest average output-oriented technical efficiency (CRS) and average output-oriented technical efficiency (VRS), and farms in VICW recorded the lowest average output-oriented scale efficiency. Age of farm manager had a negative and significant impact on four out of the eight efficiency indicators.

CHAPTER 8: CONCLUSION AND POLICY IMPLICATION

8.1 Introduction

This chapter presents the conclusion, policy implication, contribution, limitation and recommendations for further research. Section 8.2 presents the key outcomes including the conclusion of the effect of rainfall and temperature variations on productivity and profitability change, and the effects of rainfall and temperature variation on efficiency and its determinants. Sections 8.3 and 8.4 highlight the implications for Australian crop policy based on rainfall and temperature variations, respectively, across farm regions. Section 8.5 determines the limitations and challenges of this research. Section 8.6 suggests some areas that require further research in the future.

8.2 Key Findings

8.2.1 Effect of rainfall variation on productivity and profitability changes

This study presents profitability and productivity of farm businesses in 12 regions of the Wheat Belt of Australia using 27 years (1990–2016) of farm regions panel data. The effects of varying rainfall conditions, technical changes, technical efficiency, mix and scale efficiencies and farmer's TT on farm profitability and productivity have been examined. Farm areas were grouped into three rainfall regions (low, medium and high AARFRs).

The main drivers of TFP change were found to be rainfall change and technical change. The medium AARFRs experienced a greater increase in TFP index than the high and low AARFRs. The increase in the TFPI in the high and medium AARFRs was mainly due to the improvement in rainfall change (OEErI). Farmers in some parts of the high AARFRs such as QLD (Eastern Darling Downs); NSW (North West Slopes and Plains and Central West) and VIC (Central North) experienced improvement in the TFPI from 2000 to 2001 due to higher rainfall. Farmers in low AARFRs such as in southern Australia, where average annual rainfall is low (132.25 to 490.17 mm) experienced a reduction in the TFPI. Generally, OTE, OMEI and ROSEI impacted adversely on the TFPI in all AARFRs. However, OMEI had the least negative impact on TFPI in the medium AARFRs. The OSEI of the medium AARFRs contributed positively to TFP change. The medium AARFRs were found to be the most suitable farm region for output mix owing to the lowest decrease in OMEI and positive contribution of OSEI.

OSMEI impacted poorly on TFPI in all AARFRs (Figure 5.2 a). The 14 percent decrease in OSMEI over the 27-year period in the high AARFRs could be attributed to the 3 percent drop in OMEI and the 11 percent decline in ROSEI. The medium AARFRs experienced a 17 percent decrease in OSMEI with a 1 percent reduction in OMEI and a 16 percent decrease in ROSEI. In addition, the low rainfall AARFRs experienced a 13 percent decrease in OSMEI with a 2 percent fall in OMEI and an 11 percent decline in ROSEI. TSMEI also showed a negative impact on TFPI in high, medium and low AARFRs. This may suggest that over time, OTEI and OSMEI declined by approximately 12 and 14 percent, 8 and 17 percent, and 12 and 13 percent in the high, medium and low AARFRs, respectively. OSMEI and TSMEI declined, respectively, by approximately 0.76 and 1.53 percent per annum across all farm regions. Therefore, farmers did not achieve the maximum TFP due to suboptimal use of available resources in all AARFRs.

TFPI computed for the high and low AARFRs over the study period showed changes of 2.11 and 0.04 percent per annum, respectively. This could be the combined impact of TI and EFFI by approximately 2.48 and −0.36 percent and 2.48 and −2.34 percent per annum in the high and low AARFRs, respectively. For the medium AARFRs, TFPI change of approximately 2.29 percent per annum occurred owing to the TI and EFFI change of approximately 2.48 and −0.20 percent per annum, respectively.

In all AARFRs over the sample period, EFFI had a negative (approximately 0.14 percent) impact on TFPI. Year-to-year efficiency gains, however, indicated that farmers in high AARFRs experienced improvement in EFFI during 1997, 1999, 2000, 2004 and 2011 and farmers in medium AARFRs in 1991, 1992, 1994, 1997, 1999, 2000, 2004, 2006 and 2012. No improvement in efficiency gains was observed for low AARFRs. An upward shift in the best-practice production frontier was observed in 1993, 1994, 2000 and 2012 by TI values for all AARFRs.

Farms in the high AARFRs experienced positive profitability change, while farms in the medium and low AARFRs experienced negative profitability change. TFP was the main driver of PROFI for farms in the high AARFRs whereas TTI was the primary source of PROFI in the low and medium AARFRs. TT was negative for all AARFRs, which was owing to higher input

costs and less favourable movements in output prices. However, farmers in the medium AARFRs experienced the highest drop in TT.

8.2.2 Effect of temperature variation on productivity and profitability changes

This study has presented the profitability and productivity of farm businesses in 12 broadacre farm regions in the Wheat Belt of Australia using 27 years (1990–2016) of farm regions panel data. The effects of varying temperature conditions, technical changes, technical efficiency, mix and scale efficiencies and farmer's TT on farm profitability and productivity have been examined. Farm areas were grouped into three temperature regions (low, medium and high AATFRs).

Generally, the main drivers of TFP change were temperature change and technical change. OEEtI and TI were the primary sources of positive change in TFP in the high AATFRs, whereas only TI was the key driver of positive change in TFP in the medium and low AATFRs. However, TFPI of high AATFRs was the highest, which suggests that the positive effects of OEEtI and TI provided more support to improve the TFPI for farmers in high AATFRs.

The improved performance of TI contributed more positively to TFP change than crop mix and alterations of input and output quantities. TI played a significant role in TFP change from 1990 to 2016. However, the TFPI of medium and low AATFRs was more sensitive to temperature changes than that of high AATFRs. TI was the main factor that supported positive change in TFP in the medium and low AATFRs under deteriorating climatic conditions. Farmers in the medium and low AATFRs adopted new technologies and knowledge; however, those in medium AATFRs invested more in these technologies. This is because these farmers in the medium AATFRs benefitted most from the positive effect of ROSEI on TFPI.

Generally, OTEI, OSEI and OMEI impacted poorly on TFPI in all AATFRs. The medium AATFRs had ROSEI contributing positively to TFPI and also had the largest farm area. Farmers in the medium AATFRs could be more efficient in their crop mix for a given level of input and by altering the levels of both inputs and outputs to maximise TFP. Farmers had the best performance of TI in the high and medium AATFRs compared to the low AATFRs. The high, medium and low AATFRs had OMEI (approximately 3, 3 and 2 percent, respectively)

contributing negatively to OSMEI, whereas ROSEI contributed negatively in the high and low (8 and 6, respectively) AATFRs and positively in the medium (approximately 3 percent).

TSMEI was less than 1 in high, medium and low AATFRs by 17, 7 and 17 percent, respectively, over the study period. This may be because the combined effect of OTEI and OSMEI declined by 8 and 11 percent in high AATFRs, 8 and zero percent in medium AATFRs, and 11 and 8 percent in low AATFRs, respectively. OSMEI, and TSMEI had negative impacts on TFPI in all sample farm regions. Farmers in medium AATFRs may be closest to obtaining cost advantages because of increased production and operation size or scale. Therefore, TSMEI had a negative effect on the TFPI in high, medium and low AATFRs. However, farms businesses in medium AATFRs experienced the lowest decline in TSMEI.

TFPI computed for the high, medium and low AATFRs over the study period showed changes of 2.26, 1.94 and −0.16 percent per annum, respectively. Therefore, TI showed changes of approximately 2.48 percent per annum in high, medium and low AATFRs, while EFFI showed changes approximately - 0.20, - 0.49, and - 2.56 percent per annum in high, medium and low AATFRs, respectively. EFFI had a negative contribution to TFPI in all three AATFRs. The EFFI of the high AATFRs decreased the least. The TFPI of farms in low AATFRs was more sensitive not only to the OEEtI, but also to the EFFI. TI, in addition to having a positive relationship with TFPI, also supported EFFI in all AATFRs. Farmers in medium and low AATFRs could improve their management practices, against unfavourable temperature change, by adopting modern technologies and applying new knowledge.

Farms in high, medium and low AATFRs experienced negative profitability change. The main source of profitability change for the high, medium and low AATFRs was the TTI. TFPI was not the main driver for profitability change in any farm region. Medium AATFRs had the lowest decrease in profitability. TFPI of high AATFRs increased significantly relative to the base year. TT was negative for all AATFRs, which was due to the gradual increase of input costs and decreased output prices. Farmers in high AATFRs experienced the highest drop in TT.

8.2.3 Effect of rainfall variation on efficiency and its determinants

The objectives of Chapter 5 were to estimate the scores of efficiency indicators (OTE_{CRS}, OTE_{VRS}, OSE, OME, ROSE, OSME, TSME and EEr) and to examine the effect of explanatory variables on these indicators in 12 farm regions during rainfall variation analysis in the Wheat Belt of Australia.

The first stage analysis revealed that of all the 12 farm regions, farms in QLDD, QLDE and WANE recorded the highest OTE_{CRS}, OTE_{VRS} and OSE, respectively, whereas farms in NSWC recorded the lowest OTE_{CRS} and OTE_{VRS}, and farms in VICC recorded the lowest OSE. Maximum OME was observed in QLDD while minimum OME was observed in NSWC and VICW. Farms in SAMY had the highest average ROSE and average OSME. Three farm regions, namely WACS, WANE and SAMY, recorded the highest average TSME. Farms in VICC recorded the lowest ROSE, OSME and TSME. Farms in regions located in the low AARFRs had the highest average EEr and those in high AARFRs had the lowest EEr.

The variations observed in the efficiency indicators in the various farm regions can be attributed to two main reasons. First, the farm regions are located in areas with different levels of rainfall. Second, farmers might have developed long-term strategies to introduce modern technology in their farming inputs and adopting management strategies that are adapted, for instance, to low rainfall levels. According to Hughes, Lawson and Valle (2017), increasing farmers' awareness of the adoption of modern technology and adaptation to reduced rainfall levels can be reflected in increased farm productivity. For example, increasing nitrogen application in the soil by farmers in VICM resulted in increased crop yield and income (Grain Growers 2016).

The second stage analysis involved determining the effects of (1) age of farm manager, (2) age of spouse of farm manager, (3) off-farm work of farm manager, (4) off-farm work of spouse of farm manager, (5) capital-labour ratio and (6) land-labour ratio on the efficiency indicators. The age of farm manager had a non-significant effect on OTE_{CRS}, OTE_{VRS}, OSE, OME, ROSE, OSME and TSME. Additionally, there was a negative and significant effect of farm manager's age on OSME and EE by approximately 1.8 and 2.6 percent at p-values < 0.1 and 0.01, respectively.

A positive but insignificant relationship was observed between age of spouse of farm manager and OTE_{CRS}, OTE_{VRS}, OSE, ROSE and TSME. The results also showed that there was a significantly positive relationship between age of spouse of farm manager and OME and EEr by approximately 0.7 and 2 percent at p-values < 0.1 and 0.01, respectively.

For the off-farm work of farm managers, there was a significantly negative relationship with ROSE, OSME and TSME by 0.8, 0.6 and 0.6 percent at p-values < 0.05, 0.1 and 0.1, respectively. Regression coefficients of the number of hours used by spouse of farm manager for off-farm work revealed a significantly positive relationship with ROSE, OSME and TSME. ROSE, OSME and TSME increased by 1.4, 1.3 and 0.8 percent (at p-values < 0.01, 0.01 and 0.05), respectively.

A positive relationship between capital-labour ratio and OTE_{CRS}, OTE_{VRS}, OSE, ROSE, OSME and TSME and a negative relationship between capital-labour ratio and EEr by approximately 0.5, 0.4, 0.1, 0.5, 0.5 and 0.8 percent at 0.05 and 0.01 significance levels, respectively, were observed. For technical efficiency, this finding agrees with that reported by Mathijs and Vranken (2000) who stated that a higher capital-labour ratio leads to higher technical efficiency. The capital-labour ratio was a strong determinant for TSME (0.8 percent) at p-value < 0.01. This might be due to the expansion of the capital-labour ratio by farm managers to maximise TFP and their ability to use the existing technology and alter the scale of operations efficiently.

The land-labour ratio had a negative and significant impact on OTE_{CRS}, OTE_{VRS}, ROSE, OSME and TSME by approximately 51.5, 46.9, 8.2, 29, 30.4 and 58.9 percent, respectively, at varying levels of significance; however, it had a positive and significant impact on the EEr by 12.7 percent at the 0.1 level of significance. Broadacre farming in the Wheat Belt regions of Australia heavily depends on rainfall. ABARES (2016a) stated that the total number of farm employees decreased from 390,000 in 1972 to 110,000 in 2015. These have resulted in high labour costs and large farm size (land area). Thus, the strong significant and negative impact was especially prevalent on TSME.

For the double bootstrap and truncated regression model, the findings for the eight models was similar as that of the Tobit regression model. The log likelihood test indicted that the best model was the OME indictor in the farm regions. It was thus concluded that the sample size was

adequate and normally distributed. Hence, these models can be used to estimate the effect of explanatory variables on the efficiency indicators for any given population and the statistical summary results were the best estimators of the population parameters. This removed any bias of the estimated models.

8.2.4 Effect of temperature variation on efficiency and its determinants

The objectives of Chapter 5 were to estimate the scores of efficiency indicators (OTE_{CRS}, OTE_{VRS}, OSE, OME, ROSE, OSME, TSME and EEt) and to examine the effect of contextual variables on these indicators in 12 farm regions during temperature variation analysis in the Wheat Belt of Australia.

The first stage analysis revealed that of all the 12 farm regions, farms in QLDE recorded the highest average OTE_{CRS} and average OTE_{VRS}. Farms in QLDE and SAEP also recorded the highest average OSE. In contrast, farms in NSWC recorded the lowest average OTE_{CRS} and average OTE_{VRS}, and farms in VICW recorded the lowest average OSE.

Average OME was maximum in QLDD, VICW, VICC and SAMY, and minimum in NSWC. Farms in SAMY had the highest average ROSE and OSME, whereas farms in QLDD and VICC recorded the lowest average ROSE and OSME. Farms in WACS recorded the maximum TSME, whereas farms in VICC recorded the minimum TSME. Farms in farm regions located in the medium AATFRs had the highest average EEt and those in high AATFRs had the lowest average EEt. The variations observed in efficiency indicators in the various farm regions could be attributed to (1) differences in temperature and (2) varying rates of adoption of modern technologies for soil moisture conservation, especially in the root zone of soil.

The second stage analysis included determining the effects of (1) age of farm manager, (2) age of spouse of farm manager, (3) off-farm work of farm manager, (4) off-farm work of spouse of farm manager, (5) capital-labour ratio and (6) land-labour ratio on the efficiency indicators. Results of the second stage analysis revealed a positive but non-significant relationship between the age of farm manager and OSE. The age of farm manager had a significant and negative impact on OME, ROSE, OSME, and TSME. A 1-year increase in the age of farm manager resulted in an approximate 1, 1.9, 2.7 and 2.8 percent decrease in OME, ROSE, OSME and TSME at p-values < 0.01, 0.1, 0.01, and 0.01, respectively.

There was a significantly positive relationship between age of spouse of farm manager and OME and TSME. The results suggest that a 1-year increase in the age of spouse of farm manager resulted in approximately 1 and 2.2 percent increase in OME and TSME at p-values < 0.01 and 0.05, respectively. The findings also showed a positive but non-significant relationship between age of spouse of farm manager and other efficiency indicators except for OSE.

Regression coefficients of the number of hours used for off-farm work by the farm manager revealed a significantly negative relationship with ROSE, OSME and TSME. ROSE, OSME and TSME decreased by 0.9, 0.8 and 0.8 percent, respectively, with an increase of 1 hour per week in off-farm work of farm managers (at p-values < 0.01, 0.05 and 0.05, respectively). In contrast, the relationship between off-farm work and OTE_{VRS}, OME and EEt were non-significant and positive.

The results showed a significant and negative relationship between off-farm work of spouse of farm manager and OTE_{CRS}, OTE_{VRS} and OME. An hour per week increase in the off-farm work of spouse of farm manager led to a decrease in OTE_{CRS}, OTE_{VRS} and OME by 0.8, 0.6 and 0.3 percent, respectively, at p-values < 0.05. In contrast, there was a significant and positive relationship between the off-farm work of spouse of farm manager and ROSE, OSME and TSME. Increasing the time used for off-farm work by spouse of farm manager by an hour per week resulted in approximately 1.4, 1.2 and 0.7 percent higher ROSE, OSME and TSME at p-values < 0.01, 0.01 and 0.05, respectively. In addition, the relationship between off-farm work and EEt was found to be non-significant and positive.

The capital-labour ratio ($/hour) had a positive and significant impact on OTE_{CRS}, OTE_{VRS}, ROSE, OSME and TSME by approximately 0.5, 0.5, 0.4, 0.5 and 0.8 percent, respectively, at varying levels of significance. However, coefficients of regression of the capital-labour ratio revealed a significantly negative (0.1 percent at p-values < 0.01) relationship with EEt.

Significant and negative relationships existed between land-labour ratio (ha/hour) and OTE_{CRS}, OTE_{VRS}, OME, ROSE, OSME and TSME. A unit increase in the land-labour ratio led to a decrease in these efficiency indicators by 56, 55.8, 8.9, 26, 32.7 and 68.7 percent, respectively, at varying levels of significance. The land-labour ratio had a significant and positive effect on

EEt. A unit increase in the land-labour ratio resulted in an approximately 22.2 percent increase in EEt at p-value < 0.01.

The double bootstrap, the truncated regression analysis provided a similar estimate for explanatory variables and efficiency indicators as that of the Tobit regression analysis. Therefore, the models confirm the exclusion of bias during data collection.

8.3 Implications for Australian Crop Policy in Farm Regions with Different Rainfall Levels

8.3.1 Changes of the efficiency components

OSEI of the medium AARFRs contributed positively to TFP change. This could lead to an increase in efficiency and, therefore, must be given attention by policy implementers. Hence, proper measures should be established by respective institutions to monitor the progress of these efficiency components as per each farm region and the available environmental conditions and technologies. Furthermore, farms in the medium AARFRs experienced the lowest decrease in OME and positive contribution of OSEI. OEErI and TI were the main drivers for positive change in TFP in high and medium AARFRs. OEErI in medium AARFRs had the most positive effect on TFPI. Farms in low AARFRs are more sensitive to rainfall change; therefore, it is particularly important to promote the establishment of region-based technologies for reducing plant transpiration rates and conserving soil moisture in cases where there are no other options such as river or groundwater present. Thus, farmers in the medium AARFRs should be encouraged to invest and cultivate to improve their agricultural performance and increase productivity and efficiency.

