The Sustainable Intensification of farming systems: Evaluating agricultural productivity, technical and economic efficiency

Yiorgos Gadanakis

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Σαν τη λογιάζεις τη δουλειά
όρτσα και μη φοβάσαι
αμόλα τη νιότη σου
και μην τηνε λυπάσαι.

Μη χαμηλώνεις τα φτερά
κόντρα στη μπόρα πέτα
πέτρα να κάμεις τη καρδιά
και πιάσου απ' την πέτρα

Traditional song from Crete; The first verse talks about the effort that is required to successfully reach your goals in life while the second asks you to never give up and always seek for courage from the depths of your heart.

Declaration

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

Yiorgos Gadanakis

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Abstract

Sustainable Intensification (SI) of agriculture has recently received widespread political attention, in both the UK and internationally. The concept recognises the need to simultaneously raise yields, increase input use efficiency and reduce the negative environmental impacts of farming systems to secure future food production and to sustainably use the limited resources for agriculture.

Data Envelopment Analysis (DEA) techniques were used for the investigation of changes in Total Factor Productivity in East Anglia. More specifically, the Malmquist Index and its components (scale, technical and pure efficiency) was used to derive information on productivity over time. Furthermore, the research reported here provides a benchmarking tool to assess water use efficiency, to suggest pathways to improve farm level productivity and to identify best practices for reducing or preventing water pollution. The results of the analysis suggest that the majority of the farms use water resources efficiently both for irrigation and general agricultural purposes, but there is the potential for improvement on some farms. Moreover, the results suggest that farms on the efficiency frontier can provide useful information with regards to operational and managerial changes that can be made to improve the performance of irrigation systems and water productivity. In addition, the analysis of returns to scale provides pathways for long term improvements and planning. The outcome could be used to strategically position a farm in relation to the long term average cost curve and, hence, improve economic efficiency and productivity of the GCF_s.

In addition, DEA models were used to successfully assign weights to specific environmental pressures that allow the identification of appropriate production technologies for each farm and therefore indicate specific improvements that can be undertaken towards SI. Furthermore, through appropriate econometric modelling this research explored the impacts of various managerial and farm characteristics on the improvement of sustainable intensification. It is concluded that education and advanced managerial skills can increase the environmental awareness of farmers and build knowledge and understanding of the challenges of food production. Moreover, agri-environmental payments can be an effective policy for the reduction of environmental pressures deriving from farming.

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Abbreviations and Acronyms

BCC: Banker Charnes Cooper
CAMS: Catchment Abstraction Management Strategy
CCR: Charnes Cooper Rhodes
CRS: Constant Returns to Scale
DEA: Data Envelopment Analysis
DMU: Decision Making Unit
DRS: Decreasing Returns to Scale
EA: Environment Agency
EARBC: East Anglia River Basin Catchment
FADN: Farmer Accountancy Data Network
FBS: Farm Business Survey
IRS: Increasing Returns to Scale
MI: Malmquist Index
NIRS: Non-Increasing Returns to Scale
OTE: Optimal Technical Efficiency
PPS: Production Possibility Set
PTE: Pure Technical Efficiency
RTS: Returns to Scale
SE: Scale Efficiency
SFA: Stochastic Frontier Analysis
SI: Sustainable Intensification
TE_{CRS}: Technical Efficiency under assumptions of constant returns to scale
TE_{VRS}: Technical Efficiency under assumptions of variable returns to scale
TFP: Total Factor Productivity
VRS: Variable Returns to Scale
WUE: Water Use Efficiency

Part I

This part introduces the reader to the background and the objectives of this research. In addition, it presents in detail the methods and techniques used as well as a comprehensive literature review of the applications in the agricultural sector

Chapter 1

Introduction

1.1 Sustainable intensification of the agricultural sector

Sustainable Intensification provides the underlying theme of this research. The main focus of this research is the evaluation of Total Factor Productivity (TFP), Water Use Efficiency (WUE) and Sustainable Intensification (SI) at a farm level in East Anglia.

In recent years the term Sustainable Intensification (SI) of farming systems emerged as a practice and a mechanism of farm management that serves the balance between sustainability and intensification of production. It can be therefore considered as the link for the two development paths of agricultural sustainability identified by Bell and Morse (2008) (achieve sustainability in a high-input-yield conventional farming system that follows a reasonable and controlled use of natural resources). According to Pretty (1997) SI relies on the engagement of integrated methods and innovative technologies to manage limited natural resources (soil and water), pest and nutrients in the agricultural sector. In addition, sustainability also entails resilience, such that agricultural systems, including human capital and organisational components, are robust enough to withstand transitory shocks and stress.

What is therefore required and identified as the key priority for the future of agricultural systems is the promotion of SI of agricultural production (FAO, 2011; Foresight Report, 2011). Given that there are limited resources available for agriculture (water, land), that more food needs to be produced to meet the demand of an increasing global population and also that the concept of sustainability is critical, then it can be argued that SI is a priority. According to the definition given by the Foresight Project's Final Report (Foresight Report, 2011), SI means:

"*simultaneously raising yields, increasing the efficiency which inputs are used and reducing the negative environmental effects of food production. It requires economic and social changes to recognise the multiple outputs required of land managers, farmers and other food producers and a redirection of research to address a more complex set of goals than just increasing yield*"

Baulcombe *et al.* (2009) in a report published by the Royal Society discusses the need for a SI of global agriculture in which productivity is increased and the adverse environmental impacts are reduced. For the UK according to the Environment, Food and Rural Affairs Committee in a review of the EU 2013 Common Agricultural Policy (CAP) reform, SI is a need which should be promoted through the reformed CAP in order to enable EU farmers to meet the challenges of increased food demand and climate change without irrevocably damaging the natural resources (EFRA, 2011).

Hence, the fundamental goal of SI is to make the current farming systems more efficient through the utilisation and adaptation of new emerging, efficient and innovative production technologies as a response to the challenges of climate change, limited natural resources, food supply, energy and other inputs overexploited and used unsustainably. Any efforts made to intensify agricultural production are required to be balanced by farm management options that make farming sustainable (Garnett & Godfray, 2012).

Agricultural production capacity depends on the availability of natural resources (land, water, etc.) and is subject to the economic (volatility of input cost and output prices, financial flow, trade policy, etc.), social (ageing of the farming population, education, internal migration, etc.) and biophysical (extreme weather phenomena such as droughts and floods, frost, hail, etc.) environment in which farming systems operate. Hence, the sustainability of the sector depends on the availability of natural resources and the socio-economic environment.

Sustainable agriculture is approached via two different paths in the international literature. The supporters of the first path believe that sustainable agriculture is feasible in a high-input-yield conventional farming while those of the second path support the notion that farming should follow a reasonable and controlled use of natural resources (Bell & Morse, 2008). Both research groups identify the following as potential threats to the future growth of the agricultural sector and systems (both in regional and local level): soil degradation, water scarcity, loss of biodiversity, genetic mutation of crops and plants and climate change.

At a broad level sustainable agriculture is defined as a practice that meets current and long term needs for food, fibre and other related requirements of society while maximizing net benefits through the conservation of resources to maintain other ecosystem services and functions, and long term human development (Dillon *et al.*, 2009).

Sustainable farming systems therefore, are characterised as those that are able to be productive and to maintain their contribution to society in the long term. These agricultural systems by definition will be using natural resources efficiently, be competitive in the commercial market and environmentally protective (Ikerd, 1993; Rigby & Caceres, 1997). According to Pretty *et al.* (1996) those that manage agricultural systems should put effort into reducing the off farm, external and non-renewable inputs, gain impartial access to resources and a more thorough incorporation of natural resources.

Thus, SI requires farming systems to balance their production by maintaining natural capital and ecosystem, services, by increasing their resource use efficiency, by achieving better environmental outcomes (both social and economic) and by taking into consideration animal welfare.

The social aspects of SI, or as commonly referred social sustainability are identified in two dimensions at the farm scale/level and at the broader rural community/environment. At a farm scale social sustainability refers to all these social aspects revolving around the people within the farming system. However, farm management decisions and agricultural production affect the broader rural environment by directly or indirectly generating impacts to public good such as ecosystems services, in the landscape (including urban and rural links) or may have ethical or welfare implications that also need to be considered.