8.3.2 Components of TFP change

Technical change played a crucial role in the growth of TFP across the three AARFRs. Overall efficiency changes of the three AARFRs contributed to the decrease in TFP. The overall efficiency changes of the medium AARFRs were more flexible for output mix than the other two AARFRs because farms in the medium AATFRs experienced the lowest decrease in TFP. It was also found that farmers who grow more wheat than other crops improved their use of best-practice methods by adopting existing technology to improve their productivity. These findings advocate for increasing the use of modern technology in farm operations in the

medium AARFRs to obtain the best-practice methods. According to Asseng and Pannell (2012), improving TI and EFFI are important for achieving the best performance and to shift the production frontiers of farmers.

8.3.3 Profitability and productivity decomposition

A decrease in TTI resulted in a decrease in profitability in medium and low AARFRs. Additionally, the main source of profitability change for high AARFRs was TFP change. Thus, a key policy implication is that the concentration by farmers on increased productivity for wheat and non-wheat in high AARFRs may lead to an increase in profitability.

8.3.4 Age of farmer implications

Age of farm manager had a negative effect on all efficiency indicators except for OTE_{VRS}. The negative effect was significant for OSME and EEr (rainfall efficiency). Thus, it is necessary for the government or policy makers to provide incentives to motivate younger people to enter into crop production in the Wheat Belt regions of Australia.

8.3.5 Off-farm work implications

The engagement of farm managers in off-farm work has a negative impact on ROSE, OSME and TSME. Additionally, off-farm work by the spouses of farm managers has a positive relationship with ROSE, OSME, and TSME. Therefore, supporting the off-farm work of farm managers' spouses might increase the incomes of farmers' households and create new farm jobs in on-farm regions. In addition, this policy may also contribute to improving labour performance in the non-agricultural sectors through the participation of a large part of the workers in these sectors, and thus may increase the GDP value. According to ABARES (2014), off-farm income of owner–manager and spouse for all broadacre industries average per farm peaked at $32 140 in 2011–2012.

8.3.6 Capital-labour ratio implications

The capital-labour ratio had a positive effect on most of the efficiency indicators (OTE, OSE, ROSE, OSME and TSME) but had a negative impact on rainfall efficiency. In comparison to the land-labour ratio, the capital-labour ratio contributed more to the improvement of most efficiency indicators. These findings, therefore, strongly support the use modern technology to

improve management practices to reduce input costs (e.g. fertiliser, chemicals and fuel). Thus, a key policy implication is that the improvement of the ratio of production resources to labour in dryland farm regions may lead to improved efficiency indicators.

8.3.7 Land-labour ratio implications

The land-labour ratio had a negative impact on OTE, ROSE, OSME and TSME; however, it had a positive effect on the rainfall efficiency. This supports using the land-labour ratio to improve only the EEr rather than other efficiency indicators in dryland farm regions. The policy implication of this research is that an improvement in the land size-labour ratio could lead to improved EEr in dryland farm regions. Thus, it is important to encourage farmers or managers, if they intend to improve their farm efficiency indicators, to reduce the expansion in the use of farm land, taking into account the size of available labour in those farm regions as this may not improve most efficiency indicators.

8.4 Implications for Australian Crop Policy in Farm Regions with Different Temperature Levels

8.4.1 Components of efficiency change

The research analysis indicated that temperature change contributed positively to productivity change in the high AATFRs; however, it had a negative impact on productivity change in the medium and low AATFRs. These results suggest that TFP change of the medium and low AATFRs is more sensitive to temperature change, which implies that temperature change has a negative impact on crop output (Hughes et al. 2011). For example, farmers in southern Australia (Eyre Peninsula and Murray Lands and Yorke Peninsula) experienced a reduction in TFP for several years during the study period because these farm regions are located in low AAFRRs.

The finding above suggests that farms located in high AATFRs are more favourable for crop production only when there is a high amount of rainfall such as in the North West Slopes and Plains farm region and the Central West farm region. This is because this combination will give higher productivity to farmers. According to Kingwell (2006) , the price of land and grain productivity in Australia is expected to increase by 2–9 percent with an increase in rainfall in high temperature farm regions.

8.4.2 Components of TFP change

Technical and EFF change are regarded as two of the main components of TFP. The results of this research tend to support change because technical change, in addition to having a positive relationship with TFP change, also supports EFF change (overall efficiency index) in all AATFRs. This implies that farmers in the medium and low AATFRs could, in the long term, improve their management practices, against unfavourable temperature change, by adopting new technologies and using more modern approaches to crop production.

8.4.3 Profitability and productivity decomposition

The outcomes of this research reveal that even though TFP increased, PROF decreased over the study period for all the AATFRs due to a reduction in the TTI. This is because TTI is less than 1 in most of the sample years, which indicates a weakening performance relative to 1990. This implies that TTI is the main source of profitability change for the AATFRs. Low AATFRs experienced the lowest reduction in the TTI over the study period, whereas the high AATFRs experienced the greatest decrease in the TTI. Based on this finding, government intervention in supporting domestic crop prices by reducing the importation of crops that may create competition in local markets is strongly recommended. This will help increase farmers' agricultural profitability.

8.4.4 Age of farmer implications

The age of farm managers had a negative impact on OME, ROSE, OSME and TSME. The average age of farm managers was approximately 54 years, which indicates an aged/ageing work force. Younger farm managers could potentially help improve efficiency indicators in wheat and non-wheat productions. Therefore, policy decision makers could introduce measures such as increasing agricultural income, and increasing the standard of living and services to rural areas that are aimed at encouraging younger people to enter farm management.

8.4.5 Off-farm work implications

Off-farm work by the farm manager showed a negative relationship with ROSE, OSME and TSME. Off-farm work of spouse of farm manager also had a negative relationship with OTE and OME, and a positive relationship with ROSE, OSME and TSME. It can, therefore, be seen

that promoting off-farm work of spouses could increase three out of the eight efficiency indicators. This will help farmers' households to increase income and develop opportunities for labour marketing.

8.4.6 Capital-labour ratio implications

The capital-labour ratio had a positive impact on OTE, ROSE, OSME and TSME, whereas it had a negative impact on temperature efficiency. Thus, these findings advocate the use of modern technology in the application of economic resources such as fertilisers and chemicals, with careful consideration of labour availability to improve their performance in the farming operations.

8.4.7 Land-labour ratio implications

The land-labour ratio had a negative relationship with OTE, ROSE, OSME and TSME. In contrast, it had a positive impact on temperature efficiency. Therefore, increasing the land-labour ratio by increasing the land size relative to employment is not an effective approach to improving most of the efficiency indicators in the Australian Wheat Belt regions.

8.5 Limitations and Challenges of this Study

This study attempted to obtain primary data from farmers through a questionnaire; however, most of the farmers contacted declined to respond for a variety of reasons. Therefore, the researcher was forced to use secondary data available from the ABARES to prevent any further loss of time of this study. These data were officially collected via statistical surveys conducted by a group of government researchers specialised in the economics of agricultural crops.

This study was, thus, limited by a lack of direct field information from farmers and decision makers. First, long-term data were related to socioeconomic and other variables associated with plant growth are very limited in the Australian Wheat Belt regions. Such data include education, farming experience, nutrition, soil fertility, access to credit, distance from main market, access to extension services, social capital, household members, dependency ratio, poverty status and share of rented land. These variables have a significant impact on efficiency estimates and for determining which factor is important for improving the different types of efficiency indicators.

The second limitation was regarding the lack of historical data on the prices of input factors such as electricity, chemicals, fertiliser and fuel in specific farm and sub-farm regions in different states, with this information not available. These inputs are among the important factors required to provide a coherent picture of the estimated profitability change in farm regions.

The third missing data were related to specific sub-farm regions data by state. There is a gap in these data (financial and physical data) obtained from AgSurf presented by the ABARES in 1990–2016. The availability of these data is significant because the sample size would be larger, and thus the measure of models would be more accurate and robust.

8.6 Recommendations for Further Research

Further studies should be undertaken into some of the research questions.

- First, a comparative analysis between the Lowe and other index methods is recommended for future consideration. The scope of this study allowed the use of only the most suitable (one) index method as other empirical analyses were required to cover the objectives. For this reason, the Lowe index method was chosen as the most suitable because it satisfied all seven axioms of index number theory and is also the most suitable method to use when price data is available. Comparing the Lowe index method to other index methods will help verify its supposed superior accuracy over the others.
- Second, determination of why the overall efficiency over the past three decades was low in farm regions characterised by high rainfall, favourable temperature and modern technology. This must be investigated in future studies to create a deeper understanding into the interplay among rainfall conditions, modern technology, management decisions on inputs, and productivity and efficiency of broadacre farm businesses.
- Third, this research can be extended to examine how irrigation and soil fertiliser (irrigated land) variables as special inputs can influence the efficiency components, components of TFP change, profitability and productivity changes decomposition and efficiency indicators in different farming systems.
- Fourth, future studies can consider seed inputs in the analysis to examine the effect of the variation of the environmental variables on farm performance.
- Fifth, sensitivity analysis/ examination on the farm average data is recommended in future studies.

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APPENDICES

Appendix A

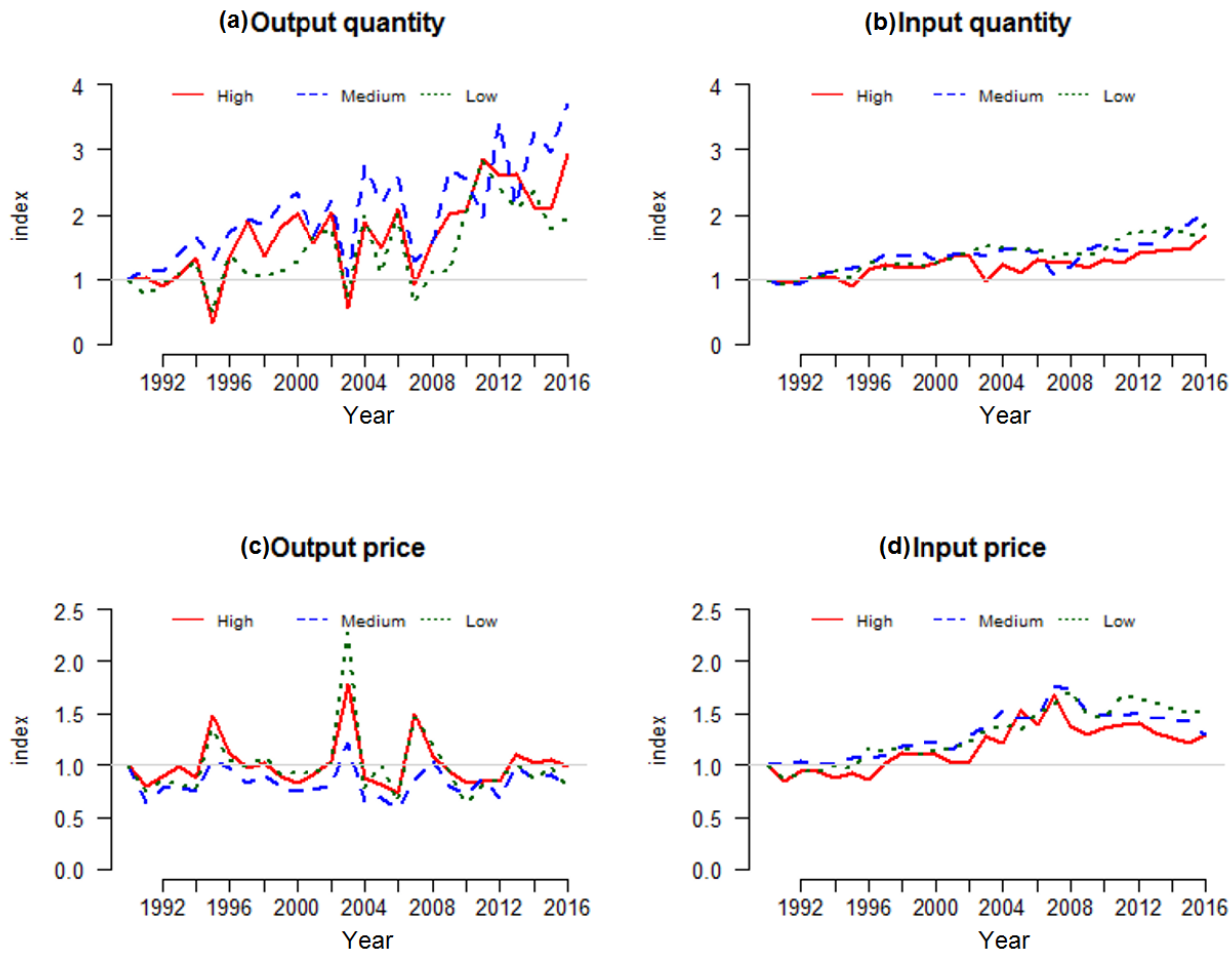

Figure A.1 Changes in aggregate output-input quantities and prices.

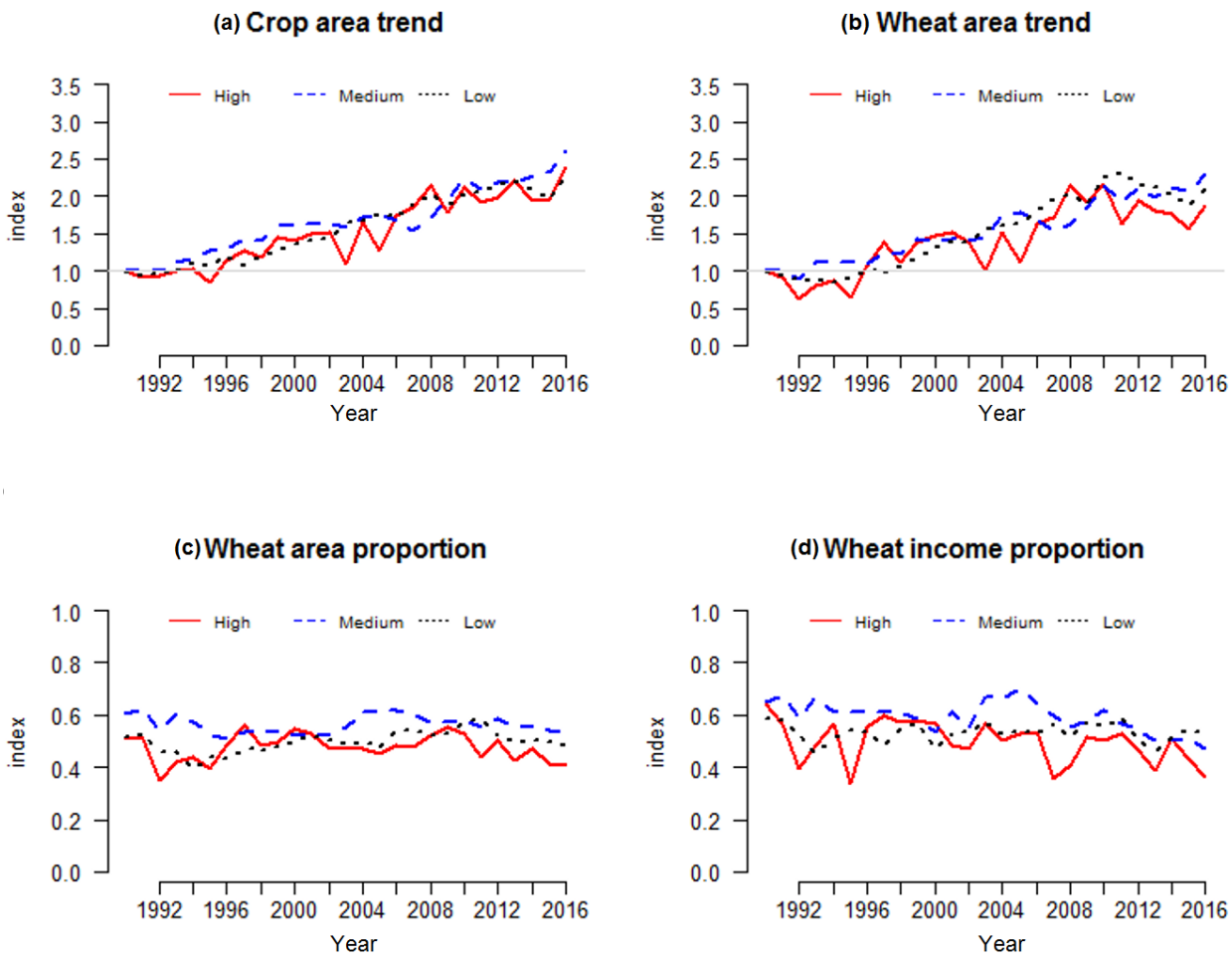

Figure A.2 Changes in crop area and wheat area and its income

Appendix B

Table B.1 Profitability, TFP, and efficiency change in high AARFRs

Year	PROFI	TFPI	TTI	TI	EFFI	OTEI	OSEI	OMEI	ROSEI	OSMEI	TSMEI	OEErI
1990	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1991	0.95	1.05	0.94	1.00	1.05	1.00	1.00	1.01	1.02	1.03	1.03	1.01
1992	0.82	0.92	0.93	1.00	0.92	0.85	1.00	1.00	1.10	1.10	0.93	0.98
1993	1.05	1.06	1.04	1.13	0.93	0.95	1.00	1.00	1.06	1.06	1.01	0.93
1994	1.18	1.24	1.00	1.23	1.00	1.00	0.86	0.92	0.99	0.91	0.91	1.09
1995	0.59	0.39	1.56	1.23	0.32	0.65	0.79	0.95	0.62	0.59	0.38	0.87
1996	1.44	1.15	1.30	1.23	0.93	0.94	0.99	0.94	0.98	0.92	0.86	1.08
1997	1.38	1.51	0.95	1.23	1.22	1.00	0.96	1.01	0.98	0.99	0.99	1.23
1998	0.97	1.09	0.91	1.23	0.89	0.92	0.91	0.98	0.81	0.79	0.73	1.21
1999	1.17	1.48	0.81	1.23	1.20	1.00	0.95	1.01	0.90	0.91	0.91	1.32
2000	1.15	1.57	0.75	1.27	1.23	1.00	1.00	1.00	0.97	0.97	0.97	1.28
2001	1.05	1.19	0.89	1.31	0.90	0.85	0.90	0.93	0.92	0.86	0.73	1.25
2002	1.42	1.44	1.01	1.39	1.04	0.97	0.90	0.95	0.96	0.91	0.88	1.17
2003	0.76	0.61	1.47	1.39	0.44	0.72	0.94	0.95	0.66	0.63	0.45	0.99
2004	1.12	1.55	0.74	1.39	1.12	0.98	0.97	0.98	0.99	0.97	0.95	1.17
2005	0.76	1.31	0.59	1.39	0.94	0.97	0.98	0.99	0.84	0.84	0.82	1.17
2006	0.82	1.55	0.52	1.41	1.10	0.98	0.93	1.01	0.97	0.98	0.96	1.15
2007	0.61	0.72	0.89	1.41	0.51	0.77	0.83	0.94	0.68	0.64	0.49	1.06
2008	0.94	1.38	0.79	1.89	0.73	0.70	0.88	0.80	0.82	0.65	0.46	1.54
2009	1.10	1.59	0.72	1.89	0.84	1.00	0.86	0.92	0.68	0.63	0.63	1.38
2010	0.90	1.56	0.61	1.89	0.82	0.86	1.00	0.99	0.70	0.69	0.59	1.39
2011	1.33	2.22	0.61	1.89	1.17	1.00	0.94	1.00	0.85	0.85	0.85	1.38
2012	1.14	1.92	0.60	1.89	1.02	0.86	0.95	0.96	0.92	0.88	0.75	1.35
2013	1.52	1.87	0.82	1.89	0.99	0.84	0.93	0.98	0.88	0.86	0.72	1.37
2014	1.16	1.47	0.79	1.89	0.78	0.66	0.96	0.92	0.92	0.85	0.56	1.38
2015	1.26	1.49	0.85	1.89	0.79	0.65	0.94	0.96	0.93	0.89	0.58	1.37
2016	1.24	1.72	0.75	1.89	0.91	0.79	0.90	0.98	0.86	0.84	0.66	1.38
Average	**1.07**	**1.33**	**0.88**	**1.46**	**0.92**	**0.88**	**0.93**	**0.97**	**0.89**	**0.86**	**0.77**	**1.20**

Continues

Table B.2 Profitability, TFP, and efficiency change in medium AARFRs

Year	PROFI	TFPI	TTI	TI	EFFI	OTEI	OSEI	OMEI	ROSEI	OSMEI	TSMEI	OEErI
1990	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1991	0.90	1.33	0.65	1.00	1.33	0.98	1.02	1.01	0.99	1.01	0.99	1.34
1992	0.89	1.14	0.76	1.00	1.14	1.00	1.02	1.01	0.84	0.85	0.85	1.34
1993	0.96	1.24	0.77	1.13	1.10	0.98	1.02	1.01	0.88	0.89	0.88	1.25
1994	1.03	1.37	0.73	1.23	1.11	1.00	1.01	1.01	0.87	0.88	0.88	1.27
1995	0.94	0.97	0.97	1.23	0.78	0.93	0.96	0.95	0.71	0.68	0.63	1.25
1996	1.21	1.32	0.92	1.23	1.07	1.00	1.02	1.01	0.83	0.84	0.84	1.27
1997	1.09	1.38	0.76	1.23	1.12	0.98	1.01	1.01	0.89	0.90	0.88	1.27
1998	1.01	1.27	0.77	1.23	1.03	1.00	1.02	1.00	0.81	0.81	0.81	1.27
1999	1.02	1.51	0.64	1.23	1.22	1.00	1.02	1.01	0.95	0.96	0.96	1.27
2000	1.09	1.69	0.61	1.27	1.33	0.95	1.02	1.01	0.92	0.93	0.88	1.50
2001	0.89	1.28	0.67	1.31	0.97	0.78	0.97	0.98	0.87	0.85	0.67	1.46
2002	0.93	1.42	0.62	1.39	1.02	0.97	1.01	1.00	0.78	0.78	0.76	1.35
2003	0.72	0.77	0.91	1.39	0.56	0.64	0.93	0.96	0.75	0.73	0.46	1.21
2004	0.85	1.75	0.44	1.39	1.26	0.96	1.01	1.00	0.92	0.92	0.89	1.42
2005	0.73	1.43	0.48	1.39	1.03	0.90	1.01	0.98	0.85	0.83	0.75	1.38
2006	0.73	1.79	0.40	1.41	1.26	1.00	1.02	1.00	0.87	0.86	0.86	1.47
2007	0.58	1.15	0.49	1.41	0.81	0.80	0.97	0.93	0.76	0.70	0.56	1.44
2008	0.70	1.16	0.60	1.89	0.62	0.74	1.01	0.90	0.86	0.78	0.57	1.10
2009	0.94	1.65	0.53	1.89	0.87	0.90	1.01	0.93	0.94	0.88	0.79	1.11
2010	0.75	1.46	0.49	1.89	0.77	0.88	1.01	1.01	0.81	0.82	0.72	1.07
2011	0.93	1.62	0.61	1.89	0.86	0.85	0.99	0.96	0.75	0.72	0.62	1.39
2012	1.01	2.14	0.45	1.89	1.13	0.96	1.02	1.01	0.86	0.87	0.83	1.36
2013	1.10	1.57	0.70	1.89	0.83	0.80	1.00	0.94	0.82	0.77	0.61	1.35
2014	1.07	1.66	0.60	1.89	0.88	0.83	1.00	0.99	0.76	0.75	0.62	1.41
2015	1.05	1.53	0.65	1.89	0.81	0.87	1.00	0.97	0.70	0.67	0.59	1.38
2016	1.11	1.80	0.59	1.89	0.95	0.99	0.98	0.99	0.71	0.70	0.69	1.37
Average	**0.93**	**1.42**	**0.66**	**1.46**	**1.00**	**0.92**	**1.00**	**0.99**	**0.84**	**0.83**	**0.76**	**1.31**

Continues

Table B.3 Profitability, TFP, and efficiency change in low AARFRs

Year	PROFI	TFPI	TTI	TI	EFFI	OTEI	OSEI	OMEI	ROSEI	OSMEI	TSMEI	OEErI
1990	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1991	0.71	0.83	0.85	1.00	0.83	1.00	0.96	1.00	0.83	0.83	0.83	1.00
1992	0.85	0.95	0.89	1.00	0.95	1.00	1.00	1.00	0.95	0.95	0.95	1.00
1993	0.89	1.07	0.82	1.13	0.94	1.00	1.00	1.00	0.94	0.94	0.94	1.00
1994	0.89	1.16	0.76	1.23	0.94	0.99	0.98	0.95	0.99	0.94	0.93	1.00
1995	0.66	0.49	1.41	1.23	0.40	0.64	0.76	0.93	0.70	0.65	0.41	0.98
1996	0.94	1.06	0.87	1.23	0.86	1.00	0.99	1.00	0.86	0.86	0.86	1.00
1997	0.79	0.94	0.84	1.23	0.76	0.89	0.95	0.97	0.88	0.86	0.76	1.00
1998	0.69	0.80	0.89	1.23	0.65	0.73	1.00	0.98	0.90	0.88	0.65	1.00
1999	0.73	0.92	0.79	1.23	0.75	0.90	0.97	0.94	0.89	0.83	0.75	1.00
2000	0.81	1.03	0.80	1.27	0.81	0.92	0.96	1.00	0.91	0.90	0.84	0.97
2001	0.99	1.27	0.77	1.31	0.97	0.99	0.99	1.00	0.98	0.98	0.97	1.00
2002	1.05	1.29	0.81	1.39	0.93	1.00	0.98	1.00	0.93	0.93	0.93	1.00
2003	0.65	0.45	1.71	1.39	0.33	0.42	0.92	0.89	0.83	0.74	0.31	1.05
2004	0.75	1.35	0.55	1.39	0.97	0.97	1.00	1.00	1.01	1.00	0.97	1.00
2005	0.57	0.78	0.74	1.39	0.56	0.69	0.95	0.97	0.85	0.82	0.56	1.00
2006	0.61	1.41	0.43	1.41	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2007	0.42	0.48	0.90	1.41	0.34	0.72	0.80	0.86	0.59	0.51	0.36	0.93
2008	0.57	0.84	0.68	1.89	0.44	0.75	0.92	0.98	0.82	0.80	0.60	0.74
2009	0.52	0.85	0.61	1.89	0.45	0.77	0.86	0.99	0.82	0.81	0.62	0.72
2010	0.61	1.43	0.43	1.89	0.76	1.00	0.98	1.00	0.95	0.95	0.95	0.80
2011	0.79	1.69	0.46	1.89	0.89	1.00	1.00	1.00	1.03	1.03	1.03	0.87
2012	0.75	1.45	0.51	1.89	0.77	0.95	0.98	0.99	0.94	0.93	0.89	0.86
2013	0.78	1.26	0.62	1.89	0.67	0.92	0.95	0.96	0.88	0.84	0.78	0.86
2014	0.72	1.33	0.55	1.89	0.70	0.90	0.99	0.98	0.91	0.89	0.81	0.87
2015	0.64	1.04	0.63	1.89	0.55	0.92	0.80	0.98	0.71	0.70	0.64	0.86
2016	0.51	1.01	0.49	1.89	0.54	0.66	0.99	0.97	0.96	0.94	0.62	0.87
Average	**0.74**	**1.04**	**0.77**	**1.46**	**0.73**	**0.88**	**0.95**	**0.98**	**0.89**	**0.87**	**0.78**	**0.94**

Continues

Table B.4 Profitability, TFP, and efficiency change in all farm AARFRs

Year	PROFI	TFPI	TTI	TI	EFFI	OTEI	OSEI	OMEI	ROSEI	OSMEI	TSMEI	OEErI
1990	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1991	0.82	1.03	0.79	1.00	1.03	0.99	0.99	1.01	0.95	0.95	0.95	1.09
1992	0.86	1.00	0.85	1.00	1.00	0.95	1.01	1.01	0.96	0.96	0.91	1.09
1993	0.94	1.11	0.85	1.13	0.99	0.98	1.00	1.00	0.96	0.96	0.94	1.05
1994	0.99	1.24	0.81	1.23	1.01	1.00	0.95	0.96	0.95	0.91	0.91	1.10
1995	0.73	0.60	1.28	1.23	0.49	0.74	0.84	0.94	0.68	0.64	0.47	1.05
1996	1.12	1.16	1.00	1.23	0.94	0.98	1.00	0.99	0.89	0.87	0.86	1.10
1997	1.00	1.22	0.84	1.23	0.99	0.96	0.97	1.00	0.92	0.91	0.87	1.13
1998	0.85	1.02	0.85	1.23	0.82	0.88	0.97	0.99	0.84	0.83	0.73	1.12
1999	0.90	1.25	0.74	1.23	1.01	0.97	0.98	0.99	0.91	0.90	0.87	1.16
2000	0.96	1.37	0.71	1.27	1.07	0.96	0.99	1.00	0.93	0.93	0.89	1.20
2001	0.97	1.25	0.76	1.31	0.95	0.87	0.95	0.97	0.93	0.90	0.78	1.21
2002	1.09	1.37	0.79	1.39	0.99	0.98	0.96	0.98	0.89	0.87	0.85	1.15
2003	0.70	0.59	1.35	1.39	0.42	0.59	0.93	0.93	0.75	0.70	0.42	1.03
2004	0.86	1.52	0.56	1.39	1.10	0.97	0.99	0.99	0.97	0.97	0.94	1.17
2005	0.66	1.11	0.61	1.39	0.80	0.85	0.98	0.98	0.85	0.83	0.71	1.14
2006	0.69	1.56	0.44	1.41	1.10	0.99	0.98	1.00	0.95	0.95	0.94	1.17
2007	0.51	0.74	0.74	1.41	0.52	0.76	0.86	0.91	0.68	0.61	0.47	1.12
2008	0.68	1.08	0.68	1.89	0.57	0.73	0.94	0.89	0.83	0.74	0.54	1.05
2009	0.76	1.28	0.61	1.89	0.68	0.89	0.91	0.95	0.82	0.78	0.69	0.99
2010	0.71	1.47	0.50	1.89	0.78	0.92	1.00	1.00	0.83	0.82	0.75	1.03
2011	0.94	1.81	0.55	1.89	0.96	0.95	0.98	0.99	0.88	0.87	0.82	1.16
2012	0.91	1.78	0.51	1.89	0.94	0.92	0.99	0.99	0.90	0.89	0.82	1.14
2013	1.03	1.51	0.70	1.89	0.80	0.85	0.96	0.96	0.86	0.82	0.70	1.14
2014	0.92	1.46	0.63	1.89	0.77	0.80	0.98	0.96	0.86	0.83	0.66	1.17
2015	0.89	1.30	0.69	1.89	0.69	0.81	0.91	0.97	0.77	0.75	0.61	1.13
2016	0.84	1.43	0.59	1.89	0.76	0.82	0.96	0.98	0.84	0.82	0.67	1.13
Average	**0.86**	**1.23**	**0.76**	**1.46**	**0.86**	**0.89**	**0.96**	**0.98**	**0.87**	**0.85**	**0.77**	**1.11**

Appendix C

Table C.1 Profitability, TFP, and efficiency change in high AATFRs

Year	PROFT	TFPI	TTI	TI	EFFI	OTEI	OSEI	OMEI	ROSEI	OSMEI	TSMEI	OEEtI
1990	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1991	0.79	1.23	0.62	1.00	1.23	1.00	1.00	1.00	1.12	1.12	1.12	1.09
1992	0.68	0.89	0.74	1.00	0.89	0.93	0.92	0.91	0.90	0.81	0.76	1.18
1993	0.81	1.07	0.75	1.13	0.94	1.00	1.00	0.98	0.92	0.91	0.91	1.04
1994	0.97	1.33	0.72	1.23	1.08	1.00	1.00	1.00	0.99	0.99	0.99	1.09
1995	0.62	0.57	1.11	1.23	0.47	0.77	0.99	0.97	0.62	0.60	0.47	1.01
1996	1.05	1.16	0.92	1.23	0.94	0.89	1.00	1.00	0.97	0.97	0.87	1.08
1997	1.13	1.54	0.72	1.23	1.24	1.00	0.97	0.99	1.02	1.01	1.01	1.23
1998	0.92	1.23	0.73	1.23	1.00	0.94	0.96	0.99	0.88	0.88	0.82	1.21
1999	1.02	1.59	0.61	1.23	1.29	1.00	1.00	1.00	0.97	0.97	0.97	1.32
2000	0.92	1.53	0.57	1.27	1.20	0.95	0.99	0.99	0.99	0.98	0.93	1.29
2001	0.69	1.09	0.60	1.31	0.83	0.83	0.87	0.85	0.96	0.82	0.68	1.21
2002	0.99	1.47	0.65	1.39	1.06	0.99	0.97	0.99	0.92	0.91	0.90	1.17
2003	0.66	0.71	0.91	1.39	0.51	0.93	0.74	0.98	0.52	0.51	0.47	1.10
2004	0.77	1.50	0.48	1.39	1.08	1.00	0.99	1.00	0.92	0.92	0.92	1.17
2005	0.71	1.51	0.45	1.39	1.08	0.94	0.99	0.99	1.00	0.99	0.93	1.17
2006	0.71	1.63	0.42	1.41	1.15	1.00	0.97	1.00	0.99	0.99	0.99	1.16
2007	0.54	1.00	0.54	1.41	0.71	0.76	0.90	0.89	0.89	0.79	0.60	1.17
2008	0.71	1.18	0.60	1.89	0.63	0.79	0.96	0.91	0.99	0.90	0.71	0.90
2009	0.93	1.72	0.52	1.89	0.91	1.00	1.00	0.98	1.00	0.98	0.98	0.93
2010	0.73	1.46	0.49	1.89	0.77	0.89	0.97	0.94	0.97	0.91	0.81	0.95
2011	0.98	1.91	0.53	1.89	1.01	1.00	0.93	0.98	0.86	0.84	0.84	1.19
2012	0.85	1.86	0.43	1.89	0.98	0.87	0.99	0.98	0.99	0.97	0.85	1.17
2013	1.08	1.63	0.63	1.89	0.86	0.94	0.88	0.96	0.80	0.77	0.72	1.19
2014	0.92	1.47	0.58	1.89	0.78	0.84	0.89	0.98	0.79	0.77	0.64	1.21
2015	0.94	1.41	0.62	1.89	0.75	0.78	0.91	0.96	0.84	0.81	0.63	1.19
2016	1.00	1.79	0.53	1.89	0.95	0.92	0.92	0.98	0.90	0.88	0.81	1.17
Average	**0.86**	**1.35**	**0.65**	**1.46**	**0.94**	**0.92**	**0.95**	**0.97**	**0.92**	**0.89**	**0.83**	**1.13**