However, according to Barnes and Thomson (2014) there is no agreed set of metrics for SI and also that although a number of measures available for analysing environmental social and economic change is available, either at a single indicator base or at a composite indicator base, there is no work directed at the specific issues of measuring sustainable intensification within an agreed indicator framework.

In this thesis, SI is viewed as a trade-off between economic and ecological performance characterised by an economic-ecological frontier that aims to reduce environmental pressures in agriculture. Economic-ecological frontiers or generally Eco-Efficiency frontiers are estimated in this thesis with the use of the Data Envelopment Analysis method, a non-parametric frontier based modelling approach. This is a method based on production efficiency models that are used to estimate frontier functions and measure the efficiency of farms in relation to the estimated frontiers.

Hence, Data Envelopment Analysis techniques allow to simultaneously account for economic and ecological performance given that the objective is to increase the desirable outputs and minimise the environmental pressure generated by the production process.

The impacts of SI of farming systems on the social sustainability are not considered on the metrics developed on Chapter 6 of this thesis. Although, the importance of the social dimension of SI is not ignored; it was decided that for the scope and the specific objectives of this thesis, (as these are in detailed explained later in section 1.3) to only focus on the dimensions of economic and environmental sustainability of farming systems.

1.2 Rationale

According to the Foresight Report (Foresight Report, 2011) the main challenges for agriculture in the future are raising yields, increasing input use efficiency, reducing the use of negative environmental inputs, securing food production, increasing resilience to climate change and developing strategies of integrated management of limited natural resources.

Climate change in the UK is likely to affect the availability of water in general while the impacts will vary according to the geographical characteristic of the areas as well as overall water availability and requirements at different times. Extreme changes in water availability will lead to changes in drought frequency, magnitude and duration. Climate change will also change the magnitude, frequency, distribution (spatially and temporally) and duration of flood events and may even lead to the loss of land in coastal areas and on floodplains. For irrigated root and vegetable crops, the continued production in the south and east of England will be dependent on assuring adequate sources of water for irrigation. In addition, harvesting in wetter autumns could also be problematic (Charlton *et al.*, 2010).

These extreme weather phenomena (droughts, floods) will thus have a direct impact on the way that crops grow, develop and yield. According to Knox *et al.* (2010) climate change in the UK will most importantly impact on productivity (yield and quality) and land suitability (indirect impact). A fall in agricultural productivity can potentially have a significant negative impact on farmers' income and sustainability. Furthermore, a reduction in yield and quality is also threatening future food production and supply. It is therefore important to review the impacts of the recent extreme weather phenomena (2007 floods, 2011-2012 drought period) on agricultural productivity especially in an area with high risk of drought (Daccache *et al.*, 2011). (Later in this research the East Anglian River Basic Catchment (EARBC) is used as a study area in order to explore changes in efficiency and technology at a farm level- see section 0).

The Environment Agency (2011) identifies climate change as one of many pressures with hydrological impacts[1]. In particular, spring and summer months are becoming drier for most of the UK leading to reduced runoff and warmer climate which will increase the demand for direct abstraction for cropping.

Overall across England, agriculture uses most water in the regions which are least capable of supplying it. In addition, this supply is generally required during the driest part of the year and is abstracted almost equally from ground and surface water sources (Charlton *et al.*, 2010). More specifically reduced summer rainfall, in the case of EARBC, could lead to irrigation water shortages, conflicts over water use, not enough water flow to dilute pollution, inability of soil to absorb rainfall, reduced crop yield and increased fire risk.

Therefore, taking into consideration all the aforementioned impacts of climate change on water in agriculture, the development and implementation of integrated water management strategies and policies becomes a crucial decision to secure the sustainability of the agricultural sector in specific parts of the UK. This suggests a need to develop guidance on what should be measured and how data might be interpreted to demonstrate efficient use of water in agriculture (Knox et al. 2012).

Agriculture in the UK is a major contributor in determining and enhancing the viability of rural economies and preserving rural landscapes but also is the main source of degradation in a range of ecosystems services (Firbank *et al.*, 2008). For UK agriculture to meet the future challenges of food demand and climate change SI may provide a viable management option. This is especially the case for areas that are experiencing a stasis in productivity growth, where a more efficient use of natural resources, production inputs and new technologies may be able to move production onto an upward trajectory and at the same time reduce the negative environmental impacts (Firbank *et al.*, 2013; Garnett *et al.*, 2013; Barnes & Thomson, 2014). Furthermore, according to Franks (2014) SI is often used as a guidance to design policy interventions and strategies in agriculture to meet the future challenges of agriculture and to safeguard and enhance ecosystem service provision.

The main challenge therefore arises in identifying the appropriate metrics and methods for the evaluation of SI of farming systems in order to provide recommendations for both policy design and improvement of farming practices.

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[1] The latest UK Climate Projections (UKCP09) provides a national assessment of seasonal changes in river flows and groundwater levels for the 2050s from 11 emission Regional Climate Model (RCM) simulations. Accessed 11/06/2014 - http://ukclimateprojections.metoffice.gov.uk/

Recent research has sought evidence of SI among farming systems in the UK (Areal *et al.*, 2012; Barnes & Poole, 2012; Firbank *et al.*, 2013; Barnes & Thomson, 2014). According to Firbank *et al.* (2013) a farm is successfully adapting SI practices when it manages to increase production output per unit of area during a period that none of the selected environmental indicators deteriorates. In Firbank's research a sample of 20 farms (arable, mixed, dairy, upland livestock farms) was selected and indicators were measured to account for both the production and environmental outputs of the farming systems. They concluded that there is evidence of SI and that farmers are motivated financially via increased input use efficiency (reducing waste and pollution) and by allocating resources through agri-environment schemes to enhance biodiversity at farm level (Firbank *et al.*, 2013). In a similar framework, Barnes and Thomson (2014) explored the relationship between sustainability and intensification in the context of Scottish Agriculture by using a balanced panel of 42 beef farms. A set of possible indicators was used for measuring SI. Moreover, they conceptualised the link between the technology frontier and sustainable intensification by identifying the need for improving input management efficiency to enhance productivity, and thus to cause an upward shift into the technology frontier. However, although there are several indicators used for the assessment and measurement of sustainability there is no evidence for the existence of an agreed set of indicators or a composite indicator for evaluating and measuring SI (Westbury *et al.*, 2011; Firbank *et al.*, 2013; Barnes & Thomson, 2014).

The main purpose of this research is to provide a holistic approach to the discussion and evaluation of the SI of farming systems. According to the definition of SI by Firbank *et al.* (2013), the Foresight Report (2011), and Baulcombe *et al.* (2009) three targets must be met in order for farming systems to successfully practice SI: a) increase productivity b) improve input use efficiency and c) reduce the damaging environmental effects of agricultural production systems. This research focuses on a set of General Cropping Farms (GCF_s) in the area of EARBC and uses data from the Farm Business Survey (FBS) in order to a) assess the impact of the recent extreme weather phenomena on Total Factor Productivity (TFP) over a period of five years b) evaluate the level of water use efficiency at a farm level and c) provide a measurement of a composite indicator to evaluate SI of farming systems.

1.3 The scope and objectives of this research

The main concern of this research is the evaluation of Total Factor Productivity (TFP), Water Use Efficiency (WUE) and Sustainable Intensification (SI) at a farm level in East Anglia. The FBS, which is a comprehensive and detailed database that provides information on the physical and economic performance of farm businesses in England, was used to obtain data for the empirical application of a series of models. In order to facilitate policy makers and farmers in the design of policies and decision making respectively, this research aims to develop a methodology that engages integrated methods and techniques allowing for a holistic approach over the evaluation of farming practices and systems. For that purpose, each empirical chapter demonstrates how data derived from the FBS is used in the analysis of productivity, technical efficiency, WUE and SI. A series of Data Envelopment Analysis (DEA) linear programming models are used to estimate the Malmquist Index (MI) of TFP, WUE at a farm level and specific input reductions to improve the SI performance of farming systems.

In the light of the previous discussion, the main objectives and research questions are set as follows.

Research question 1: How is FBS data used to develop an index of TFP in order to assess the impact of extreme weather phenomena in agriculture? – Sub-question: How are existing DEA techniques used to build on improving benchmarking methods in agriculture by considering non-discretionary variables in the production function?

The main objective is to explore the impacts that the recent extreme weather phenomena of 2007 (floods) and 2010, 2011 (drought) had on technical efficiency and agricultural productivity at a farm level in the EARBC. A contemporaneous production frontier is constructed to estimate and compare the performance of TFP across a five year period (2007-2011). The decomposition of the MI of TFP into the Efficiency and Technical Efficiency change enables the discussion of changes at a farm level efficiency (the distance of farms to the frontier) and of inward or outwards shifts of the frontier. Thus, the Technical Change index is used to identify if exogenous factors such as the weather extremes have an impact on the frontier or if technical changes were followed up by similar or not efficiency changes (Piesse & Thirtle, 2010a). In addition, further decompositions of the components of the MI of TFP as suggested by Färe *et al.* (1994b) and Wheelock and Wilson (1999) enable a more detailed analysis over the drivers of agricultural productivity change by estimating the technical, pure technical, pure efficiency and scale efficiency indices.

Although, non-discretionary inputs, such as rainfall, are out of the control of the farmer, they are important for securing production and thus farmers' income. Not accounting for variations in non-discretionary inputs in benchmarking methods like DEA can potentially lead to biased estimates of performance measurements between farming systems (Dyson *et al.*, 2001). Within the context of the overall analysis of TFP change, this research is also exploring the importance of accounting for variations in the characteristics of the physical environment (rainfall) or not in the specifications of the DEA linear programme. Technical efficiency estimates of the conventional DEA and the sub-vector DEA models are compared for the same set of farms in terms of ranking and the peer reference set for each individual farm.

In the context of SI, the analysis aims to provide an insight on the development of agricultural productivity for GCF$_s$ in the EARBC. Changes in yield patterns caused by extreme weather phenomena have an impact on both farmers' income and food prices. Meeting the future challenges of increased food demand and climate change requires improved technical efficiency, mitigation of the climate change impacts and improvement of productivity. The results of the analysis aim to inform policy makers towards the direction that agricultural strategies should be developed in order to enhance productivity and increase the resilience of farming systems.

Research question 2: How can FBS data be used to improve benchmarking techniques and to identify farm management practices to reduce water consumption at a farm level?

The objective behind asking this question is to provide an estimate of excess water use at a farm level. Specifically, this research not only focuses on irrigating farms but also discusses the use of water at a farm level for other general agricultural purposes (i.e. washing buildings, machinery). Inefficient use of water (excess use) has an economic impact (increased production costs) and also can be the source of environmental degradation. In the context of SI, farming systems are required to improve their input use efficiency. Hence, in the case of East Anglia where the risk of drought is higher than in other parts of the UK and the use of irrigation is required to secure yield and income for the farmer managing water resources efficiently is of significant importance. This research aims to provide a measure of WUE which has an economic rather than an engineering meaning that allows for a reduction in the volume of water used at a farm level without altering the production output and the quantities of other inputs used.

In addition, by considering the importance of the human factor in decision making and the role of management practices in production efficiency, the estimates of WUE are used to discuss the determinants of efficiency. In particular the objective is to use the information derived from the DEA sub-vector efficiency estimates to identify the set of best performing farms in the sample. These farms will then be linked to a set of WUE management practices in order to identify areas of improvement and thus to provide a focus for policy makers.

In the same context, this research provides also estimates of technical efficiency which are then decomposed into pure technical efficiency (short run changes) and scale efficiency change (long run changes). The specific objective under this analysis is to indicate potential benefits from adjusting farm size and setting targets of improving efficiency and management of water resources in the short and long run.

Research question 3: Is it possible to build on existing methodological research to derive an FBS data based composite indicator to explore the different levels of intensification between farming systems in the context of SI?

According to Barnes and Thomson (2014) there is no evidence in the litarature about the existence of an agreed set of indicators or a composite indicator for evaluating and measuring SI. The main objective is therefore to fill this gap in the literautre by providing a composite indicator of SI that is based on the measurement of Eco-Efficiency with the use of DEA techniques. In particular, environmental pressures generated at a farm level are used as an indication of the level of intensification of the agricultural production in an effort to secure yields and increase profit. This metric of SI aims to inform both farmers and policy makers to identify excess input use and explore the different levels of intensification between farms of the same type.

Further characteristics of the farming systems (e.g. farm size, farmer's education level, agri-environmental paymets) are also used at a second stage analysis in order to explore the determinats of farming systems that succesfully practice SI. This aims to identify factors that could be improved or reverse their negative impact in order to imrove the performance of agricultural systems in the context of SI.

1.4 Contributions to research

Numerous studies have explored the TFP in the UK agricultural industry with the majority of them using an estimation of an ideal Fisher index, which is the geometric mean of the Laspeyres and Paache indices and the Tornqvist-Theil TFP index (Amadi *et al.*, 2004; Thirtle *et al.*, 2004; Renwick *et al.*, 2005; Thirtle *et al.*, 2008; Piesse & Thirtle, 2010a). This research adds to the existing literature of TFP in UK agriculture by estimating for the first time a MI of TFP based on DEA methods. The MI of TFP allows for the discussion of technical and efficiency change of farming systems in a period of time and hence, it provides more detailed estimates of TFP than the Tornqvist-Theil index used in previous studies in the UK. Moreover, this research shows that the MI of TFP is the most appropriate method to use FBS data to assess TFP since the DEA techniques used allow for the estimation of multi-input and multi-output technologies in the absence of price data. In addition, this research demonstrates how the method described by Simar and Wilson (1999) is used to enable statistical inference for the MI of TFP for the first time in the UK agricultural sector.

Further, this research adds to the existing literature of DEA studies in the agricultural sector in two directions. First, it discusses the importance of accounting for non-discretionary inputs in the model specifications. Various exogenous factors such as rainfall have a significant importance in the production technology of farming systems. Drought or flood periods can potentially have a negative impact on both yields and farmers' income. This research suggests that studies on technical efficiency of farming systems employing DEA methods need or adopt the sub-vector approach in order to improve the benchmarking method and also to avoid any bias in performance measurements.

The second contribution to the DEA literature is the estimation of a composite indicator (Eco-Efficiency) of SI of farming systems. Little, if any previously published research has so far applied DEA estimates of Eco-Efficiency for the assessment of SI of agricultural systems. The main advantage of the method suggested in this research is the use of DEA methods to assign weights for the different environmental pressures generated at a farm level. This technique overcomes any bias of arbitrary assigned weights or subjective judgments from expert panels and workshops. In addition, this research demonstrates how the use of a representative and validated sources of secondary data such as the FBS could potentially be used to develop a long-term monitoring mechanism for the SI of different farm systems in the UK.

In addition, this research also contributes to the environmental economics literature. Through the context of SI of farming systems, specific input reductions are identified. The DEA linear programme used sets as an objective the maximisation of economic value added at a farm level while at the same time the damaging environmental inputs are minimised. That allows for the reduction of any excess in use of the damaging inputs and consequently for the improvement of the environmental performance of the farming systems without any reductions in output (economic value added).

Finally, this research contributes to the literature of SI by applying a set of integrated non-parametric and parametric methods to evaluate the SI of farming and suggest a holistic approach to account for the main future challenges of agriculture (increase productivity, improve input use efficiency, climate change) . The effort made in this research to incorporate the technology frontier in the context of SI adds also to the literature of efficiency. Different DEA models are used throughout the research to assess the need for improving input management efficiency to enhance productivity, to identify specific management practices for the improvement of WUE and to reduce the use of environmental damaging inputs. Moreover, this research is the first to use the double bootstrapped truncated regression in DEA efficiency studies in the UK agricultural sector.

1.5 Structure of this research

This research is organised into three parts. Part I presents the background and the objectives of the study, the methodology used and the related literature review. Part II consists of three chapters providing empirical evidence on the explanation of agricultural productivity, the excess in water use efficiency and the evaluation of the SI of farming systems. Part III delivers the main conclusions and policy implications.