Continues

Table C.2 Profitability, TFP, and efficiency change in medium AATFRs

Year	PROFI	TFPI	TTI	TI	EFFI	OTEI	OSEI	OMEI	ROSEI	OSMEI	TSMEI	OEEtI
1990	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1991	0.90	1.09	0.86	1.00	1.09	0.99	0.99	0.99	1.12	1.11	1.10	1.00
1992	0.94	1.14	0.86	1.00	1.14	1.00	1.00	1.00	1.14	1.14	1.14	1.00
1993	0.96	1.15	0.91	1.13	1.01	1.00	1.00	0.99	1.15	1.15	1.15	0.88
1994	0.95	1.16	0.85	1.23	0.94	0.96	0.96	0.89	1.25	1.13	1.08	0.87
1995	0.85	0.75	1.22	1.23	0.61	0.86	0.93	0.93	0.91	0.83	0.71	0.85
1996	1.23	1.15	1.15	1.23	0.93	1.00	1.00	1.00	1.07	1.07	1.07	0.87
1997	0.98	1.18	0.87	1.23	0.95	0.98	0.99	0.97	1.16	1.12	1.10	0.87
1998	0.94	1.14	0.83	1.23	0.92	1.00	1.00	1.00	1.06	1.06	1.06	0.87
1999	0.95	1.32	0.74	1.23	1.07	1.00	1.00	1.00	1.23	1.23	1.23	0.87
2000	1.10	1.46	0.82	1.27	1.14	0.96	0.99	1.00	1.16	1.16	1.12	1.02
2001	1.06	1.26	0.89	1.31	0.96	0.94	0.98	0.98	1.06	1.04	0.97	0.99
2002	1.01	1.31	0.80	1.39	0.94	0.98	0.96	0.94	1.08	1.03	1.01	0.93
2003	0.75	0.72	1.13	1.39	0.52	0.66	0.92	0.97	0.92	0.90	0.59	0.88
2004	0.93	1.56	0.63	1.39	1.12	1.00	1.00	1.00	1.17	1.17	1.17	0.96
2005	0.67	1.07	0.64	1.39	0.77	0.86	0.99	0.99	0.97	0.95	0.82	0.94
2006	0.76	1.59	0.49	1.41	1.12	1.00	1.00	0.99	1.12	1.11	1.11	1.01
2007	0.52	0.77	0.73	1.41	0.55	0.88	0.94	0.94	0.68	0.63	0.55	0.99
2008	0.73	1.21	0.75	1.89	0.64	0.63	0.99	0.90	0.99	0.89	0.56	1.14
2009	0.88	1.36	0.68	1.89	0.72	0.82	0.99	0.97	0.88	0.85	0.70	1.03
2010	0.78	1.49	0.55	1.89	0.79	0.85	0.99	0.95	0.96	0.91	0.78	1.02
2011	0.93	1.69	0.63	1.89	0.90	0.91	0.98	1.00	0.95	0.95	0.86	1.04
2012	1.00	1.85	0.57	1.89	0.98	0.91	0.99	0.98	1.08	1.06	0.97	1.01
2013	1.06	1.43	0.82	1.89	0.76	0.87	0.97	0.91	0.95	0.87	0.76	1.00
2014	1.00	1.52	0.69	1.89	0.80	0.88	0.98	0.97	0.92	0.89	0.78	1.03
2015	1.03	1.50	0.73	1.89	0.79	0.94	0.98	0.96	0.86	0.83	0.78	1.02
2016	1.06	1.65	0.68	1.89	0.88	0.94	0.98	0.99	0.93	0.92	0.87	1.01
Average	**0.92**	**1.28**	**0.80**	**1.46**	**0.89**	**0.92**	**0.98**	**0.97**	**1.03**	**1.00**	**0.93**	**0.97**

Table C.3 Profitability, TFP, and efficiency change in low AATFRs

Year	PROFT	TFPI	TTI	TI	EFFI	OTEI	OSEI	OMEI	ROSEI	OSMEI	TSMEI	OEEtI
1990	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1991	0.77	0.84	0.91	1.00	0.84	1.00	0.95	0.99	0.84	0.84	0.84	1.00
1992	0.91	0.95	0.96	1.00	0.95	1.00	1.00	1.00	0.95	0.95	0.95	1.00
1993	1.02	1.12	0.91	1.13	0.99	1.00	0.99	1.00	0.99	0.99	0.99	1.00
1994	1.04	1.24	0.86	1.23	1.01	1.00	1.00	1.00	1.01	1.01	1.01	1.00
1995	0.71	0.49	1.51	1.23	0.40	0.85	0.58	0.97	0.56	0.54	0.46	0.90
1996	1.08	1.17	0.94	1.23	0.95	1.00	1.00	1.00	0.95	0.95	0.95	1.00
1997	0.93	1.03	0.92	1.23	0.83	0.92	0.98	1.00	0.92	0.91	0.84	0.99
1998	0.72	0.75	0.98	1.23	0.61	0.73	0.93	0.95	0.89	0.85	0.62	0.98
1999	0.78	0.92	0.87	1.23	0.75	0.90	0.97	1.00	0.85	0.85	0.76	0.98
2000	0.88	1.17	0.76	1.27	0.92	0.94	0.99	1.00	1.01	1.01	0.96	0.96
2001	1.09	1.36	0.81	1.31	1.04	0.99	0.96	1.00	1.05	1.05	1.04	1.00
2002	1.22	1.35	0.93	1.39	0.97	0.95	0.96	0.99	1.02	1.02	0.97	1.00
2003	0.68	0.38	2.01	1.39	0.28	0.53	0.92	0.93	0.71	0.66	0.35	0.81
2004	0.85	1.50	0.57	1.39	1.08	0.98	0.99	1.00	1.11	1.11	1.08	1.00
2005	0.61	0.86	0.73	1.39	0.62	0.70	0.91	0.96	0.94	0.90	0.62	0.99
2006	0.61	1.49	0.42	1.41	1.05	0.99	1.00	1.00	1.06	1.06	1.05	1.00
2007	0.48	0.51	0.97	1.41	0.36	0.82	0.84	0.95	0.53	0.50	0.41	0.89
2008	0.62	0.89	0.69	1.89	0.47	0.77	0.82	0.96	0.85	0.82	0.63	0.75
2009	0.54	0.88	0.63	1.89	0.46	0.80	0.92	0.98	0.84	0.82	0.66	0.71
2010	0.64	1.47	0.45	1.89	0.78	0.99	0.98	1.00	0.99	0.99	0.98	0.80
2011	0.92	1.85	0.51	1.89	0.98	1.00	0.96	1.00	1.13	1.13	1.13	0.87
2012	0.87	1.65	0.54	1.89	0.87	0.94	0.97	0.96	1.11	1.07	1.01	0.86
2013	0.97	1.50	0.66	1.89	0.80	0.93	0.98	0.94	1.06	1.00	0.93	0.86
2014	0.84	1.40	0.61	1.89	0.74	0.83	0.97	0.96	1.07	1.03	0.85	0.87
2015	0.73	1.05	0.73	1.89	0.56	0.77	0.80	0.96	0.91	0.88	0.68	0.83
2016	0.53	0.96	0.57	1.89	0.51	0.56	0.97	0.95	1.10	1.05	0.59	0.87
Average	**0.82**	**1.10**	**0.83**	**1.46**	**0.77**	**0.89**	**0.94**	**0.98**	**0.94**	**0.92**	**0.83**	**0.92**

Continues

Table C.4 Profitability, TFP, and efficiency change in all AATFRs

Year	PROFT	TFPI	TTI	TI	EFFI	OTEI	OSEI	OMEI	ROSEI	OSMEI	TSMEI	OEEtI
1990	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1991	0.82	1.03	0.79	1.00	1.03	1.00	0.98	1.00	1.03	1.02	1.02	1.02
1992	0.86	1.00	0.85	1.00	1.00	0.98	0.97	0.97	0.99	0.96	0.94	1.06
1993	0.94	1.11	0.85	1.13	0.99	1.00	1.00	0.99	1.02	1.01	1.01	0.98
1994	0.99	1.24	0.81	1.23	1.01	0.99	0.99	0.96	1.07	1.04	1.02	0.98
1995	0.73	0.60	1.28	1.23	0.49	0.82	0.83	0.96	0.69	0.65	0.53	0.92
1996	1.12	1.16	1.00	1.23	0.94	0.96	1.00	1.00	0.99	0.99	0.96	0.98
1997	1.00	1.22	0.84	1.23	0.99	0.97	0.98	0.99	1.03	1.01	0.98	1.01
1998	0.85	1.02	0.85	1.23	0.82	0.89	0.96	0.98	0.94	0.92	0.82	1.00
1999	0.90	1.25	0.74	1.23	1.01	0.97	0.99	1.00	1.01	1.01	0.98	1.03
2000	0.96	1.37	0.71	1.27	1.07	0.95	0.99	1.00	1.05	1.04	1.00	1.08
2001	0.97	1.25	0.76	1.31	0.95	0.92	0.94	0.94	1.02	0.97	0.89	1.07
2002	1.09	1.37	0.79	1.39	0.99	0.97	0.96	0.98	1.01	0.98	0.96	1.03
2003	0.70	0.59	1.35	1.39	0.42	0.71	0.86	0.96	0.71	0.67	0.47	0.89
2004	0.86	1.52	0.56	1.39	1.10	0.99	0.99	1.00	1.06	1.06	1.05	1.04
2005	0.66	1.11	0.61	1.39	0.80	0.83	0.97	0.98	0.97	0.95	0.79	1.02
2006	0.69	1.56	0.44	1.41	1.10	1.00	0.99	0.99	1.06	1.05	1.05	1.05
2007	0.51	0.74	0.74	1.41	0.52	0.82	0.89	0.93	0.70	0.64	0.52	0.99
2008	0.68	1.08	0.68	1.89	0.57	0.73	0.92	0.92	0.94	0.86	0.63	0.91
2009	0.76	1.28	0.61	1.89	0.68	0.87	0.97	0.97	0.91	0.88	0.77	0.88
2010	0.71	1.47	0.50	1.89	0.78	0.91	0.98	0.96	0.98	0.94	0.85	0.91
2011	0.94	1.81	0.55	1.89	0.96	0.97	0.96	0.99	0.98	0.97	0.94	1.02
2012	0.91	1.78	0.51	1.89	0.94	0.91	0.98	0.97	1.06	1.03	0.94	1.00
2013	1.03	1.51	0.70	1.89	0.80	0.91	0.95	0.94	0.94	0.88	0.80	1.00
2014	0.92	1.46	0.63	1.89	0.77	0.85	0.95	0.97	0.92	0.89	0.76	1.02
2015	0.89	1.30	0.69	1.89	0.69	0.83	0.90	0.96	0.87	0.84	0.69	0.99
2016	0.84	1.43	0.59	1.89	0.76	0.81	0.95	0.97	0.98	0.95	0.77	0.99
Average	**0.86**	**1.23**	**0.76**	**1.46**	**0.86**	**0.91**	**0.96**	**0.97**	**0.96**	**0.93**	**0.86**	**1.00**

Appendix D

Table D.1 Results of first stage analysis (DEA) of OTE_{CRS} indicator score for rainfall variation analysis

	High AARFRs				Medium AARFRs				Low AARFRs				All
Year	**NSWN**	**NSWC**	**QLDE**	**VICC**	**NSWR**	**QLDD**	**WACS**	**WANE**	**VICM**	**VICW**	**SAEP**	**SAMY**	**AARFRs**
1990	1.00	1.00	1.00	1.00	1.00	1.00	0.91	1.00	1.00	1.00	1.00	1.00	0.99
1991	1.00	1.00	1.00	1.00	1.00	1.00	0.91	1.00	1.00	0.86	0.99	1.00	0.98
1992	0.50	0.88	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95
1993	0.79	1.00	1.00	1.00	1.00	1.00	0.93	1.00	1.00	0.98	1.00	1.00	0.98
1994	1.00	1.00	0.62	0.83	1.00	1.00	0.95	1.00	1.00	1.00	0.89	1.00	0.94
1995	0.37	0.18	1.00	0.30	0.71	1.00	0.80	1.00	0.33	0.40	0.46	0.68	0.60
1996	0.94	0.78	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	1.00	0.97
1997	1.00	1.00	1.00	0.84	1.00	1.00	0.90	1.00	0.80	0.90	0.84	0.84	0.93
1998	0.85	0.79	1.00	0.67	1.00	1.00	1.00	1.00	0.49	0.58	1.00	0.86	0.85
1999	1.00	1.00	1.00	0.80	1.00	1.00	1.00	1.00	0.59	0.89	1.00	1.00	0.94
2000	1.00	0.98	1.00	1.00	1.00	0.78	1.00	1.00	0.99	1.00	0.77	0.77	0.94
2001	0.57	0.97	0.65	0.85	1.00	0.68	0.58	0.72	1.00	1.00	1.00	0.92	0.83
2002	0.90	0.97	0.79	0.81	0.85	1.00	1.00	1.00	0.94	1.00	1.00	1.00	0.94
2003	0.34	0.42	1.00	1.00	0.47	0.69	0.69	0.37	0.25	0.21	0.55	0.59	0.55
2004	1.00	0.86	0.94	1.00	1.00	0.80	1.00	1.00	1.00	1.00	1.00	0.89	0.96
2005	1.00	0.82	1.00	1.00	0.73	1.00	0.88	0.96	0.48	0.69	0.68	0.76	0.83
2006	0.87	1.00	1.00	0.75	1.00	1.00	0.99	1.00	1.00	1.00	1.00	0.99	0.97
2007	0.72	0.24	0.99	0.50	0.49	1.00	0.73	0.85	0.61	0.41	0.58	0.55	0.64
2008	0.80	0.33	1.00	0.38	0.25	1.00	1.00	0.69	0.69	0.79	0.60	0.64	0.68
2009	1.00	0.96	0.90	0.56	0.58	1.00	1.00	1.00	0.69	0.57	0.68	0.64	0.80
2010	1.00	0.45	1.00	1.00	0.52	1.00	1.00	1.00	0.93	1.00	1.00	0.98	0.91
2011	1.00	1.00	0.82	0.95	1.00	1.00	0.71	0.60	1.00	1.00	1.00	1.00	0.92
2012	0.79	0.61	0.93	0.93	0.81	1.00	1.00	1.00	1.00	1.00	0.92	0.84	0.90
2013	0.81	0.62	0.83	0.85	0.90	0.89	0.84	0.48	1.00	0.98	0.77	0.76	0.81
2014	0.59	0.68	0.55	0.73	0.86	0.47	1.00	0.95	0.78	1.00	0.97	0.83	0.78
2015	0.51	0.63	0.72	0.55	0.81	0.67	1.00	0.91	0.73	0.41	0.88	0.89	0.73
2016	0.77	0.70	0.85	0.46	0.84	1.00	1.00	1.00	0.62	0.34	0.86	0.80	0.77
Average	**0.82**	**0.77**	**0.91**	**0.81**	**0.85**	**0.93**	**0.92**	**0.91**	**0.81**	**0.82**	**0.87**	**0.86**	**0.86**

Table D.2 Results of first stage analysis (DEA) of OTE_{VRS} indicator score for rainfall variation analysis

	High AARFRs				Medium AARFRs				Low AARFRs				All
Year	**NSWN**	**NSWC**	**QLDE**	**VICC**	**NSWR**	**QLDD**	**WACS**	**WANE**	**VICM**	**VICW**	**SAEP**	**SAMY**	**AARFRs**
1990	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1991	1.00	1.00	1.00	1.00	1.00	1.00	0.93	1.00	1.00	1.00	1.00	1.00	0.99
1992	0.51	0.89	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95
1993	0.79	1.00	1.00	1.00	1.00	1.00	0.94	1.00	1.00	1.00	1.00	1.00	0.98
1994	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	1.00	1.00
1995	0.43	0.18	1.00	1.00	0.86	1.00	0.85	1.00	0.39	0.60	0.55	1.00	0.74
1996	0.95	0.79	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98
1997	1.00	1.00	1.00	1.00	1.00	1.00	0.94	1.00	0.81	1.00	0.90	0.85	0.96
1998	0.94	0.80	1.00	0.93	1.00	1.00	1.00	1.00	0.49	0.58	1.00	0.86	0.88
1999	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.62	0.98	1.00	1.00	0.97
2000	1.00	1.00	1.00	1.00	1.00	0.80	1.00	1.00	1.00	1.00	0.93	0.77	0.96
2001	0.62	0.97	0.80	1.00	1.00	0.78	0.58	0.77	1.00	1.00	1.00	0.95	0.87
2002	0.91	1.00	0.95	1.00	0.88	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98
2003	0.36	0.52	1.00	1.00	0.47	1.00	0.72	0.37	0.30	0.23	0.55	0.59	0.59
2004	1.00	0.90	1.00	1.00	1.00	0.85	1.00	1.00	1.00	1.00	1.00	0.89	0.97
2005	1.00	0.90	1.00	1.00	0.73	1.00	0.92	0.96	0.53	0.71	0.75	0.76	0.86
2006	0.90	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99
2007	0.84	0.25	1.00	1.00	0.57	1.00	0.74	0.89	0.66	0.98	0.62	0.62	0.76
2008	0.92	0.36	1.00	0.53	0.26	1.00	1.00	0.69	0.71	1.00	0.61	0.67	0.73
2009	1.00	1.00	1.00	1.00	0.61	1.00	1.00	1.00	1.00	0.64	0.69	0.74	0.89
2010	1.00	0.46	1.00	1.00	0.53	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.92
2011	1.00	1.00	1.00	1.00	1.00	1.00	0.80	0.61	1.00	1.00	1.00	1.00	0.95
2012	0.80	0.63	1.00	1.00	0.82	1.00	1.00	1.00	1.00	1.00	0.95	0.86	0.92
2013	0.81	0.67	0.86	1.00	0.91	0.94	0.86	0.48	1.00	1.00	0.91	0.78	0.85
2014	0.59	0.73	0.57	0.77	0.86	0.50	1.00	0.95	0.79	1.00	1.00	0.83	0.80
2015	0.52	0.66	0.83	0.59	0.81	0.69	1.00	0.98	0.76	1.00	1.00	0.94	0.81
2016	0.94	0.81	0.95	0.46	0.98	1.00	1.00	1.00	0.62	0.35	0.87	0.83	0.82
Average	**0.85**	**0.80**	**0.96**	**0.94**	**0.86**	**0.95**	**0.94**	**0.92**	**0.84**	**0.89**	**0.90**	**0.89**	**0.89**

Table D.3 Results of first stage analysis (DEA) of OSE indicator score for rainfall variation analysis