Chapter 2 introduces the relevant efficiency theory and its estimation through DEA techniques. It provides a comprehensive discussion over the production technology concept and the main assumptions underlying the development of DEA models and measures of farm efficiency. Furthermore, it presents in detail the basic input and output oriented DEA mathematical programs and extends those in the evaluation of the performance over time with the use of a contemporaneous MI of TFP. In addition, the concepts of sub-vector DEA efficiency and Scale Efficiency are introduced and linked to the objectives of this thesis. Specific emphasis is given also to the methods used to enable the statistical inference in DEA models and to the method of detecting outliers in deterministic non-parametric frontier models with multiple inputs and outputs.

Chapter 3 provides a comprehensive review of the DEA literature in agriculture. It reviews previous research on efficiency of farming systems employing DEA techniques and presents the main paths of knowledge dissemination. Particular attention is given to the fields of interest and to the model specifications. The chapter discusses studies on decomposing economic efficiency to technical and allocative efficiency, evaluating the environmental performance of farming systems, water use efficiency, productivity change over time at country, regional and farm level and how the methods are used to evaluate agricultural policies. Moreover, it presents the main methodological considerations in relation to the selection of the appropriate

DEA models, the type of farming systems, the selection of input and output set and the assumptions made on returns to scale for DEA models in the literature.

Chapter 4 provides an empirical estimation of TFP for the GCF_s in the EARBC over a period of five years. The analysis is divided into two parts. For the first part an input oriented sub-vector DEA model is used to account for non-discretionary exogenous variables (rainfall) in the estimation of technical efficiency of farming systems. The assumptions of variable returns to scale (VRS) and constant returns to scale (CRS) are used to also provide an estimation of scale efficiency (SE). In addition, a model with non-increasing returns to scale (NIRS) is also employed to characterise the scales of operation (increasing, decreasing and constant returns to scale) for the farms during the five year period. In the second part an input oriented bootstrapped MI of TFP is estimated. Productivity change is then decomposed into technical and efficiency change in order to account for changes in efficiency (farms moving towards the frontier) and technological changes (inward or outward shifts of the frontier). The bootstrapped method is used to enable statistical inference. In particular, bootstrapped estimates of the distance functions allow the calculation of a set of MIs of TFP and their components which account for the bias and enable the estimation of confidence intervals. Further, the indices of pure efficiency, pure technical, scale efficiency and scale technical change are estimated and discussed. Detailed tables presenting the estimated indices over the five year period can be found in Appendix A, Appendix B, Appendix C, and Appendix D.

Chapter 5 serves two main objectives 1) to assess the technical efficiency of irrigating GCF_s in the EARBC and 2) to provide an estimate of excess water use at farm level. For these an input oriented VRS sub-vector DEA model is used in a sample of farms derived from the FBS of 2009/2010. The identification of excessive water use at farm level is then used to provide recommendations for improvements of WUE and policy interventions. In addition, management practices for efficient water use practised at a farm level are related to the set of peer farms in the sample in order to identify areas for management improvement. Further, two additional DEA models under the assumption of CRS and NIRS are solved in order to assess the impact of scale size on the productivity of the farm.

Chapter 6 suggests that environmental pressures generated at a farm level, as defined by Picazo-Tadeo *et al.* (2011), can be interpreted as an indication of the level of intensification of agricultural production in an effort to secure yields and maximise profit. Higher levels of inputs (fertilisers, crop protection costs, water, fuel, etc.) for individual farms in a benchmarked sample indicate that these farmers are using more intensive production methods when compared with others in the same sample. The main objective of this chapter is to measure the SI of farming systems, which can be used by both farmers and policy makers to identify excess input use and explore the different levels of intensification between farms of the same type. For that purpose, an input oriented DEA with CRS and the additive DEA models are used to provide estimates of Eco-Efficiency and slack values in the model respectively. The slack values are used in the discussion of causes of economic inefficiency. In particular, any excess in environmental pressures identified by the slacks in the model is related to an intensified agricultural production unit that could reduce its environmentally-damaging inputs. In addition, a double bootstrapped truncated regression model is used to analyse the specific characteristics of farming systems that may have an impact on the improvement of the index of Eco-Efficiency and subsequently to the balance between sustainable production and intensification of farming systems.

Finally, Chapter 7 summarises the key aspects and findings of this research in the context of SI of farming systems, discusses the possibilities of future research and the potential policy implications. Furthermore, of particular interest is the discussion of the use of FBS in this research and to the further improvements in the data coverage that could enable the development of a persistent monitoring mechanism towards the SI of agricultural systems in the UK.

Note: work from Chapter 6 had formed the basis for a paper which is under minor revision following peer review with the Journal of Environmental Management entitled “Evaluating the Sustainable Intensification of arable farms”. A further paper from Chapter 5 is currently under review with the Agricultural Water Management Journal entitled, “Improving productivity and efficient water use: a case study of farms on East Anglia”.

Chapter 2

Methodology

2.1 Introduction

There are three themes covered in this research. The first theme refers to the farm's productivity and its decomposition into technical and efficiency change for a five year period. The second theme is related to the efficient use of natural resources and specifically concentrates on the measurement of WUE at farm level whilst underlining the characteristics of the farms on the frontier. Finally, the third theme is based on the derivation of a composite indicator estimated by non-parametric techniques, its relationship with measurements of Eco-Efficiency and the evaluation of the Sustainable Intensification of farming systems.

This chapter introduces the relevant efficiency theory focusing specifically on technical efficiency and its estimation through Data Envelopment Analysis (DEA). It also covers the theory underlying a dynamic approach to efficiency and productivity through a Malmquist Index of Total Factor Productivity based on distance functions measured by DEA techniques. In the following sections the theory and the methods used to construct the DEA models for the estimation of specific input measures of efficiency (i.e. WUE) and specific input reductions (i.e. reducing environmental pressures) as highlighted before are described.

The chapter is organised as follows: Section 2 defines the production possibility set and explains the underlying basic assumptions; Section 3 illustrates the use of DEA techniques for the estimation of technical efficiency; Section 4 provides a description of the Malmquist index used for a dynamic performance measurement of farms and finally; Section 5 explains the method of bootstrapping that enables statistical inference in nonparametric frontier models (Simar & Wilson, 1998a; 1999; 2000; 2007); while section 6 presents the method of Wilson (1993) for detecting outliers.

2.2 The production technology

2.2.1 The set of inputs and outputs in a farming system

A farm is considered as a Decision Making Unit (DMU) that decides over the selection of the production plan (i.e. the set of inputs for the production of a set of outputs). Consequently, the farm serves as the system that transforms inputs into outputs.

To formalise the above let us assume that we observe a set of n farms and each farm $i = \{1, .., n\}$ has a set of j inputs and s outputs representing multiple performance measures. For the i^{th} farm then the $j - vector$ of inputs and the $s - vector$ of outputs are defined as $x^i = (x_1^i, \cdots, x_j^i) \in \mathbb{R}_+^j$ and $y^i = (y_1^i, \cdots, y_s^i) \in \mathbb{R}_+^s$ respectively[2]. The production plan for the i^{th} farm is thus defined as a pair of input and output vectors:

$$(x^i, y^i) \in \mathbb{R}_+^j \times \mathbb{R}_+^s$$

Note that $\mathbb{R}_+ = \{\alpha \in \mathbb{R} | \alpha \geq 0\}$ and it is therefore presumed that both inputs and outputs for the i^{th} farm are non-negative numbers i.e. they are positive or zero.

For a set of n farms the input data matrix X and the output data matrix Y can be arranged as follows:

$$X = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_j^1 \\ x_1^2 & x_2^2 & \cdots & x_j^2 \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ x_1^n & x_2^n & \cdots & x_j^n \end{bmatrix}$$

$$Y = \begin{bmatrix} y_1^1 & y_2^1 & \cdots & y_s^1 \\ y_1^2 & y_2^2 & \cdots & y_s^2 \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ y_1^n & y_2^n & \cdots & y_s^n \end{bmatrix}$$

2.2.2 The production possibility set

In benchmarking theory the basic assumption is that the DMUs compared have a common and homogenous underlying technology defined by the technology or production possibility set P,

$$P = \{(x, y) \in \mathbb{R}_+^j \times \mathbb{R}_+^s | x \; can \; produce \; y\}$$

The production possibility set (PPS) is denoted by the social, technical, mechanical, chemical and biological environment in which the production process takes place (Bogetoft & Otto, 2010). Conceptually the PPS is defined as the minimum technology that satisfies the following assumptions about the production technology without specifying any functional form (Banker *et al.*, 1984; Bogetoft & Otto, 2010):

***Assumption* 1 (A1)**: The set of the observed input and output combinations are feasible. An input output set (x, y) is feasible when the input bundle x can produce the output bundle y. Suppose there exists a set of n farms producing s outputs from j inputs. Let $x^i = (x_1^i, \cdots, x_j^i)$ be the observed input bundle and $y^i = (y_1^i, \cdots, y_s^i)$ the observed output bundle. Then according to (*Assumption 1*) each (x^i, y^i) $i = (1, \cdots, n)$ is a feasible input output combination.

[2] Superscripts are used to denote the different farms and subscripts to denote the different types of inputs and outputs. Note that in the absence of subscripts we consider all inputs and outputs in a vector format

***Assumption* 2 (A2)**: The PPS is convex. Formally, $P\ is\ convex$ if any two points

$(x^A, y^A) \in P, (x^B, y^B) \in P$, and any weight $0 \leq \lambda \leq 1$,

the weighted sum $(1-\lambda)(x^A, y^A) + \lambda(x^B, y^B)$ is also in P, i.e.,

$(x^A, y^A) \in P, (x^B, y^B) \in P, 0 \leq \lambda \leq 1 \implies (1-\lambda)(x^A, y^A) + \lambda(x^B, y^B) \in P$

The weighted sum of the two plans $(x^\lambda, y^\lambda) = (1-\lambda)(x^A, y^A) + \lambda(x^B, y^B)$ $(0 \leq \lambda \leq 1)$ is called a convex combination of (x^A, y^A) and (x^B, y^B) with weight λ. In geometric terms, this would mean that for any two points in the technology set P, the plans on the line between them are also in P

***Assumption* 3 (A3)**: Free disposability of input and output. Formally, when $(x, y) \in P$, $x' \geq x$ and $y' \leq y$, the $(x', y') \in P$ i.e.,

$$(x, y) \in P, x' \geq x, y' \leq y \Longrightarrow (x', y') \in P$$

(Assumption 3) means that inputs and outputs can freely be disposed of or in other words, we can always produce fewer outputs with more inputs.

If in addition, we make the assumption that constant returns to scale (CRS) holds, formally;

***Assumption* 4 (A4)**: If (x, y) is feasible, then for any $\beta \geq 0$, $(\beta x, \beta y)$ is also feasible.

The above four assumptions are used to empirically construct a PPS from the observed data without any explicit specification of a production function. Consider that the following input output bundle $(\hat{x},\ \hat{y})$ is observed where $\hat{x} = \sum_1^n \mu^i x^i, \hat{y} = \sum_1^n \mu^i y^i, \sum_1^i \mu^i = 1$ and $\sum_1^i \mu^i \geq 0\ (i = 1,2 \cdots n)$. By the first two assumptions (A1 and A2), $(\hat{x},\ \hat{y})$ is feasible. Also, due to assumption A3, if $x \geq \hat{x}$ and if $y \leq \hat{y}$ then the input output combination $(\hat{x},\ \hat{y})$ is also feasible. Furthermore, if CRS is assumed, $(\beta\hat{x}, \beta\hat{y})$ is also a feasible set for any $\beta \geq 0$. Define $\tilde{x} = \beta\hat{x}$ and $\tilde{y} = \beta\hat{y}$ for some $\beta \geq 0$. Then by construction, $\sum_1^n \tilde{y} \leq \beta \sum_1^n \mu^i y^i$ and $\sum_1^n \tilde{x} \geq \beta \sum_1^n \mu^i x^i$. Next define $\lambda^i = \beta\mu^i$, then $\lambda^i \geq 0$ and $\sum_1^n \lambda^i = \beta$. But β is only restricted to be non-negative, thus, beyond non-negativity, there are no additional restrictions on the λ^i.

The PPS or technology set can be therefore defined based on the assumptions A1-A4 and the observed input output set as follows where the superscript C indicates that the technology is characterised by CRS:

$$P^C = \left\{(x, y): x \geq \sum_{i=1}^{n} \mu^i x^i\,; y \leq \sum_{i=1}^{n} \mu^i x^i\,; \mu^i \geq 0; (i = 1,2, \cdots, n\right\}$$

Hence, convex combinations are formed that do not require (x, y) to precisely match this convex combination due to the assumption A3, which implies that we only need weakly more input x and weakly less output y to ensure feasibility (Cooper *et al.*, 2006; Bogetoft & Otto, 2010).

2.2.3 Evaluating the performance of farms

The most common methods to evaluate the performance of a farm are the use of a productivity ratio (i.e. a ratio of inputs to outputs), the comparison of the performance in different time periods, the benchmarking of the current performance of a farm relative to other farms or relative to a specific efficient production function (i.e. the production frontier). Despite however the choice of a specific method, the efficient performance of a farm is defined by its position relative to the production frontier. The production frontier represents the maximum output produced by each given input level. A farm can therefore be defined as technically efficient when it manages to maximise output produced by each level of input (i.e. the farm operates on the production frontier).

Measurements of efficiency were introduced in the literature through the work of Koopmans (1951), Debreu (1951) and (Shephard, 1953; 1970). Koopmans (1951) was the first to provide a formal definition of efficiency that distinguishes between efficient and inefficient production plans. On the other hand (Debreu, 1951) and (Shephard, 1953; 1970) were the first to provide a measure of technical efficiency with the introduction of a measurement of radial distance from a production plan to the frontier with the introduction of distance functions to model multi output technology (Kumbhakar & Lovell, 2003).

There are broadly two main definitions used in the literature concerning technical efficiency a) Koopmans (1951) defined a producer as technically efficient when "*an increase in an output requires a reduction in at least one other output or an increase in at least one input, and if a reduction in any input requires an increase in at least one other input or a reduction in at least one output*" and b) Debreu (1951) and Farrell (1957) defined technical efficiency as "*one minus the maximum equiproportionate reduction in all inputs that still allows the production of given outputs, a value of one indicates technical efficiency and a score less than unity indicates the severity of technical inefficiency*" this is known in the literature as the Debreu – Farrell efficiency or Farrell efficiency.

Technical efficiency as defined above is measured by two approaches:

a) the input approach, i.e. evaluate the ability of minimising inputs keeping outputs fixed and;

b) the output approach, i.e. evaluate the ability of maximising outputs keeping inputs fixed.

Formally, the input based Farrell efficiency or just input efficiency of a plan (x, y) relative to a technology P is defined as

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

which is the maximal equiproportional contraction of all inputs x that allows the production of y (input distance function).

Accordingly, the output based Farrell efficiency or output efficiency of a plan (x, y) relative to a technology P is defined as

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

which is the maximal equiproportional expansion of all outputs y that is feasible with the given inputs x (output distance function).

The above described input (E) and output (F) distance functions can also provide an alternative description of the technology. Specifically, knowing $E(x, y)$ or $F(x, y)$ for all $(x, y) \in \mathbb{R}_+^j \times \mathbb{R}_+^s$ we essentially know P as well. Hence, each of these distance functions provides a complete characterisation of the technology P since

$$E(x, y) \leq 1 \Leftrightarrow (x, y) \in P$$

$$F(x, y) \geq 1 \Leftrightarrow (x, y) \in P$$

or, equivalently

$$P = \left\{(x, y) \in \mathbb{R}_+^j \times \mathbb{R}_+^s \middle| E(x, y) \leq 1\right\}$$

$$P = \left\{(x, y) \in \mathbb{R}_+^j \times \mathbb{R}_+^s \middle| F(x, y) \geq 1\right\}$$

Another common measure in the literature of technical efficiency for the above distance functions is the *Shephard distance functions* which are simply the inverse of the Farrell.

Formally the Shephard distance functions are defined as:

$$D_i = max\left\{D > 0 \middle| \left(\frac{x}{D}, y\right) \in P\right\}$$

$$D_o = min\left\{D > 0 \middle| \left(x, \frac{y}{D}\right) \in P\right\}$$

where D_i is the Shephard input distance function, and D_o the Shephard output distance function.