	High AARFRs				Medium AARFRs				Low AARFRs				All
Year	**NSWN**	**NSWC**	**QLDE**	**VICC**	**NSWR**	**QLDD**	**WACS**	**WANE**	**VICM**	**VICW**	**SAEP**	**SAMY**	**AARFRs**
1990	1.00	1.00	1.00	1.00	1.00	1.00	0.91	1.00	1.00	1.00	1.00	1.00	0.99
1991	1.00	1.00	1.00	1.00	1.00	1.00	0.97	1.00	1.00	0.86	0.99	1.00	0.99
1992	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1993	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	0.98	1.00	1.00	1.00
1994	1.00	1.00	0.62	0.83	1.00	1.00	0.96	1.00	1.00	0.99	0.92	1.00	0.94
1995	0.87	1.00	1.00	0.30	0.83	1.00	0.94	1.00	0.86	0.66	0.84	0.68	0.83
1996	0.98	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	1.00	0.99
1997	1.00	1.00	1.00	0.84	1.00	1.00	0.96	1.00	0.99	0.90	0.93	0.98	0.97
1998	0.91	0.99	1.00	0.72	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97
1999	1.00	1.00	1.00	0.80	1.00	1.00	1.00	1.00	0.96	0.90	1.00	1.00	0.97
2000	1.00	0.98	1.00	1.00	1.00	0.97	1.00	1.00	0.99	1.00	0.83	0.99	0.98
2001	0.93	1.00	0.82	0.85	1.00	0.87	0.99	0.93	1.00	1.00	1.00	0.97	0.95
2002	0.99	0.97	0.83	0.81	0.97	1.00	1.00	1.00	0.94	1.00	1.00	1.00	0.96
2003	0.95	0.80	1.00	1.00	1.00	0.69	0.96	0.99	0.82	0.88	1.00	1.00	0.92
2004	1.00	0.95	0.94	1.00	1.00	0.95	1.00	1.00	1.00	1.00	1.00	1.00	0.99
2005	1.00	0.91	1.00	1.00	1.00	1.00	0.96	1.00	0.91	0.98	0.91	0.99	0.97
2006	0.97	1.00	1.00	0.75	1.00	1.00	0.99	1.00	1.00	1.00	1.00	0.99	0.97
2007	0.86	0.95	0.99	0.50	0.86	1.00	0.98	0.96	0.93	0.42	0.94	0.90	0.86
2008	0.88	0.92	1.00	0.71	0.95	1.00	1.00	0.99	0.98	0.78	0.99	0.95	0.93
2009	1.00	0.96	0.90	0.56	0.95	1.00	1.00	1.00	0.69	0.89	0.98	0.86	0.90
2010	1.00	1.00	1.00	1.00	0.97	1.00	1.00	1.00	0.93	1.00	1.00	0.98	0.99
2011	1.00	1.00	0.82	0.95	1.00	1.00	0.89	0.97	1.00	1.00	1.00	1.00	0.97
2012	0.99	0.96	0.93	0.93	0.98	1.00	1.00	1.00	1.00	1.00	0.96	0.98	0.98
2013	1.00	0.92	0.96	0.85	1.00	0.95	0.98	1.00	1.00	0.98	0.84	0.98	0.96
2014	0.99	0.93	0.97	0.95	1.00	0.94	1.00	0.99	0.99	1.00	0.97	1.00	0.98
2015	1.00	0.96	0.87	0.93	1.00	0.97	1.00	0.93	0.95	0.41	0.88	0.95	0.90
2016	0.82	0.87	0.90	1.00	0.85	1.00	1.00	1.00	1.00	0.99	0.99	0.97	0.95
Average	**0.97**	**0.96**	**0.95**	**0.86**	**0.98**	**0.98**	**0.98**	**0.99**	**0.96**	**0.91**	**0.96**	**0.97**	**0.96**

Table D.4 Results of first stage analysis (DEA) of OME indicator score for rainfall variation analysis

	High AARFRs				Medium AARFRs				Low AARFRs				All
Year	**NSWN**	**NSWC**	**QLDE**	**VICC**	**NSWR**	**QLDD**	**WACS**	**WANE**	**VICM**	**VICW**	**SAEP**	**SAMY**	**AARFRs**
1990	1.00	1.00	0.96	1.00	1.00	1.00	0.94	1.00	1.00	1.00	1.00	1.00	0.99
1991	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00
1992	1.00	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1993	1.00	0.95	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00
1994	1.00	1.00	0.63	1.00	1.00	1.00	0.97	1.00	1.00	1.00	0.80	1.00	0.95
1995	0.77	0.99	1.00	1.00	0.84	1.00	0.92	1.00	0.86	0.99	0.85	1.00	0.93
1996	0.86	0.96	0.91	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98
1997	1.00	1.00	1.00	1.00	1.00	1.00	0.97	1.00	1.00	1.00	0.91	0.99	0.99
1998	1.00	1.00	1.00	0.90	1.00	0.96	0.97	1.00	0.97	0.95	1.00	1.00	0.98
1999	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.76	1.00	1.00	0.98
2000	1.00	0.94	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99
2001	0.92	0.86	0.89	1.00	1.00	0.95	1.00	0.91	1.00	1.00	1.00	1.00	0.96
2002	0.96	0.94	0.86	1.00	0.97	1.00	0.96	1.00	1.00	1.00	1.00	1.00	0.97
2003	0.98	0.76	1.00	1.00	1.00	1.00	0.86	0.94	0.82	0.88	0.99	0.88	0.93
2004	1.00	0.95	0.93	1.00	1.00	0.97	0.98	1.00	1.00	1.00	1.00	0.99	0.98
2005	1.00	0.92	1.00	1.00	0.98	1.00	0.93	0.95	0.91	1.00	0.96	1.00	0.97
2006	1.00	1.00	0.99	1.00	1.00	1.00	0.95	0.98	1.00	1.00	1.00	1.00	0.99
2007	0.94	0.77	1.00	1.00	0.86	1.00	0.98	0.84	0.77	0.89	0.84	0.94	0.90
2008	0.87	0.61	1.00	0.69	0.67	1.00	0.93	0.94	0.98	1.00	0.96	0.98	0.89
2009	1.00	0.64	1.00	1.00	0.81	1.00	0.86	1.00	1.00	0.97	1.00	1.00	0.94
2010	1.00	0.90	1.00	1.00	0.96	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99
2011	1.00	1.00	0.95	1.00	1.00	1.00	0.78	1.00	1.00	1.00	1.00	1.00	0.98
2012	0.99	0.90	0.92	0.98	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.99	0.98
2013	0.98	0.93	0.96	1.00	0.99	0.97	0.78	0.97	1.00	0.94	0.91	1.00	0.95
2014	0.97	0.85	0.94	0.89	1.00	0.98	1.00	0.92	0.93	1.00	1.00	1.00	0.96
2015	0.98	0.91	0.98	0.93	0.99	0.99	0.92	0.91	0.96	1.00	1.00	0.97	0.96
2016	0.91	0.98	0.99	0.99	0.97	1.00	0.92	1.00	0.99	0.93	0.99	0.98	0.97
Average	**0.97**	**0.92**	**0.96**	**0.98**	**0.96**	**0.99**	**0.95**	**0.98**	**0.97**	**0.97**	**0.97**	**0.99**	**0.97**

Table D.5 Results of first stage analysis (DEA) of ROSE indicator score for rainfall variation analysis

	High AARFRs				Medium AARFRs				Low AARFRs				All
Year	**NSWN**	**NSWC**	**QLDE**	**VICC**	**NSWR**	**QLDD**	**WACS**	**WANE**	**VICM**	**VICW**	**SAEP**	**SAMY**	**AARFRs**
1990	1.00	0.82	0.78	0.65	1.00	0.69	1.00	0.99	1.00	0.79	0.98	0.98	0.89
1991	0.96	1.00	0.86	0.50	0.90	0.88	0.89	1.00	0.84	0.67	0.79	0.83	0.84
1992	1.00	0.87	0.99	0.62	0.89	0.38	0.94	0.87	0.86	0.85	0.96	0.91	0.84
1993	1.00	1.00	0.61	0.77	1.00	0.36	0.95	0.94	1.00	0.84	0.85	0.85	0.85
1994	1.00	0.95	0.74	0.55	0.92	0.36	0.94	1.00	1.00	0.87	0.90	0.96	0.85
1995	0.81	0.64	0.36	0.21	0.67	0.28	0.89	0.79	0.78	0.53	0.76	0.56	0.61
1996	0.96	0.90	0.60	0.71	0.86	0.36	0.94	0.91	0.80	0.88	0.72	0.84	0.79
1997	1.00	0.91	0.69	0.60	0.78	0.72	0.89	0.88	0.87	0.75	0.85	0.84	0.82
1998	0.82	0.86	0.43	0.51	0.77	0.48	0.88	0.88	0.92	0.79	0.84	0.83	0.75
1999	0.81	1.00	0.64	0.48	0.97	0.66	0.96	0.91	0.80	0.80	0.84	0.88	0.81
2000	0.87	0.89	0.80	0.60	0.92	0.61	0.85	1.00	0.94	0.86	0.69	0.92	0.83
2001	0.85	0.96	0.51	0.69	0.99	0.51	0.86	0.83	1.00	0.89	0.90	0.91	0.83
2002	1.00	0.88	0.57	0.65	0.82	0.37	0.85	0.84	0.73	0.88	0.89	1.00	0.79
2003	0.84	0.68	0.49	0.16	0.78	0.30	0.84	0.85	0.77	0.65	0.85	0.84	0.67
2004	0.83	0.86	0.64	0.91	0.90	0.58	0.90	1.00	0.93	0.98	0.92	0.95	0.87
2005	0.88	0.91	0.50	0.45	0.90	0.57	0.87	0.79	0.84	0.78	0.67	0.88	0.76
2006	0.96	0.97	0.57	0.67	1.00	0.42	0.89	0.88	0.96	1.00	0.90	0.90	0.84
2007	0.66	0.83	0.48	0.26	0.68	0.50	0.91	0.70	0.65	0.24	0.62	0.70	0.60
2008	0.45	0.68	1.00	0.53	0.98	0.50	0.93	0.78	0.74	0.70	0.75	0.86	0.74
2009	0.67	0.73	0.60	0.23	0.89	0.62	0.95	0.99	0.53	0.92	0.80	0.83	0.73
2010	0.64	0.59	0.56	0.48	0.90	0.49	0.85	0.76	0.68	1.00	1.00	0.90	0.74
2011	0.76	0.86	0.50	0.64	1.00	0.44	0.72	0.61	0.98	0.95	0.95	1.00	0.78
2012	0.76	0.90	0.67	0.65	0.92	0.61	0.77	0.87	0.76	0.94	0.86	0.97	0.81
2013	0.78	0.78	0.68	0.64	0.85	0.58	0.80	0.80	0.69	0.89	0.78	0.94	0.77
2014	0.77	0.84	0.64	0.75	0.78	0.53	0.74	0.74	0.83	0.86	0.85	0.88	0.77
2015	0.80	0.85	0.67	0.72	0.77	0.49	0.69	0.62	0.74	0.36	0.75	0.81	0.69
2016	0.75	0.69	0.66	0.70	0.69	0.57	0.68	0.67	0.83	0.98	0.91	0.90	0.75
Average	**0.84**	**0.85**	**0.64**	**0.57**	**0.87**	**0.51**	**0.87**	**0.85**	**0.83**	**0.80**	**0.84**	**0.88**	**0.78**

Table D.6 Results of first stage analysis (DEA) of OSME indicator score for rainfall variation analysis

	High AARFRs				Medium AARFRs				Low AARFRs				All
Year	**NSWN**	**NSWC**	**QLDE**	**VICC**	**NSWR**	**QLDD**	**WACS**	**WANE**	**VICM**	**VICW**	**SAEP**	**SAMY**	**AARFRs**
1990	1.00	0.82	0.74	0.65	1.00	0.69	0.94	0.99	1.00	0.79	0.98	0.98	0.88
1991	0.96	1.00	0.86	0.50	0.90	0.88	0.88	1.00	0.84	0.67	0.79	0.83	0.84
1992	1.00	0.85	0.99	0.62	0.89	0.38	0.94	0.87	0.86	0.85	0.96	0.91	0.85
1993	1.00	1.00	0.61	0.77	1.00	0.36	0.94	0.94	1.00	0.84	0.85	0.85	0.85
1994	1.00	0.95	0.47	0.55	0.92	0.36	0.91	1.00	1.00	0.87	0.72	0.96	0.81
1995	0.62	0.63	0.36	0.21	0.56	0.28	0.82	0.79	0.67	0.52	0.65	0.56	0.56
1996	0.83	0.87	0.55	0.71	0.86	0.36	0.94	0.91	0.80	0.88	0.72	0.84	0.77
1997	1.00	0.91	0.69	0.60	0.78	0.72	0.87	0.88	0.87	0.75	0.77	0.83	0.81
1998	0.82	0.86	0.43	0.45	0.77	0.46	0.85	0.88	0.90	0.75	0.84	0.83	0.74
1999	0.81	1.00	0.64	0.48	0.97	0.66	0.96	0.91	0.80	0.61	0.84	0.88	0.80
2000	0.87	0.83	0.80	0.60	0.92	0.61	0.85	1.00	0.94	0.86	0.68	0.91	0.82
2001	0.79	0.83	0.45	0.69	0.99	0.49	0.86	0.76	1.00	0.89	0.90	0.91	0.80
2002	0.99	0.83	0.49	0.65	0.80	0.37	0.82	0.84	0.73	0.88	0.89	1.00	0.77
2003	0.82	0.52	0.49	0.16	0.78	0.30	0.73	0.80	0.64	0.57	0.84	0.74	0.62
2004	0.83	0.82	0.59	0.91	0.90	0.57	0.89	1.00	0.93	0.98	0.92	0.94	0.86
2005	0.88	0.84	0.50	0.45	0.88	0.57	0.81	0.75	0.77	0.78	0.65	0.88	0.73
2006	0.96	0.97	0.56	0.67	1.00	0.42	0.85	0.86	0.96	1.00	0.90	0.90	0.84
2007	0.62	0.63	0.48	0.26	0.58	0.50	0.89	0.59	0.50	0.22	0.52	0.66	0.54
2008	0.39	0.42	1.00	0.37	0.65	0.50	0.86	0.73	0.72	0.70	0.73	0.85	0.66
2009	0.67	0.46	0.60	0.23	0.72	0.62	0.82	0.99	0.53	0.89	0.80	0.83	0.68
2010	0.64	0.53	0.56	0.48	0.87	0.49	0.85	0.76	0.68	1.00	1.00	0.89	0.73
2011	0.76	0.86	0.47	0.64	1.00	0.44	0.56	0.61	0.98	0.95	0.95	1.00	0.77
2012	0.75	0.81	0.62	0.64	0.92	0.61	0.77	0.87	0.76	0.94	0.84	0.96	0.79
2013	0.76	0.73	0.65	0.64	0.84	0.56	0.62	0.77	0.69	0.83	0.70	0.94	0.73
2014	0.74	0.72	0.60	0.66	0.78	0.52	0.74	0.69	0.77	0.86	0.85	0.88	0.73
2015	0.78	0.77	0.65	0.67	0.76	0.48	0.64	0.56	0.71	0.36	0.75	0.78	0.66
2016	0.68	0.68	0.65	0.69	0.67	0.57	0.63	0.67	0.81	0.91	0.90	0.88	0.73
Average	0.82	0.78	0.61	0.55	0.84	0.51	0.82	0.83	0.81	0.78	0.81	0.87	0.75

Table D.7 Results of first stage analysis (DEA) of TSME indicator score for rainfall variation analysis

	High AARFRs				Medium AARFRs				Low AARFRs				All
Year	**NSWN**	**NSWC**	**QLDE**	**VICC**	**NSWR**	**QLDD**	**WACS**	**WANE**	**VICM**	**VICW**	**SAEP**	**SAMY**	**AARFRs**
1990	1.00	0.82	0.74	0.65	1.00	0.69	0.94	0.99	1.00	0.79	0.98	0.98	0.88
1991	0.96	1.00	0.86	0.50	0.90	0.88	0.82	1.00	0.84	0.67	0.79	0.83	0.84
1992	0.55	0.75	0.99	0.62	0.89	0.38	0.94	0.87	0.86	0.85	0.96	0.91	0.80
1993	0.82	1.00	0.61	0.77	1.00	0.36	0.88	0.94	1.00	0.84	0.85	0.85	0.83
1994	1.00	0.95	0.47	0.55	0.92	0.36	0.91	1.00	1.00	0.87	0.69	0.96	0.81
1995	0.27	0.11	0.36	0.21	0.48	0.28	0.69	0.79	0.26	0.32	0.36	0.56	0.39
1996	0.79	0.69	0.55	0.71	0.86	0.36	0.94	0.91	0.80	0.88	0.72	0.84	0.75
1997	1.00	0.91	0.69	0.60	0.78	0.72	0.81	0.88	0.70	0.75	0.69	0.71	0.77
1998	0.77	0.68	0.43	0.42	0.77	0.46	0.85	0.88	0.44	0.44	0.84	0.71	0.64
1999	0.81	1.00	0.64	0.48	0.97	0.66	0.96	0.91	0.49	0.60	0.84	0.88	0.77
2000	0.87	0.83	0.80	0.60	0.92	0.49	0.85	1.00	0.94	0.86	0.63	0.70	0.79
2001	0.48	0.80	0.36	0.69	0.99	0.38	0.50	0.58	1.00	0.89	0.90	0.86	0.70
2002	0.90	0.83	0.46	0.65	0.71	0.37	0.82	0.84	0.73	0.88	0.89	1.00	0.76
2003	0.29	0.27	0.49	0.16	0.36	0.30	0.52	0.30	0.19	0.13	0.46	0.44	0.33
2004	0.83	0.74	0.59	0.91	0.90	0.48	0.89	1.00	0.93	0.98	0.92	0.83	0.83
2005	0.88	0.76	0.50	0.45	0.64	0.57	0.75	0.72	0.41	0.56	0.49	0.67	0.62
2006	0.86	0.97	0.56	0.67	1.00	0.42	0.85	0.86	0.96	1.00	0.90	0.90	0.83
2007	0.52	0.16	0.48	0.26	0.33	0.50	0.66	0.52	0.33	0.21	0.32	0.41	0.39
2008	0.36	0.15	1.00	0.19	0.17	0.50	0.86	0.51	0.52	0.70	0.44	0.57	0.50
2009	0.67	0.46	0.60	0.23	0.44	0.62	0.82	0.99	0.53	0.57	0.55	0.61	0.59
2010	0.64	0.24	0.56	0.48	0.46	0.49	0.85	0.76	0.68	1.00	1.00	0.89	0.67
2011	0.76	0.86	0.47	0.64	1.00	0.44	0.45	0.37	0.98	0.95	0.95	1.00	0.74
2012	0.60	0.51	0.62	0.64	0.75	0.61	0.77	0.87	0.76	0.94	0.80	0.82	0.72
2013	0.62	0.49	0.56	0.64	0.76	0.53	0.54	0.37	0.69	0.83	0.64	0.73	0.62
2014	0.44	0.53	0.34	0.51	0.67	0.26	0.74	0.65	0.61	0.86	0.85	0.73	0.60
2015	0.40	0.51	0.54	0.39	0.62	0.33	0.64	0.55	0.54	0.36	0.75	0.73	0.53
2016	0.64	0.55	0.62	0.31	0.65	0.57	0.63	0.67	0.50	0.31	0.78	0.73	0.58
Average	**0.69**	**0.65**	**0.59**	**0.52**	**0.74**	**0.48**	**0.77**	**0.77**	**0.69**	**0.71**	**0.74**	**0.77**	**0.68**