Therefore similarly to Farrell,

$$D_i(x, y) \geq 1 \Leftrightarrow (x, y) \in P$$

$$D_o(x, y) \leq 1 \Leftrightarrow (x, y) \in P$$

and

$$P = \left\{(x, y) \in \mathbb{R}_+^j \times \mathbb{R}_+^s \middle| D_i(x, y) \geq 1\right\}$$

$$P = \left\{(x, y) \in \mathbb{R}_+^j \times \mathbb{R}_+^s \middle| D_o(x, y) \leq 1\right\}$$

Further, it is emphasised that the measurement of efficiency through the above distance functions is of particular importance as it is stated by Farrell (1957) since, failing to account for inefficiencies may lead to misspecifications of the production function and hence misguide the decision making process of policy makers and farm managers.

Figure 2.1 illustrates the concepts of technical efficiency, Farrell's distance functions and the production possibility set using a simple example of a set of farms $\{A, B, C, D, E, F\}$, using a one input (x) one output (y) production plan.

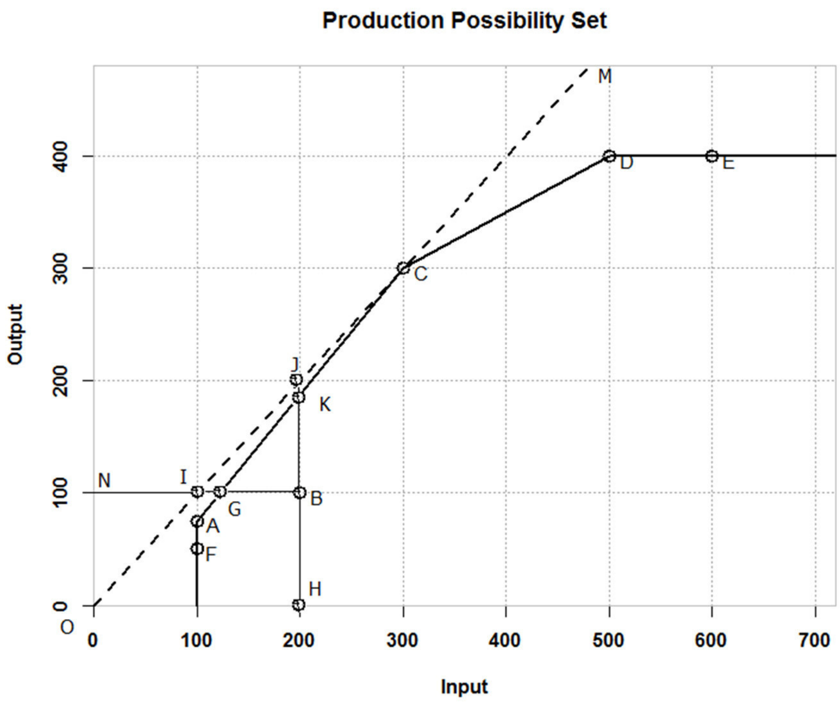

Figure 2.1: The production possibility set

The straight line OM represents a production frontier under the assumption A4 (CRS), while the concave envelope FAKCDE represents the frontier under the assumption of variable returns to scale (VRS). Note that when we allow for CRS, the production frontier is forced through the origin and when VRS are allowed this does not happen. Farm B is used as an example to provide several technical efficiency measures.

Under the CRS assumption (OM frontier) the input oriented Farrell measure of technical efficiency is the ratio NI/NB, accordingly the output oriented Farrell measure of technical efficiency is the ratio HB/HJ. Note that under the CRS assumption the input and output oriented measure of technical efficiency provide equivalent measure of technical efficiency (i.e. $NI/NB = HB/HJ$).

The input oriented Farrell measure of technical efficiency under the VRS assumption is equal to the ratio NG/NB, while the output oriented Farrell technical efficiency is defined by the ratio HB/HK. In contrast to the CRS the VRS assumption does not provide equivalent measures of technical efficiency. According to Coelli *et al.* (2005), measures of technical efficiency under the VRS assumption are always greater than or equal to those obtained under CRS and that is due to the fact that data is enveloped more tightly under VRS rather than CRS.

It is therefore clear from the above discussion that measures of technical efficiency are affected by two components a) the assumption made concerning the underlying technology which influences the form of the envelopment surfaces and b) the assumption about orientation (i.e. input or output oriented). In this research these assumptions are defined and justified in each relevant chapter in the section of methodology.

2.3 Using Data Envelopment Analysis to evaluate the performance of farms

In the literature there are broadly two approaches used to obtain efficiency estimates at a farm level; parametric techniques (i.e. Stochastic Frontier Analysis (SFA)) and non-parametric techniques (i.e. Data Envelopment Analysis (DEA)). Parametric techniques are used for the specification and estimation of a parametric production function which is representative of the best available technology (Chavas *et al.*, 2005). The Stochastic Frontier Analysis (SFA) was introduced by Aigner *et al.* (1977) and (Meeusen & Vandenbroeck, 1977). The advantage of this technique is that it provides the researcher with a robust framework for performing hypothesis testing, and the construction of confidence intervals. However, its drawbacks lie in the *a priori* assumptions in relation to the functional form of the frontier technology and the distribution of the technical inefficiency term, in addition to the results being sensitive to the parametric form chosen (Wadud & White, 2000).

Data Envelopment Analysis (DEA) is an alternative nonparametric method of measuring efficiency that uses mathematical programming rather than econometric methods. Farrell (1957) formulated a linear programming model to measure the technical efficiency of a firm with reference to a benchmark technology characterized by constant returns to scale. This efficiency measure corresponds to the coefficient of resource utilization defined by Debreu (1951) and is the same as Shephard's distance function (1953). This chapter discusses DEA methods for the construction of production frontiers and the assessment of technical efficiency of farms.

In DEA the main objective is to determine the efficiently performing farms in relation to each other and benchmark the remaining farms relative to the farms allocated on the defined production possibility frontier. Linear programming methods are used for the calculation of efficiency scores for the farms on or below the efficient frontier. DEA is a non-parametric method in the sense that it requires only a limited number of *a-priori* assumptions regarding the functional relationship between inputs and outputs. Instead, the production frontier is constructed as a piecewise linear envelopment of the observed data points. Different units of measurement can be used for the various inputs and outputs and knowledge of their relative prices is not required. The DMUs enclosed by the envelope are the ones considered to be inefficient and, depending on the model of DEA used (either input or output oriented), should adjust their inputs or outputs to move on the frontier. Output oriented DEA maximizes output for a given level of the inputs used, while input-oriented DEA minimizes inputs for a given level of output. While using DEA two different approaches can be considered based on the assumptions taken on returns to scale: constant returns to scale (the Charnes, Cooper and Rhodes (CCR) model (Charnes *et al.*, 1978)) and variable returns to scale (the Banker, Charnes and Cooper (BCC) model (Banker *et al.*, 1984)). A more detailed discussion of the different DEA models and the development of the techniques is available in Cooper *et al.* (2006).

Depending on the type of data available (cross section, or panel data), and the availability or not of prices DEA techniques can be used for the estimation of both technical and economic efficiency. Data on input and output quantities is used for the estimation of technical efficiency while additional information on prices is required for the estimation of economic efficiency. Further, the employment of a two stage DEA procedure and the assumption of behavioural goals, such as cost minimisation is used for the estimation of technical and allocative efficiency.

2.3.1 Minimal extrapolation

Recall from section 2.2.2 that the technology or production possibility set P, is defined as:

$$P = \{(x, y) \in \mathbb{R}_+^j \times \mathbb{R}_+^s | x \ can \ produce \ y\}$$

However, we seldom know the real technology P and we therefore need to estimate this. In DEA, the empirical reference technology P^*, i.e. the estimate of the technology P, is constructed according to the minimal extrapolation principle: P^* is the smallest subset of $\mathbb{R}_+^j \times \mathbb{R}_+^s$ that contains the data (x^i, y^i) $i = (1, \cdots, n)$ and satisfies certain technological assumptions as the free disposability and some form of convexity.