Table D.8 Results of first stage analysis (DEA) of EEr indicator score for rainfall variation analysis

	High AARFRs				Medium AARFRs				Low AARFRs				All
Year	**NSWN**	**NSWC**	**QLDE**	**VICC**	**NSWR**	**QLDD**	**WACS**	**WANE**	**VICM**	**VICW**	**SAEP**	**SAMY**	**AARFRs**
1990	0.72	0.72	0.72	0.72	0.67	0.67	0.67	0.67	1.00	1.00	1.00	1.00	0.80
1991	0.73	0.73	0.73	0.73	0.90	0.90	0.90	0.90	1.00	1.00	1.00	1.00	0.88
1992	0.73	0.73	0.73	0.73	0.90	0.90	0.90	0.90	1.00	1.00	1.00	1.00	0.88
1993	0.68	0.68	0.68	0.68	0.85	0.85	0.85	0.85	1.00	1.00	1.00	1.00	0.84
1994	0.79	0.79	0.79	0.79	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.88
1995	0.79	0.79	0.79	0.79	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.88
1996	0.79	0.79	0.79	0.79	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.88
1997	0.89	0.89	0.89	0.89	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.92
1998	0.89	0.89	0.89	0.89	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.92
1999	0.96	0.96	0.96	0.96	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.94
2000	0.93	0.93	0.93	0.93	1.00	1.00	1.00	1.00	0.97	0.97	0.97	0.97	0.97
2001	0.90	0.90	0.90	0.90	0.97	0.97	0.97	0.97	1.00	1.00	1.00	1.00	0.96
2002	0.85	0.85	0.85	0.85	0.92	0.92	0.92	0.92	1.00	1.00	1.00	1.00	0.92
2003	0.85	0.85	0.85	0.85	0.92	0.92	0.92	0.92	1.00	1.00	1.00	1.00	0.92
2004	0.85	0.85	0.85	0.85	0.94	0.94	0.94	0.94	1.00	1.00	1.00	1.00	0.93
2005	0.85	0.85	0.85	0.85	0.94	0.94	0.94	0.94	1.00	1.00	1.00	1.00	0.93
2006	0.83	0.83	0.83	0.83	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	0.94
2007	0.83	0.83	0.83	0.83	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	0.94
2008	1.00	1.00	1.00	1.00	0.74	0.74	0.74	0.74	0.75	0.75	0.75	0.75	0.83
2009	1.00	1.00	1.00	1.00	0.74	0.74	0.74	0.74	0.75	0.75	0.75	0.75	0.83
2010	1.00	1.00	1.00	1.00	0.74	0.74	0.74	0.74	0.80	0.80	0.80	0.80	0.85
2011	1.00	1.00	1.00	1.00	0.93	0.93	0.93	0.93	0.87	0.87	0.87	0.87	0.93
2012	1.00	1.00	1.00	1.00	0.93	0.93	0.93	0.93	0.87	0.87	0.87	0.87	0.93
2013	1.00	1.00	1.00	1.00	0.93	0.93	0.93	0.93	0.87	0.87	0.87	0.87	0.93
2014	1.00	1.00	1.00	1.00	0.93	0.93	0.93	0.93	0.87	0.87	0.87	0.87	0.93
2015	1.00	1.00	1.00	1.00	0.93	0.93	0.93	0.93	0.87	0.87	0.87	0.87	0.93
2016	1.00	1.00	1.00	1.00	0.93	0.93	0.93	0.93	0.87	0.87	0.87	0.87	0.93
Average	0.88	0.88	0.88	0.88	0.89	0.89	0.89	0.89	0.94	0.94	0.94	0.94	0.90

Appendix E

Table E.1 Results of first stage analysis (DEA) of OTE_{CRS} indicator score for temperature variation analysis

	High AATFRs				Medium AATFRs				Low AATFRs				All
Year	**NSWN**	**NSWC**	**QLDD**	**WACS**	**NSWR**	**QLDE**	**SAEP**	**WANE**	**VICM**	**VICW**	**VICC**	**SAMY**	**AATFRs**
1990	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1991	1.00	1.00	1.00	1.00	1.00	1.00	0.91	1.00	1.00	0.80	1.00	1.00	0.97
1992	0.57	0.89	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.67
1993	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	1.00	0.97	0.96
1994	1.00	1.00	1.00	1.00	1.00	0.84	0.84	1.00	1.00	1.00	1.00	1.00	0.95
1995	1.00	0.19	1.00	0.87	0.78	1.00	0.47	0.98	0.34	0.39	0.28	0.76	0.86
1996	0.85	0.71	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96
1997	1.00	1.00	1.00	0.90	1.00	1.00	0.87	1.00	0.80	0.96	1.00	0.86	0.95
1998	0.86	0.74	1.00	1.00	1.00	1.00	1.00	1.00	0.49	0.55	0.80	0.86	0.87
1999	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.58	0.88	1.00	1.00	0.94
2000	1.00	0.97	0.80	1.00	1.00	1.00	0.83	1.00	0.99	1.00	1.00	0.77	0.60
2001	0.60	0.97	0.74	0.58	1.00	0.94	1.00	0.73	1.00	1.00	0.89	0.93	0.99
2002	0.89	0.93	1.00	1.00	0.88	0.88	1.00	1.00	0.83	1.00	0.83	1.00	0.80
2003	0.38	0.62	1.00	0.69	0.48	1.00	0.55	0.42	0.26	0.19	1.00	0.59	0.99
2004	1.00	0.95	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.89	0.72
2005	1.00	0.87	1.00	0.87	0.73	1.00	0.72	0.96	0.48	0.69	0.56	0.77	0.67
2006	0.88	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.85
2007	0.67	0.25	1.00	0.80	0.77	1.00	0.64	0.89	0.64	0.41	1.00	0.59	0.90
2008	0.72	0.34	1.00	1.00	0.25	1.00	0.59	0.67	0.70	0.79	0.39	0.61	0.93
2009	1.00	1.00	1.00	1.00	0.61	1.00	0.66	1.00	0.74	0.58	1.00	0.65	0.90
2010	1.00	0.50	1.00	1.00	0.49	0.92	1.00	0.94	0.94	1.00	1.00	0.97	0.86
2011	1.00	1.00	1.00	0.72	1.00	1.00	1.00	0.59	1.00	1.00	0.84	1.00	0.80
2012	0.84	0.61	1.00	1.00	0.81	0.98	0.84	1.00	0.91	1.00	0.93	0.82	0.74
2013	0.81	0.73	0.92	0.85	0.93	0.98	0.96	0.48	0.94	0.97	1.00	0.76	0.77
2014	0.74	0.75	0.49	1.00	0.90	0.58	1.00	0.97	0.72	1.00	0.70	0.80	1.00
2015	0.50	0.65	0.69	1.00	0.81	1.00	1.00	0.91	0.61	0.36	0.55	0.82	0.97
2016	0.77	0.64	1.00	1.00	0.81	1.00	0.86	1.00	0.57	0.35	0.41	0.83	0.67
Average	**0.85**	**0.79**	**0.95**	**0.94**	**0.86**	**0.97**	**0.88**	**0.91**	**0.80**	**0.81**	**0.86**	**0.86**	**0.81**

Table E.2 Results of first stage analysis (DEA) of OTE_{VRS} indicator score for temperature variation analysis

	High AATFRs				Medium AATFRs				Low AATFRs				All
Year	**NSWN**	**NSWC**	**QLDD**	**WACS**	**NSWR**	**QLDE**	**SAEP**	**WANE**	**VICM**	**VICW**	**VICC**	**SAMY**	**AATFRs**
1990	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1991	1.00	1.00	1.00	1.00	1.00	1.00	0.95	1.00	1.00	1.00	1.00	1.00	1.00
1992	0.83	0.90	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98
1993	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1994	1.00	1.00	1.00	1.00	1.00	0.95	0.88	1.00	1.00	1.00	1.00	1.00	0.99
1995	1.00	0.19	1.00	0.89	0.87	1.00	0.57	0.99	0.39	1.00	1.00	1.00	0.83
1996	0.86	0.71	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96
1997	1.00	1.00	1.00	1.00	1.00	1.00	0.90	1.00	0.81	1.00	1.00	0.87	0.97
1998	1.00	0.75	1.00	1.00	1.00	1.00	1.00	1.00	0.50	0.76	0.80	0.87	0.89
1999	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.60	1.00	1.00	1.00	0.97
2000	1.00	1.00	0.81	1.00	1.00	1.00	0.86	1.00	1.00	1.00	1.00	0.78	0.95
2001	0.77	0.98	0.97	0.62	1.00	1.00	1.00	0.76	1.00	1.00	1.00	0.97	0.92
2002	1.00	0.95	1.00	1.00	0.93	1.00	1.00	1.00	0.84	1.00	0.98	1.00	0.98
2003	1.00	1.00	1.00	0.72	0.48	1.00	0.55	0.61	0.28	0.25	1.00	0.59	0.71
2004	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.91	0.99
2005	1.00	0.88	1.00	0.88	0.73	1.00	0.74	0.97	0.51	0.90	0.59	0.78	0.83
2006	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	1.00
2007	0.89	0.26	1.00	0.90	1.00	1.00	0.64	0.89	0.65	1.00	1.00	0.61	0.82
2008	0.81	0.35	1.00	1.00	0.26	1.00	0.59	0.67	0.71	1.00	0.70	0.65	0.73
2009	1.00	1.00	1.00	1.00	0.63	1.00	0.66	1.00	0.82	0.72	1.00	0.67	0.88
2010	1.00	0.56	1.00	1.00	0.50	0.93	1.00	0.97	1.00	1.00	1.00	0.98	0.91
2011	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.63	1.00	1.00	1.00	1.00	0.97
2012	0.86	0.62	1.00	1.00	0.82	1.00	0.84	1.00	0.93	1.00	1.00	0.84	0.91
2013	1.00	0.81	0.99	0.97	0.98	1.00	1.00	0.48	0.99	0.97	1.00	0.77	0.91
2014	1.00	0.76	0.59	1.00	0.94	0.60	1.00	0.98	0.76	1.00	0.76	0.80	0.85
2015	0.72	0.69	0.70	1.00	0.86	1.00	1.00	0.92	0.63	1.00	0.60	0.86	0.83
2016	1.00	0.70	1.00	1.00	0.89	1.00	0.86	1.00	0.60	0.35	0.44	0.84	0.81
Average	**0.95**	**0.82**	**0.97**	**0.96**	**0.89**	**0.98**	**0.89**	**0.92**	**0.82**	**0.92**	**0.92**	**0.88**	**0.91**

Table E.3 Results of first stage analysis (DEA) of OSE indicator score for temperature variation analysis

	High AATFRs				Medium AATFRs				Low AATFRs				All
Year	**NSWN**	**NSWC**	**QLDD**	**WACS**	**NSWR**	**QLDE**	**SAEP**	**WANE**	**VICM**	**VICW**	**VICC**	**SAMY**	**AATFRs**
1990	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1991	1.00	1.00	1.00	1.00	1.00	1.00	0.96	1.00	1.00	0.80	1.00	1.00	0.98
1992	0.69	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97
1993	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	1.00	0.97	1.00
1994	1.00	1.00	1.00	1.00	1.00	0.88	0.95	1.00	1.00	1.00	1.00	1.00	0.99
1995	1.00	1.00	1.00	0.98	0.90	1.00	0.83	0.99	0.88	0.39	0.28	0.76	0.83
1996	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1997	1.00	1.00	1.00	0.90	1.00	1.00	0.97	1.00	0.99	0.96	1.00	0.99	0.98
1998	0.86	0.98	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.72	0.99	0.99	0.96
1999	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.88	1.00	1.00	0.99
2000	1.00	0.97	0.99	1.00	1.00	1.00	0.97	1.00	0.99	1.00	1.00	0.99	0.99
2001	0.78	0.99	0.77	0.93	1.00	0.94	1.00	0.97	1.00	1.00	0.89	0.96	0.94
2002	0.89	0.98	1.00	1.00	0.95	0.88	1.00	1.00	1.00	1.00	0.85	1.00	0.96
2003	0.38	0.62	1.00	0.95	0.99	1.00	1.00	0.68	0.92	0.77	1.00	1.00	0.86
2004	1.00	0.95	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.99
2005	1.00	0.99	1.00	0.99	0.99	1.00	0.98	1.00	0.94	0.76	0.95	0.99	0.97
2006	0.88	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99
2007	0.75	0.98	1.00	0.88	0.77	1.00	1.00	1.00	0.98	0.41	1.00	0.97	0.90
2008	0.88	0.95	1.00	1.00	0.97	1.00	0.99	0.99	0.98	0.79	0.56	0.94	0.92
2009	1.00	1.00	1.00	1.00	0.97	1.00	1.00	1.00	0.90	0.81	1.00	0.96	0.97
2010	1.00	0.89	1.00	1.00	0.99	0.99	1.00	0.97	0.94	1.00	1.00	1.00	0.98
2011	1.00	1.00	1.00	0.72	1.00	1.00	1.00	0.94	1.00	1.00	0.84	1.00	0.96
2012	0.97	0.98	1.00	1.00	0.99	0.99	1.00	1.00	0.98	1.00	0.93	0.98	0.99
2013	0.81	0.91	0.93	0.87	0.94	0.98	0.96	0.99	0.95	1.00	1.00	0.99	0.94
2014	0.74	0.99	0.84	1.00	0.96	0.97	1.00	0.99	0.95	1.00	0.93	1.00	0.95
2015	0.70	0.95	0.99	1.00	0.94	1.00	1.00	0.99	0.98	0.36	0.92	0.96	0.90
2016	0.77	0.91	1.00	1.00	0.91	1.00	1.00	1.00	0.96	1.00	0.92	0.99	0.96
Average	**0.89**	**0.96**	**0.98**	**0.97**	**0.97**	**0.99**	**0.99**	**0.98**	**0.97**	**0.87**	**0.93**	**0.98**	**0.96**

Table E.4 Results of first stage analysis (DEA) of OME indicator score for temperature variation analysis

	High AATFRs				Medium AATFRs				Low AATFRs				All
Year	**NSWN**	**NSWC**	**QLDD**	**WACS**	**NSWR**	**QLDE**	**SAEP**	**WANE**	**VICM**	**VICW**	**VICC**	**SAMY**	**AATFRs**
1990	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1991	1.00	1.00	1.00	1.00	1.00	1.00	0.97	1.00	1.00	1.00	1.00	0.97	1.00
1992	0.69	0.94	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97
1993	0.94	1.00	1.00	1.00	1.00	1.00	0.97	1.00	1.00	1.00	1.00	1.00	0.99
1994	1.00	1.00	1.00	1.00	1.00	0.67	0.88	1.00	1.00	1.00	1.00	1.00	0.96
1995	1.00	0.90	1.00	0.99	0.85	1.00	0.84	1.00	0.86	1.00	1.00	1.00	0.95
1996	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1997	1.00	1.00	1.00	0.95	1.00	1.00	0.89	1.00	1.00	1.00	1.00	0.99	0.99
1998	1.00	0.98	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.92	0.94	0.98	0.98
1999	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00
2000	1.00	0.95	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00
2001	0.75	0.87	0.79	0.99	1.00	1.00	1.00	0.91	1.00	1.00	1.00	1.00	0.94
2002	1.00	0.96	1.00	1.00	0.88	0.89	1.00	1.00	0.99	1.00	0.98	1.00	0.98
2003	1.00	1.00	1.00	0.93	0.97	1.00	1.00	0.92	0.86	0.95	1.00	0.89	0.96
2004	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2005	1.00	0.99	1.00	0.98	1.00	1.00	1.00	0.95	0.96	0.93	0.95	0.99	0.98
2006	1.00	1.00	1.00	1.00	1.00	0.98	1.00	0.98	1.00	1.00	1.00	0.98	1.00
2007	0.83	0.81	1.00	0.94	1.00	1.00	0.92	0.85	0.83	1.00	1.00	0.98	0.93
2008	1.00	0.63	1.00	1.00	0.66	1.00	0.98	0.97	0.94	1.00	0.95	0.95	0.92
2009	1.00	0.91	1.00	1.00	0.88	1.00	0.97	1.00	0.95	0.98	1.00	0.98	0.97
2010	1.00	0.76	1.00	1.00	0.88	0.96	1.00	0.95	1.00	1.00	1.00	0.98	0.96
2011	1.00	1.00	1.00	0.92	1.00	1.00	1.00	0.98	1.00	1.00	1.00	1.00	0.99
2012	1.00	0.92	1.00	1.00	0.99	0.92	1.00	1.00	0.85	1.00	1.00	1.00	0.97
2013	1.00	0.99	0.96	0.89	0.94	0.88	0.87	0.95	0.83	0.97	1.00	0.98	0.94
2014	1.00	0.96	0.95	1.00	0.97	1.00	1.00	0.91	0.90	1.00	0.95	0.99	0.97
2015	0.92	0.97	1.00	0.97	0.96	1.00	1.00	0.87	0.93	1.00	0.93	0.99	0.96
2016	1.00	0.99	1.00	0.93	0.98	1.00	0.99	1.00	0.94	0.94	0.97	0.97	0.98
Average	**0.97**	**0.95**	**0.99**	**0.98**	**0.96**	**0.97**	**0.97**	**0.97**	**0.96**	**0.99**	**0.99**	**0.99**	**0.97**

Table E.5 Results of first stage analysis (DEA) of ROSE indicator score for temperature variation analysis