Consider that P' technologies exist and that are subsets of $\mathbb{R}_+^j \times \mathbb{R}_+^s$ and that (D) contains data: $(x^i, y^i) \in P', i = (1, \cdots, n)$, and (R) satisfy the regularity assumptions. Then the set of such candidate technologies is denoted as

$$\mathcal{P} = \{P' \subset \mathbb{R}_+^j \times \mathbb{R}_+^s | P' satisfy \ (D) \ and \ (R)\}$$

The minimal extrapolation principle means that we estimate the underlying but unknown technology P by the set

$$P^* = \bigcap_{P' \in \mathcal{P}} P'$$

According to the regularity assumptions, P^* is the smallest set that is consistent with the data. In addition, if the true technology P satisfies the regularity properties, then $P \in \mathcal{P}$. The estimated technology will be a subset of the true technology $P^* \subseteq P$ and this is referred as the inner approximation of the technology.

2.3.2 The different technologies in DEA

The different assumptions made about the technology P leads to different DEA models. These assumptions were introduced in section 2.2.2. Here we expand the assumption about returns to scale.

***Assumption* 4 (A4)**: γ - returns to scale. Production can be scaled with any of a give set of factors: $(x, y) \in P, \beta \in \Gamma(\gamma) \Longrightarrow \beta(x, y) \in P$

Where for $\gamma = crs, drs, irs \ or \ vrs$ and where the sets of possible scaling factors are given by $\Gamma(crs) = \mathbb{R}_{0,}\Gamma(drs) = [0,1]$, and $\Gamma(irs) = [1, \infty], \Gamma(vrs) = \{1\}$, respectively. Note also that drs (or non-increasing returns to scale NIRS) denotes decreasing returns to scale and irs (or non-decreasing returns to scale NDRS) increasing returns to scale.

The above technologies and the different assumptions of DEA models are summarised in Table 2.1. The set Λ in the last row is used to define the parameters used for the construction of the technologies form the actual sets. The PPS for the different models is then illustrated in Figure 2.2.

Table 2.1: DEA model assumptions

Model	Regularity assumptions			
	Free disposability	Convexity	γ - returns to scale	Parameter set $\Lambda(\gamma)$ $\lambda \in \mathbb{R}_+^{\iota}$
VRS	✓	✓	$\beta = 1$	$\sum \lambda^{\iota} = 1$
DRS	✓	✓	$\beta \leq 1$	$\sum \lambda^{\iota} \leq 1$
IRS	✓	✓	$\beta \geq 1$	$\sum \lambda^{\iota} \geq 1$
CRS	✓	✓	$\beta \geq 0$	$\lambda^{\iota} \geq 0$

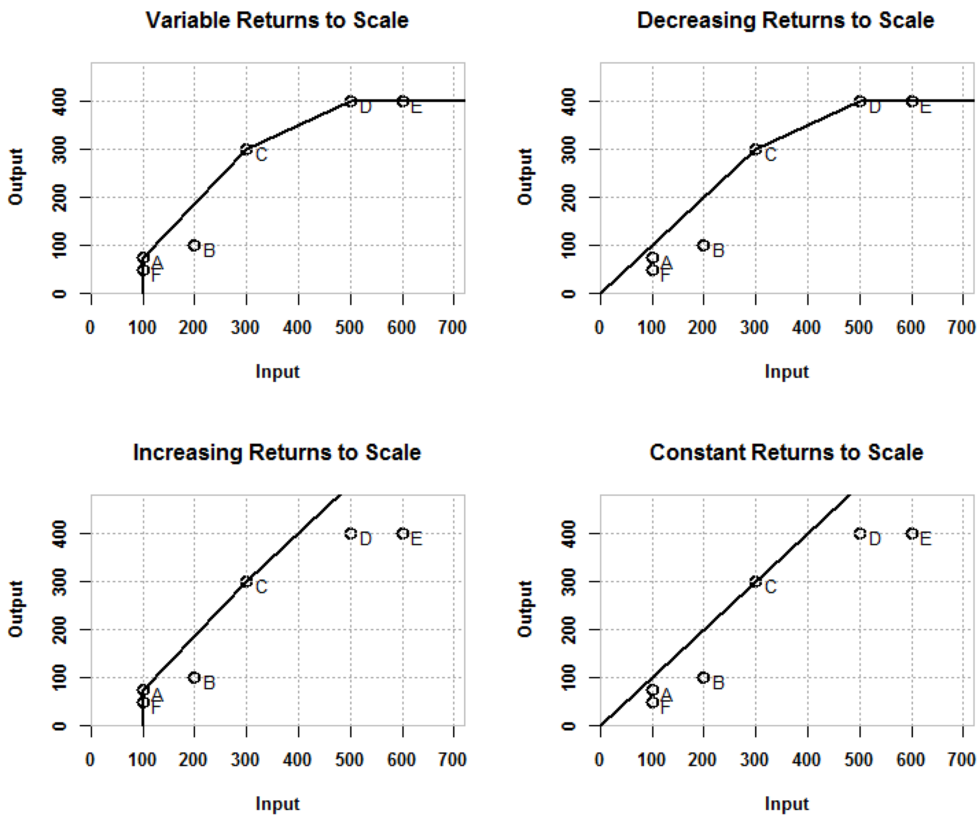

Figure 2.2: The DEA technology sets under different assumptions for model γ

The minimal extrapolation technologies for the four models are defined as:

$$P^*(\gamma) = \{(x, y) \in \mathbb{R}_+^j \times \mathbb{R}_+^s | \exists \lambda \in \Lambda^i(\gamma): x \geq \sum_{i=1}^n \lambda^i x^i, y \leq \sum_{i=1}^n \lambda^i y^i,\}$$

Where:

$$\Lambda^i(vrs) = \{\lambda \in \mathbb{R}_+^i | \sum_{i=1}^n \lambda^i = 1\}$$

$$\Lambda^i(drs) = \{\lambda \in \mathbb{R}_+^i | \sum_{i=1}^n \lambda^i \leq 1\}$$

$$\Lambda^i(irs) = \{\lambda \in \mathbb{R}_+^i | \sum_{i=1}^n \lambda^i \geq 1\}$$

$$\Lambda^i(crs) = \{\lambda \in \mathbb{R}_+^i | \sum_{i=1}^n \lambda^i\ free\} = \mathbb{R}_+^i$$

Therefore, the set of estimates of the $P^*(\gamma)$ is derived from the feasibility of the observations and the regularity assumptions using the minimal extrapolation principle. Formally, the mathematical set $P^*(\gamma)$ is the smallest set containing data and fulfilling the assumptions presented in

Table 2.1 in the model denoted $\gamma = crs, drs, vrs\ or\ irs$.

2.3.3 DEA mathematical programs

The combination of the minimal extrapolation principle and the Farrell's estimate of efficiency provide the mathematical programs of the DEA approach. Two alternative approaches are available in DEA to determine the efficient frontier that is characterised by the assumptions in Table 2.1. The input oriented and the output oriented DEA models.

2.3.3.1 Input oriented DEA models

Recall from section 2.2.3 that the Farrell input efficiency was defined as

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

Therefore, for a specific farm o the Farrell input efficiency is defined as

$$E^o = E((x^o, y^o; P^*) = min\{E \in \mathbb{R}_+ | (Ex^o, y^o) \in P^*\}$$

Inserting the minimal extrapolation technology principle, $P^*(\gamma)$ the above for a set of farms $i = \{1, .., n\}$ is written as

$$\min_{E, \lambda^1, \cdots, \lambda^i} E$$

$$st. Ex_j^o \geq \sum_{i=1}^n \lambda^i x_j^i$$

$$y^o \leq \sum_{i=1}^n \lambda^i y_s^i$$

$$\lambda \in \Lambda^i(\gamma)$$

Where j and s are the $j - vector$ of inputs and the $s - vector$ of outputs defined as $x^i = (x_1^i, \cdots, x_j^i) \in \mathbb{R}_+^j$ and $y^i = (y_1^i, \cdots, y_s^i) \in \mathbb{R}_+^s$ respectively[3].