	High AATFRs				Medium AATFRs				Low AATFRs				All
Year	**NSWN**	**NSWC**	**QLDD**	**WACS**	**NSWR**	**QLDE**	**SAEP**	**WANE**	**VICM**	**VICW**	**VICC**	**SAMY**	**AATFRs**
1990	1.00	0.82	0.64	0.88	0.69	0.55	1.00	0.68	1.00	0.79	0.47	0.98	0.79
1991	0.89	0.93	1.00	0.94	0.83	0.64	0.87	0.92	0.84	0.67	0.37	0.86	0.81
1992	0.84	0.77	0.40	1.00	0.81	0.74	0.98	0.80	0.86	0.85	0.45	0.91	0.78
1993	0.79	0.91	0.41	0.99	0.97	0.48	1.00	0.91	1.00	0.84	0.52	0.85	0.81
1994	1.00	0.95	0.39	0.99	0.92	0.68	1.00	1.00	1.00	0.87	0.43	0.96	0.85
1995	0.27	0.67	0.30	0.84	0.65	0.33	0.88	0.80	0.77	0.32	0.16	0.56	0.55
1996	0.91	0.96	0.39	1.00	0.86	0.51	0.84	0.91	0.80	0.88	0.56	0.84	0.79
1997	1.00	0.91	0.69	0.81	0.78	0.72	1.00	0.88	0.87	0.75	0.54	0.82	0.81
1998	0.77	0.93	0.44	0.82	0.77	0.45	0.98	0.88	0.92	0.63	0.50	0.84	0.74
1999	0.81	1.00	0.59	0.86	0.97	0.72	0.98	0.91	0.83	0.60	0.46	0.88	0.80
2000	0.87	0.88	0.65	0.91	0.92	0.74	0.72	1.00	0.94	0.86	0.58	0.91	0.83
2001	0.84	0.95	0.54	0.88	0.99	0.33	0.92	0.84	1.00	0.89	0.62	0.89	0.81
2002	0.90	0.91	0.40	0.88	0.86	0.48	0.97	0.84	0.87	0.88	0.57	1.00	0.80
2003	0.29	0.27	0.33	0.84	0.77	0.45	0.93	0.53	0.79	0.56	0.13	0.84	0.56
2004	0.83	0.74	0.53	0.98	0.90	0.54	0.97	1.00	0.93	0.98	0.77	0.92	0.84
2005	0.88	0.87	0.63	0.96	0.88	0.45	0.70	0.79	0.83	0.66	0.68	0.87	0.77
2006	0.86	0.96	0.50	1.00	1.00	0.49	0.91	0.88	0.96	1.00	0.56	0.94	0.84
2007	0.70	0.76	0.59	0.92	0.33	0.41	0.55	0.68	0.60	0.21	0.22	0.68	0.55
2008	0.69	1.00	0.58	1.00	0.74	1.00	0.57	0.58	0.77	0.70	0.39	0.92	0.75
2009	1.00	0.76	0.68	0.90	0.60	0.60	0.64	0.74	0.68	0.81	0.30	0.93	0.72
2010	0.94	0.84	0.54	0.93	0.78	0.62	0.79	0.61	0.68	1.00	0.60	0.93	0.77
2011	0.88	1.00	0.48	0.53	0.93	0.47	0.82	0.55	0.98	0.95	0.74	1.00	0.78
2012	0.81	1.00	0.66	0.82	0.86	0.67	0.82	0.80	0.96	0.94	0.74	0.98	0.84
2013	0.71	0.70	0.60	0.67	0.76	0.64	0.64	0.75	0.84	0.89	0.73	0.97	0.74
2014	0.51	0.84	0.50	0.79	0.68	0.57	0.74	0.68	0.89	0.86	0.81	0.91	0.73
2015	0.70	0.88	0.51	0.71	0.69	0.54	0.65	0.64	0.93	0.36	0.81	0.86	0.69
2016	0.74	0.92	0.61	0.73	0.69	0.62	0.80	0.62	0.90	0.95	0.85	0.90	0.78
Average	**0.79**	**0.86**	**0.54**	**0.87**	**0.80**	**0.57**	**0.84**	**0.79**	**0.87**	**0.77**	**0.54**	**0.89**	**0.76**

Table E.6 Results of first stage analysis (DEA) of OSME indicator score for temperature variation analysis

	High AATFRs				Medium AATFRs				Low AATFRs				All
Year	**NSWN**	**NSWC**	**QLDD**	**WACS**	**NSWR**	**QLDE**	**SAEP**	**WANE**	**VICM**	**VICW**	**VICC**	**SAMY**	**AATFRs**
1990	1.00	0.82	0.64	0.88	0.69	0.55	1.00	0.68	1.00	0.79	0.47	0.98	0.79
1991	0.89	0.93	1.00	0.94	0.83	0.64	0.85	0.92	0.84	0.67	0.37	0.83	0.81
1992	0.58	0.72	0.40	1.00	0.81	0.74	0.98	0.80	0.86	0.85	0.45	0.91	0.76
1993	0.74	0.91	0.41	0.99	0.97	0.48	0.97	0.91	1.00	0.84	0.52	0.85	0.80
1994	1.00	0.95	0.39	0.99	0.92	0.45	0.92	1.00	1.00	0.87	0.43	0.96	0.82
1995	0.27	0.61	0.30	0.84	0.56	0.33	0.74	0.80	0.66	0.32	0.16	0.56	0.51
1996	0.90	0.96	0.39	1.00	0.86	0.51	0.84	0.91	0.80	0.88	0.56	0.84	0.79
1997	1.00	0.91	0.69	0.78	0.78	0.72	0.89	0.88	0.87	0.75	0.54	0.81	0.80
1998	0.77	0.91	0.44	0.82	0.77	0.45	0.98	0.88	0.89	0.58	0.47	0.82	0.73
1999	0.81	1.00	0.59	0.86	0.97	0.72	0.98	0.91	0.82	0.60	0.46	0.88	0.80
2000	0.87	0.83	0.65	0.91	0.92	0.74	0.71	1.00	0.94	0.86	0.58	0.91	0.83
2001	0.63	0.82	0.43	0.87	0.99	0.33	0.92	0.77	1.00	0.89	0.62	0.89	0.76
2002	0.90	0.88	0.40	0.88	0.76	0.43	0.97	0.84	0.87	0.88	0.56	1.00	0.78
2003	0.29	0.27	0.33	0.78	0.75	0.45	0.92	0.49	0.68	0.54	0.13	0.75	0.53
2004	0.83	0.74	0.53	0.98	0.90	0.54	0.97	1.00	0.93	0.98	0.77	0.91	0.84
2005	0.88	0.86	0.63	0.94	0.88	0.45	0.70	0.75	0.79	0.62	0.65	0.86	0.75
2006	0.86	0.96	0.50	1.00	1.00	0.48	0.91	0.86	0.96	1.00	0.56	0.92	0.83
2007	0.58	0.62	0.59	0.87	0.33	0.41	0.51	0.58	0.50	0.21	0.22	0.67	0.51
2008	0.69	0.66	0.58	1.00	0.48	1.00	0.56	0.56	0.72	0.70	0.37	0.87	0.68
2009	1.00	0.69	0.68	0.90	0.52	0.60	0.63	0.74	0.64	0.80	0.30	0.91	0.70
2010	0.94	0.64	0.54	0.93	0.69	0.60	0.79	0.58	0.68	1.00	0.60	0.91	0.74
2011	0.88	1.00	0.48	0.48	0.93	0.47	0.82	0.54	0.98	0.95	0.74	1.00	0.77
2012	0.80	0.95	0.66	0.82	0.85	0.62	0.82	0.80	0.82	0.94	0.74	0.97	0.82
2013	0.71	0.70	0.57	0.59	0.72	0.56	0.56	0.72	0.70	0.86	0.73	0.95	0.70
2014	0.51	0.80	0.47	0.79	0.67	0.57	0.74	0.62	0.80	0.86	0.77	0.90	0.71
2015	0.65	0.85	0.51	0.68	0.66	0.54	0.65	0.56	0.86	0.36	0.76	0.86	0.66
2016	0.74	0.91	0.61	0.68	0.68	0.62	0.79	0.62	0.84	0.89	0.82	0.87	0.76
Average	**0.77**	**0.81**	**0.53**	**0.86**	**0.77**	**0.56**	**0.82**	**0.77**	**0.83**	**0.76**	**0.53**	**0.87**	**0.74**

Table E.7 Results of first stage analysis (DEA) of TSME indicator score for temperature variation analysis

	High AATFRs				Medium AATFRs				Low AATFRs				All
Year	**NSWN**	**NSWC**	**QLDD**	**WACS**	**NSWR**	**QLDE**	**SAEP**	**WANE**	**VICM**	**VICW**	**VICC**	**SAMY**	**AATFRs**
1990	1.00	0.82	0.64	0.88	0.69	0.55	1.00	0.68	1.00	0.79	0.47	0.98	0.79
1991	0.89	0.93	1.00	0.94	0.83	0.64	0.80	0.92	0.84	0.67	0.37	0.83	0.81
1992	0.48	0.65	0.40	1.00	0.81	0.74	0.98	0.80	0.86	0.85	0.45	0.91	0.74
1993	0.74	0.91	0.41	0.99	0.97	0.48	0.97	0.91	1.00	0.84	0.52	0.85	0.80
1994	1.00	0.95	0.39	0.99	0.92	0.43	0.81	1.00	1.00	0.87	0.43	0.96	0.81
1995	0.27	0.11	0.30	0.75	0.48	0.33	0.42	0.79	0.26	0.32	0.16	0.56	0.40
1996	0.78	0.68	0.39	1.00	0.86	0.51	0.84	0.91	0.80	0.88	0.56	0.84	0.75
1997	1.00	0.91	0.69	0.78	0.78	0.72	0.81	0.88	0.70	0.75	0.54	0.71	0.77
1998	0.77	0.68	0.44	0.82	0.77	0.45	0.98	0.88	0.44	0.44	0.38	0.71	0.65
1999	0.81	1.00	0.59	0.86	0.97	0.72	0.98	0.91	0.49	0.60	0.46	0.88	0.77
2000	0.87	0.83	0.53	0.91	0.92	0.74	0.61	1.00	0.94	0.86	0.58	0.70	0.79
2001	0.48	0.80	0.41	0.54	0.99	0.33	0.92	0.58	1.00	0.89	0.62	0.86	0.70
2002	0.90	0.83	0.40	0.88	0.71	0.43	0.97	0.84	0.73	0.88	0.55	1.00	0.76
2003	0.29	0.27	0.33	0.56	0.36	0.45	0.51	0.30	0.19	0.13	0.13	0.44	0.33
2004	0.83	0.74	0.53	0.98	0.90	0.54	0.97	1.00	0.93	0.98	0.77	0.83	0.83
2005	0.88	0.76	0.63	0.83	0.64	0.45	0.51	0.72	0.41	0.56	0.38	0.67	0.62
2006	0.86	0.96	0.50	1.00	1.00	0.48	0.91	0.86	0.96	1.00	0.56	0.90	0.83
2007	0.51	0.16	0.59	0.78	0.33	0.41	0.33	0.52	0.33	0.21	0.22	0.41	0.40
2008	0.56	0.23	0.58	1.00	0.13	1.00	0.33	0.38	0.52	0.70	0.26	0.57	0.52
2009	1.00	0.69	0.68	0.90	0.33	0.60	0.41	0.74	0.53	0.57	0.30	0.61	0.61
2010	0.94	0.36	0.54	0.93	0.34	0.56	0.79	0.56	0.68	1.00	0.60	0.89	0.68
2011	0.88	1.00	0.48	0.48	0.93	0.47	0.82	0.34	0.98	0.95	0.74	1.00	0.76
2012	0.69	0.59	0.66	0.82	0.70	0.62	0.69	0.80	0.76	0.94	0.74	0.82	0.74
2013	0.71	0.57	0.57	0.57	0.70	0.56	0.56	0.35	0.69	0.83	0.73	0.73	0.63
2014	0.51	0.61	0.28	0.79	0.62	0.34	0.74	0.60	0.61	0.86	0.59	0.73	0.61
2015	0.47	0.59	0.36	0.68	0.57	0.54	0.65	0.51	0.54	0.36	0.45	0.73	0.54
2016	0.74	0.63	0.61	0.68	0.60	0.62	0.67	0.62	0.50	0.31	0.36	0.73	0.59
Average	**0.74**	**0.68**	**0.52**	**0.83**	**0.70**	**0.54**	**0.74**	**0.72**	**0.69**	**0.71**	**0.48**	**0.77**	**0.68**

Table E.8 Results of first stage analysis (DEA) of EEt indicator score for temperature variation analysis

	High AATFRs				Medium AATFRs				Low AATFRs				All
Year	**NSWN**	**NSWC**	**QLDD**	**WACS**	**NSWR**	**QLDE**	**SAEP**	**WANE**	**VICM**	**VICW**	**VICC**	**SAMY**	**AATFRs**
1990	0.72	0.72	0.72	0.72	0.98	0.98	0.98	0.98	1.00	1.00	1.00	1.00	0.90
1991	0.79	0.79	0.79	0.79	0.98	0.98	0.98	0.98	1.00	1.00	1.00	1.00	0.92
1992	0.85	0.85	0.85	0.85	0.98	0.98	0.98	0.98	1.00	1.00	1.00	1.00	0.94
1993	0.75	0.75	0.75	0.75	0.87	0.87	0.87	0.87	1.00	1.00	1.00	1.00	0.87
1994	0.79	0.79	0.79	0.79	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.88
1995	0.79	0.79	0.79	0.79	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.88
1996	0.80	0.80	0.80	0.80	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.89
1997	0.89	0.89	0.89	0.89	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.92
1998	0.89	0.89	0.89	0.89	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.92
1999	0.96	0.96	0.96	0.96	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.94
2000	0.93	0.93	0.93	0.93	1.00	1.00	1.00	1.00	0.97	0.97	0.97	0.97	0.97
2001	0.90	0.90	0.90	0.90	0.97	0.97	0.97	0.97	1.00	1.00	1.00	1.00	0.96
2002	0.85	0.85	0.85	0.85	0.92	0.92	0.92	0.92	1.00	1.00	1.00	1.00	0.92
2003	0.85	0.85	0.85	0.85	0.92	0.92	0.92	0.92	1.00	1.00	1.00	1.00	0.92
2004	0.85	0.85	0.85	0.85	0.94	0.94	0.94	0.94	1.00	1.00	1.00	1.00	0.93
2005	0.85	0.85	0.85	0.85	0.94	0.94	0.94	0.94	1.00	1.00	1.00	1.00	0.93
2006	0.84	0.84	0.84	0.84	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	0.94
2007	0.84	0.84	0.84	0.84	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	0.94
2008	0.64	0.64	0.64	0.64	1.00	1.00	1.00	1.00	0.75	0.75	0.75	0.75	0.80
2009	0.67	0.67	0.67	0.67	1.00	1.00	1.00	1.00	0.75	0.75	0.75	0.75	0.81
2010	0.67	0.67	0.67	0.67	1.00	1.00	1.00	1.00	0.80	0.80	0.80	0.80	0.82
2011	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.87	0.87	0.87	0.87	0.91
2012	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.87	0.87	0.87	0.87	0.91
2013	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.87	0.87	0.87	0.87	0.91
2014	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.87	0.87	0.87	0.87	0.91
2015	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.87	0.87	0.87	0.87	0.91
2016	0.86	0.86	0.86	0.86	1.00	1.00	1.00	1.00	0.87	0.87	0.87	0.87	0.91
Average	**0.83**	**0.83**	**0.83**	**0.83**	**0.95**	**0.95**	**0.95**	**0.95**	**0.94**	**0.94**	**0.94**	**0.94**	**0.91**

Appendix F

Table F.1 Results of a random effects Tobit models: Determinants of efficiency indicators for Rainfall

	Dependent variable							
	OTEcrs	**OTEvrs**	**OSE**	**OME**	**ROSE**	**OSME**	**TSME**	**EE**
	(1.000)	(2.000)	(3.000)	(4.000)	(5.000)	(6.000)	(7.000)	(8.000)
Constant	1.338***	1.305**	1.174***	0.955***	1.271***	1.097***	0.771**	1.148***
	(0.412)	(0.564)	(0.275)	(0.135)	(0.276)	(0.310)	(0.331)	(0.203)
Independent variables								
Age of farm manager (ev_1)	-0.01	-0.013	-0.005	-0.005	-0.015	-0.018	-0.013	-0.040***
	(0.020)	(0.025)	(0.012)	(0.007)	(0.019)	(0.015)	(0.014)	(0.012)
Age of spouse of farm manager (ev_2)	0.004	0.01	0.002	0.006	0.004	0.01	0.009	0.038***
	(0.019)	(0.026)	(0.010)	(0.007)	(0.018)	(0.014)	(0.015)	(0.012)
Off-farm work of farm manager (ev_3)	-0.003	0.006	-0.004	0.001	-0.008	-0.006	-0.008*	-0.001
	(0.005)	(0.008)	(0.004)	(0.002)	(0.006)	(0.005)	(0.004)	(0.006)
Off-farm work of spouse of farm manager (ev_4)	-0.016***	-0.020**	-0.004	-0.002	0.011**	0.011*	0.007*	0.004
	(0.006)	(0.010)	(0.003)	(0.002)	(0.005)	(0.005)	(0.004)	(0.005)
Capital-labour ratio (ev_5)	0.006***	0.006**	0.002	0.00004	0.004***	0.004***	0.007***	-0.001
	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Land-labour ratio (ev_6)	-0.663**	-0.810*	-0.143	-0.012	-0.262	-0.267	-0.568***	0.125
	(0.326)	(0.414)	(0.196)	(0.106)	(0.266)	(0.260)	(0.170)	(0.189)
LogSigmaMu	-1.562***	-1.468***	-2.697***	-3.764***	-2.519***	-2.273***	-1.883***	-3.606**
	(0.238)	(0.316)	(0.392)	(0.365)	(0.358)	(0.215)	(0.106)	(1.411)
LogSigmaNu	-1.437***	-1.281***	-2.072***	-2.803***	-1.851***	-1.855***	-1.803***	-2.124***
	(0.068)	(0.079)	(0.070)	(0.051)	(0.055)	(0.043)	(0.038)	(0.158)
Observations	324	324	324	324	324	324	324	324
Log Likelihood	-115.164	-134.167	10.975	424.677	80.449	77.972	54.212	53.103
Akaike Inf. Crit.	248.328	286.335	-3.95	-831.354	-142.898	-137.943	-90.425	-88.206
Bayesian Inf. Crit.	282.355	320.361	30.077	-797.328	-108.872	-103.916	-56.398	-54.179

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

Table F.2 Results of lag dependent variables for rainfall analysis

	Dependent variable							
	lagOTEcrs	**lagOTEvrs**	**lagOSE**	**lagOME**	**lagROSE**	**lagOSME**	**lagTSME**	**lagEE**
Constant	0.004	0.005	-0.0004	0.0005	-0.014	-0.014	-0.009	-0.001
Independent variables	(0.011)	(0.011)	(0.007)	(0.005)	(0.011)	(0.011)	(0.011)	(0.006)
Age of farm manager (ev_1)	-0.003	0.001	-0.004	-0.004	-0.002	-0.006	-0.004	-0.018***
	(0.009)	(0.009)	(0.006)	(0.004)	(0.009)	(0.009)	(0.009)	(0.005)
Age of spouse of farm manager (ev_2)	0.008	0.004	0.004	0.009**	-0.006	0.001	0.002	0.013***
	(0.008)	(0.008)	(0.006)	(0.004)	(0.009)	(0.009)	(0.009)	(0.004)
Off-farm work of farm manager (ev_3)	-0.001	0.0004	-0.001	0.004***	-0.003	-0.0005	-0.001	-0.00002
	(0.003)	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)
Off-farm work of spouse of farm manager (ev_4)	-0.002	0.0003	-0.002	-0.001	0.006**	0.005*	0.005	-0.001
	(0.003)	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)
Capital-labour ratio (ev_5)	0.006***	0.005***	0.001	0.001*	0.004***	0.004***	0.007***	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Land-labour ratio (ev_6)	-0.508***	-0.474***	-0.071	-0.045	-0.143	-0.161	-0.446***	0.108*
	(0.107)	(0.108)	(0.070)	(0.050)	(0.110)	(0.110)	(0.110)	(0.057)
Observations	297	297	297	297	297	297	297	297
F Statistic (df = 6; 290)	5.770***	4.388***	1.042	3.799***	8.961***	7.918***	12.155***	4.523***

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

Table F.3 Comparison regression estimations with Tobit, Double bootstrap, Random effects Tobit and Lag models for rainfall analysis

	Regression model	**Age of farm manager (ev_1)**		**Age of spouse of farm manager (ev_2)**		**Off-farm work of farm manager (ev_3)**		**Off-farm work of spouse of farm manager (ev_4)**		**Capital-labour ratio (ev_5)**		Land-labour ratio (ev_6)	
OTE_{CRS}	Tobit	-0.001	(0.010)	0.004	(0.010)	-0.003	(0.003)	-0.005*	(0.003)	0.005***	(0.001)	-0.515***	(0.127)
	Bootstrap	-0.001	(0.010)	0.004	(0.010)	-0.003	(0.003)	-0.005*	(0.003)	0.005***	(0.001)	-0.516***	(0.127)
	Random effects	-0.01	(0.020)	0.004	(0.019)	-0.003	(0.005)	-0.016***	(0.006)	0.006***	(0.002)	-0.663**	(0.326)
	Lag	-0.003	(0.009)	0.008	(0.008)	-0.001	(0.003)	-0.002	(0.003)	0.006***	(0.001)	-0.508***	(0.107)
OTE_{VRS}	Tobit	0.0001	(0.010)	0.003	(0.010)	-0.0002	(0.003)	-0.006*	(0.003)	0.004***	(0.001)	-0.469***	(0.124)
	Bootstrap	0.0001	(0.010)	0.003	(0.010)	-0.0002	(0.003)	-0.006*	(0.003)	0.004***	(0.001)	-0.469***	(0.124)
	Random effects	-0.013	(0.025)	0.01	(0.026)	0.006	(0.008)	-0.020**	(0.010)	0.006**	(0.003)	-0.810*	(0.414)
	Lag	0.001	(0.009)	0.004	(0.008)	0.0004	(0.003)	0.0003	(0.003)	0.005***	(0.001)	-0.474***	(0.108)
OSE	Tobit	-0.001	(0.005)	0.001	(0.005)	-0.002	(0.002)	0.0004	(0.002)	0.001**	(0.001)	-0.082	(0.070)
	Bootstrap	-0.001	(0.005)	0.001	(0.005)	-0.002	(0.002)	0.0004	(0.002)	0.001**	(0.001)	-0.082	(0.070)
	Random effects	-0.005	(0.012)	0.002	(0.010)	-0.004	(0.004)	-0.004	(0.003)	0.002	(0.001)	-0.143	(0.196)
	Lag	-0.004	(0.006)	0.004	(0.006)	-0.001	(0.002)	-0.002	(0.002)	0.001	(0.001)	-0.071	(0.070)
OME	Tobit	-0.005	(0.004)	0.007*	(0.004)	0.002	(0.001)	-0.002	(0.001)	0.0004	(0.000)	-0.034	(0.050)
	Bootstrap	-0.005	(0.004)	0.007*	(0.004)	0.002	(0.001)	-0.002	(0.001)	0.0004	(0.000)	-0.034	(0.049)
	Random effects	-0.005	(0.007)	0.006	(0.007)	0.001	(0.002)	-0.002	(0.002)	0.00004	(0.001)	-0.012	(0.106)
	Lag	-0.004	(0.004)	0.009**	(0.004)	0.004***	(0.001)	-0.001	(0.001)	0.001*	(0.001)	-0.045	(0.050)

	Regression model	Age of farm manager (ev_1)		Age of spouse of farm manager (ev_2)		Off-farm work of farm manager (ev_3)		Off-farm work of spouse of farm manager (ev_4)		Capital-labour ratio (ev_5)		Land-labour ratio (ev_6)	
ROSE	Tobit	-0.014	(0.009)	0.009	(0.009)	-0.008**	(0.003)	0.014***	(0.003)	0.005***	(0.001)	-0.290**	(0.121)
	Bootstrap	-0.014	(0.009)	0.009	(0.009)	-0.008**	(0.003)	0.014***	(0.003)	0.005***	(0.001)	-0.290**	(0.121)
	Random effects	-0.015	(0.019)	0.004	(0.018)	-0.008	(0.006)	0.011**	(0.005)	0.004***	(0.002)	-0.262	(0.266)
	Lag	-0.002	(0.009)	-0.006	(0.009)	-0.003	(0.003)	0.006**	(0.003)	0.004***	(0.001)	-0.143	(0.110)
OSME	Tobit	-0.018*	(0.009)	0.014	(0.010)	-0.006*	(0.003)	0.013***	(0.003)	0.005***	(0.001)	-0.304**	(0.122)
	Bootstrap	-0.018*	(0.009)	0.014	(0.010)	-0.006*	(0.003)	0.013***	(0.003)	0.005***	(0.001)	-0.304**	(0.122)
	Random effects	-0.018	(0.015)	0.01	(0.014)	-0.006	(0.005)	0.011*	(0.005)	0.004***	(0.002)	-0.267	(0.260)
	Lag	-0.006	(0.009)	0.001	(0.009)	-0.0005	(0.003)	0.005*	(0.003)	0.004***	(0.001)	-0.161	(0.110)
TSME	Tobit	-0.016	(0.010)	0.014	(0.010)	-0.006*	(0.003)	0.008**	(0.003)	0.008***	(0.001)	-0.589***	(0.128)
	Bootstrap	-0.016	(0.010)	0.015	(0.010)	-0.006*	(0.003)	0.008**	(0.003)	0.008***	(0.001)	-0.592***	(0.129)
	Random effects	-0.013	(0.014)	0.009	(0.015)	-0.008*	(0.004)	0.007*	(0.004)	0.007***	(0.001)	-0.568***	(0.170)
	Lag	-0.004	(0.009)	0.002	(0.009)	-0.001	(0.003)	0.005	(0.003)	0.007***	(0.001)	-0.446***	(0.110)
EEr	Tobit	-0.026***	(0.005)	0.020***	(0.005)	-0.001	(0.002)	-0.0004	(0.002)	-0.002***	(0.001)	0.127*	(0.067)
	Bootstrap	-0.026***	(0.005)	0.020***	(0.005)	-0.001	(0.002)	-0.0004	(0.002)	-0.002***	(0.001)	0.127*	(0.067)
	Random effects	-0.040***	(0.012)	0.038***	(0.012)	-0.001	(0.006)	0.004	(0.005)	-0.001	(0.001)	0.125	(0.189)
	Lag	-0.018***	(0.005)	0.013***	(0.004)	-0.00002	(0.002)	-0.001	(0.002)	-0.001**	(0.001)	0.108*	(0.057)

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

Table F.4 Results of a random effects Tobit models: Determinants of efficiency indicators for temperature analysis

	Dependent variable							
	OTEcrs	**OTEvrs**	**OSE**	**OME**	**ROSE**	**OSME**	**TSME**	**EE**
Constant	1.326**	1.373**	1.211***	1.037***	1.464***	1.434***	1.398***	0.880***
	(0.53)	(0.63)	(0.42)	(0.08)	(0.26)	(0.27)	(0.28)	(0.25)
Independent variables								
Age of farm manager (ev_1)	-0.009	-0.022	0.004	-0.009**	-0.019	-0.027**	-0.028**	-0.009
	(0.02)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age of spouse of farm manager (ev_2)	0.005	0.02	-0.007	0.009*	0.004	0.013	0.014	0.01
	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Off-farm work of farm manager (ev_3)	0.002	0.005	-0.001	0.001	-0.010*	-0.009	-0.008*	0.007*
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
Off-farm work of spouse of farm manager (ev_4)	-0.022***	-0.023**	-0.008	-0.002	0.011**	0.009*	0.0005	-0.001
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
Capital-labour ratio (ev_5)	0.007*	0.007**	0.002	0.0004	0.004**	0.004***	0.007***	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Land-labour ratio (ev_6)	-0.899	-1.063**	-0.182	-0.081	-0.229	-0.317	-0.640***	0.351
	(0.57)	(0.47)	(0.35)	(0.09)	(0.24)	(0.23)	(0.24)	(0.29)
LogSigmaMu	-1.586***	-1.557***	-2.561***	-4.174***	-2.644***	-2.486***	-1.732***	-3.687***
	(0.21)	(0.27)	(0.41)	(0.53)	(0.42)	(0.32)	(0.11)	(0.89)
LogSigmaNu	-1.334***	-1.269***	-1.870***	-2.920***	-1.726***	-1.751***	-1.728***	-2.105***
	(0.07)	(0.08)	(0.07)	(0.05)	(0.06)	(0.05)	(0.04)	(0.12)
Observations	324	324	324	324	324	324	324	324
Log Likelihood	-129.471	-129.874	-33.86	441.897	43.472	54.066	35.906	47.732
Akaike Inf. Crit.	276.943	277.747	85.72	-865.793	-68.945	-90.132	-53.812	-77.465
Bayesian Inf. Crit.	310.97	311.774	119.747	-831.766	-34.918	-56.105	-19.785	-43.438

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

Table F.5 Results of lag dependent variables for temperature analysis

	Dependent variable							
	lagOTEcrs	**lagOTEvrs**	**lagOSE**	**lagOME**	**lagROSE**	**lagOSME**	**lagTSME**	**lagEE**
Constant	0.004	-0.004	0.008	0.002	-0.014	-0.012	-0.014	0.005
Independent variables	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Age of farm manager (ev_1)	-0.001	0.0001	-0.001	-0.008**	-0.014	-0.019**	-0.016*	0.00004
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Age of spouse of farm manager (ev_2)	0.007	0.004	0.004	0.009***	0.004	0.01	0.011	0.002
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Off-farm work of farm manager (ev_3)	0.001	0.001	-0.00004	0.001	-0.001	-0.001	-0.001	-0.00003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Off-farm work of spouse of farm manager (ev_4)	-0.002	-0.002	0.0004	-0.0005	0.004	0.003	0.001	0.005**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Capital-labour ratio (ev_5)	0.006***	0.006***	-0.00004	0.001**	0.002*	0.003***	0.007***	-0.00003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Land-labour ratio (ev_6)	-0.549***	-0.613***	0.033	-0.125***	-0.023	-0.127	-0.559***	0.170**
	(0.11)	(0.11)	(0.07)	(0.04)	(0.13)	(0.12)	(0.12)	(0.08)
Observations	297	297	297	297	297	297	297	297
F Statistic (df = 6; 290)	5.235***	5.930***	0.355	3.057***	5.394***	5.487***	10.972***	3.203***

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

Table F.6 Comparison regression estimations with Tobit, Double bootstrap, Random effects Tobit and Lag models for temperature analysis

	Regression model	**Age of farm manager (ev_1)**		**Age of spouse of farm manager (ev_2)**		**Off-farm work of farm manager (ev_3)**		**Off-farm work of spouse of farm manager (ev_4)**		**Capital-labour ratio (ev_5)**		**Land-labour ratio (ev_6)**	
OTE_{CRS}	Tobit	-0.003	(0.010)	0.006	(0.010)	-0.001	(0.003)	-0.008**	(0.003)	0.005***	(0.001)	-0.560***	(0.128)
	Bootstrap	-0.003	(0.010)	0.006	(0.010)	-0.001	(0.003)	-0.008**	(0.003)	0.005***	(0.001)	-0.560***	(0.128)
	Random effects	-0.009	(0.020)	0.005	(0.020)	0.002	(0.010)	-0.022***	(0.010)	0.007*	(0.00)	-0.899	(0.570)
	Lag	-0.001	(0.009)	0.007	(0.009)	0.001	(0.003)	-0.002	(0.003)	0.006***	(0.001)	-0.549***	(0.114)
OTE_{VRS}	Tobit	-0.006	(0.009)	0.01	(0.009)	0.001	(0.003)	-0.006**	(0.003)	0.005***	(0.001)	-0.558***	(0.118)
	Bootstrap	-0.006	(0.009)	0.01	(0.009)	0.001	(0.003)	-0.006**	(0.003)	0.005***	(0.001)	-0.558***	(0.118)
	Random effects	-0.022	(0.030)	0.02	(0.030)	0.005	(0.010)	-0.023**	(0.010)	0.007**	(0.00)	-1.063**	(0.470)
	Lag	0.0001	(0.009)	0.004	(0.009)	0.001	(0.003)	-0.002	(0.003)	0.006***	(0.001)	-0.613***	(0.114)
OSE	Tobit	0.003	(0.006)	-0.003	(0.006)	-0.002	(0.002)	-0.002	(0.002)	0.001	(0.001)	-0.029	(0.079)
	Bootstrap	0.003	(0.006)	-0.003	(0.006)	-0.002	(0.002)	-0.002	(0.002)	0.001	(0.001)	-0.029	(0.079)
	Random effects	0.004	(0.020)	-0.007	(0.010)	-0.001	(0.010)	-0.008	(0.010)	0.002	(0.00)	-0.182	(0.350)
	Lag	-0.001	(0.006)	0.004	(0.006)	-0.00004	(0.002)	0.0004	(0.002)	-0.00004	(0.001)	0.033	(0.074)
OME	Tobit	-0.010***	(0.003)	0.010***	(0.003)	0.001	(0.001)	-0.003**	(0.001)	0.001	(0.000)	-0.089**	(0.044)
	Bootstrap	-0.010***	(0.003)	0.010***	(0.003)	0.001	(0.001)	-0.003**	(0.001)	0.001	(0.000)	-0.089**	(0.044)
	Random effects	-0.009**	(0.010)	0.009*	(0.010)	0.001	(0.000)	-0.002	(0.000)	0.0004	(0.000)	-0.081	(0.090)
	Lag	-0.008**	(0.003)	0.009***	(0.003)	0.001	(0.001)	-0.0005	(0.001)	0.001**	(0.000)	-0.125***	(0.040)

	Regression model	Age of farm manager (ev_1)		Age of spouse of farm manager (ev_2)		Off-farm work of farm manager (ev_3)		Off-farm work of spouse of farm manager (ev_4)		Capital-labour ratio (ev_5)		Land-labour ratio (ev_6)	
ROSE	Tobit	-0.019*	(0.010)	0.009	(0.011)	-0.009***	(0.004)	0.014***	(0.003)	0.004***	(0.001)	-0.260*	(0.136)
	Bootstrap	-0.019*	(0.010)	0.009	(0.011)	-0.009***	(0.004)	0.014***	(0.003)	0.004***	(0.001)	-0.260*	(0.136)
	Random effects	-0.019	(0.010)	0.004	(0.010)	-0.010*	(0.010)	0.011**	(0.010)	0.004**	(0.00)	-0.229	(0.240)
	Lag	-0.014	(0.010)	0.004	(0.010)	-0.001	(0.003)	0.004	(0.004)	0.002*	(0.001)	-0.023	(0.125)
OSME	Tobit	-0.027***	(0.010)	0.017	(0.010)	-0.008**	(0.003)	0.012***	(0.003)	0.005***	(0.001)	-0.327**	(0.134)
	Bootstrap	-0.027***	(0.010)	0.017	(0.010)	-0.008**	(0.003)	0.012***	(0.003)	0.005***	(0.001)	-0.328**	(0.134)
	Random effects	-0.027**	(0.010)	0.013	(0.010)	-0.009	(0.010)	0.009*	(0.010)	0.004***	(0.000)	-0.317	(0.230)
	Lag	-0.019**	(0.010)	0.01	(0.010)	-0.001	(0.003)	0.003	(0.003)	0.003***	(0.001)	-0.127	(0.122)
TSME	Tobit	-0.028***	(0.011)	0.022**	(0.011)	-0.008**	(0.004)	0.007**	(0.003)	0.008***	(0.001)	-0.687***	(0.137)
	Bootstrap	-0.029***	(0.011)	0.022**	(0.011)	-0.008**	(0.004)	0.007**	(0.004)	0.008***	(0.001)	-0.692***	(0.138)
	Random effects	-0.028**	(0.010)	0.014	(0.010)	-0.008*	(0.000)	0.0005	(0.010)	0.007***	(0.000)	-0.640***	(0.240)
	Lag	-0.016*	(0.009)	0.011	(0.009)	-0.001	(0.003)	0.001	(0.003)	0.007***	(0.001)	-0.559***	(0.117)
EEt	Tobit	-0.005	(0.005)	0.007	(0.005)	0.003	(0.002)	0.001	(0.002)	-0.001**	(0.001)	0.222***	(0.070)
	Bootstrap	-0.005	(0.005)	0.007	(0.005)	0.003	(0.002)	0.001	(0.002)	-0.001**	(0.001)	0.222***	(0.070)
	Random effects	-0.009	(0.010)	0.01	(0.010)	0.007*	(0.000)	-0.001	(0.000)	-0.002	(0.000)	0.351	(0.290)
	Lag	0.00004	(0.006)	0.002	(0.006)	-0.00003	(0.002)	0.005**	(0.002)	-0.00003	(0.001)	0.170**	(0.075)

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