2.3.3.2 Output oriented DEA models

For the output oriented DEA models, we similarly measure the output Farrell efficiency for farm o as

$$F^o = F((x^o, y^o; P^*) = max\{F \in \mathbb{R}_+ | (x^o, Fy^o) \in P^*\}$$

Inserting the minimal extrapolation technology principle, $P^*(\gamma)$, the above for a set of farms $i = \{1, .., n\}$ is written as

$$\max_{F, \lambda^1, \cdots, \lambda^i} F$$

$$st. x^o \geq \sum_{i=1}^{n} \lambda^i x_j^i$$

$$Fy_s^o \leq \sum_{i=1}^{n} \lambda^i y_s^i$$

$$\lambda \in \Lambda^i(\gamma)$$

Where j and s are the $j - vector$ of inputs and the $s - vector$ of outputs defined as $x^i = (x_1^i, \cdots, x_j^i) \in \mathbb{R}_+^j$ and $y^i = (y_1^i, \cdots, y_s^i) \in \mathbb{R}_+^s$ respectively.

2.3.4 A measure specific DEA model – Non-discretionary variables

The DEA models presented in section 2.3.3 and their mathematical formulation, rely on the Farell approach to efficiency as it is presented in section 2.2.3; where according to Farrell (1957) inputs and outputs are reduced or are expanded equiproportionate. However, in some cases, certain improvements may be impossible, or in some other cases the farm may only control some of its inputs, say the set VA of $variable\ or\ discretionary\ inputs, VA \subset \{1, \cdots, j\}$. Others, the $fixed, non-discretionary\ inputs\ FI = \{1,2, \cdots n\} \backslash VA = \{h \in \{1, \cdots, j\} | h \notin VA\}$ cannot be adjusted – at least not at the level of the farm in which the production units operate or with the time horizon that we study. In the case of agriculture these inputs could be rainfall or area farmed which are not under the control of the farmer or cannot easily change in a year's time. Let $x = (x_{VA}, x_{FI})$ denote the variable and fixed inputs.

In such cases, a traditional and popular variation of the Farrell procedure is to look for the largest proportional reduction in the variable inputs alone

$$E\big((x_{VA}^o, x_{FI}^o, y^o); P\big) = \min_E \{E | (x_{VA}^o, x_{FI}^o, y^o) \in P\}.$$

---

[3] Recall that superscripts are used to denote the different farms and subscripts to denote the different types of inputs and outputs. Note that in the absence of subscripts we consider all inputs and outputs in a vector format

This leads to simple modifications of the DEA programme presented in 2.3.3.1 in which we only reduce in the input rows where the inputs are considered to be variable

$$\min_{E,\lambda^1,\cdots,\lambda^i} E$$

$$st. Ex_j^o \geq \sum_{i=1}^{n} \lambda^i x_j^i \;\; j \in VA$$

$$x_j^o \geq \sum_{i=1}^{n} \lambda^i x_j^i \;\; j \in FI$$

$$y^o \leq \sum_{i=1}^{n} \lambda^i y^i$$

$$\lambda \in \Lambda^{\mathrm{i}}(\gamma)$$

In order to enable the solution of the above model, the DEA linear programme can be rewritten in the following form where fixed or non-discretionary inputs are treated as negative outputs in a input based mode (Bogetoft & Otto, 2010):

$$\min_{E,\lambda^1,\cdots,\lambda^i} E$$

$$st. Ex_j^o \geq \sum_{i=1}^{n} \lambda^i x_j^i \;\; j \in VA$$

$$-x_j^o \geq \sum_{i=1}^{n} \lambda^i (-x_j^i) \;\; j \in FI$$

$$y^o \leq \sum_{i=1}^{n} \lambda^i y^i$$

$$\lambda \in \Lambda^{\mathrm{i}}(\gamma)$$

Hence, the fixed, non-discretionary input corresponds to a negative output. This approach is also referred to the literature as the sub-vector DEA efficiency approach.

2.3.5 The reference set or peer group

For both the input and output oriented models the right hand side of the constraints i.e.

$$\left(\sum_{i=1}^{n} \lambda^i x_j^i \,, \sum_{i=1}^{n} \lambda^i y_s^i \right)$$

defines the reference set or peer group for farm o. The linear programming techniques in DEA identify the specific reference set for which the optimal positive weights $(\lambda^i, i = (1, \cdots, n))$ produce equality between the left and right hand sides since, otherwise E could be enlarged (Charnes *et al.*, 1978; Cooper *et al.*, 2006). Let the set of such $i \in \{1, \cdots n\}$ be

$$R'_u = \left\{ i\colon \sum_{i=1}^{n} \lambda^i x_j^i \; = \sum_{i=1}^{n} \lambda^i y_s^i \right\}$$

The subset R_u of R'_u composed of efficient farms, is called the reference set or the peer group to the farm o. We can therefore say that DEA "*identifies explicit real peer-units for every evaluated unit*" (Bogetoft & Otto, 2010).

Graphically this is illustrated as the farms on the technological frontier that farm o is projected onto. The reference set of farms is the set of units that spans the part of the frontier where the reference unit is located.

2.4 The impact of scale on the productivity of the farm

The DEA model under the VRS assumption decomposes technical efficiency into pure technical efficiency (PTE) and scale efficiency (SE) (Färe *et al.*, 1994a). Therefore, by estimating technical efficiency scores under assumptions of CRS (TE_{CRS}) - known as a measure of overall technical efficiency (OTE) - and VRS (TE_{VRS}) one can measure the SE which measures the impact of scale size on the productivity of the farm. SE efficiency is therefore defined as follows:

$$SE = \frac{TE_{CRS}}{TE_{VRS}}$$

SE can take values between 0 and 1. When $SE = 1$ a farm is operating at optimal scale size and otherwise if $S < 1$. The information revealed by SE is used to indicate potential benefits from adjusting farm size. Furthermore, $SE = \frac{TE_{CRS}}{TE_{VRS}}$ can be used to decompose TE_{CRS} into two mutually exclusive and non-additive components, the pure technical efficiency (PTE) (estimated by the VRS specification) and SE.

$$TE_{CRS} = TE_{VRS} * SE$$

This allows an insight into the source of inefficiencies. The TE_{VRS} specifies the possible efficiency improvement that can be achieved without altering the scale of operations. On the other hand, the TE_{CRS} and SE measures require the farm to adjust its scale of operation to improve efficiency and therefore should be viewed as long run measure that aims to reduce inputs for the long run improvement in efficiency.

One shortcoming of the measurement of SE is that when $SE < 1$ it is difficult to indicate whether the farm operates in an area of Increasing Returns to Scale (IRS), Decreasing Returns to Scale (DRS) or Constant Returns to Scale (CRS). For that reason a detailed analysis and discussion regarding the nature of Returns to Scale (RTS) is required. The nature of RTS is determined by the relationship of the proportion of inputs used to yield the desirable output for a farm. Whether IRS, DRS or CRS prevail depends on the relationship between the proportional change of inputs and outputs (Varian H., 2010). This shortcoming can be bypassed if an additional DEA problem with non-increasing returns to scale (NIRS) is imposed. This can easily be achieved by substituting the $\gamma = \sum_{i-1}^{n} \lambda^i = 1$ restriction in the linear programme presented in 2.3.3.1 with $\gamma = \sum_{i-1}^{n} \lambda^i \leq 1$ and then calculating the relevant technical efficiency (TE_{NIRS}). According to Färe *et al.* (1985b) these three estimated frontiers under CRS, VRS, and NIRS can be used to identify the returns to scale characteristics of the technology at any given point. Specifically, a) if $TE_{CRS} = TE_{NIRS} < TE_{VRS}$, the input-oriented projection of the VRS frontier is under increasing returns to scale b) if $TE_{VRS} = TE_{NIRS} > TE_{CRS}$, diminishing returns hold and c) constant returns to scale hold if and only if $SE = 1 = TE_{CRS} = TE_{NIRS} = TE_{VRS}$.

2.5 Evaluating the performance of farms over time

The method presented in the previous section of this chapter concerns the evaluation of the performance of farms only for one period of time i.e. cross section data. In the setting described before the performance of a farm is evaluated relative to the performance of a group of homogenous farms in the same period. However, when panel data is available, one can measure the performance of farms in a dynamic setting and compare the relative performance of a farm over time. In this research, this approach is used to provide measures of total factor productivity (TFP) based on the calculation of a Malmquist productivity index (MI). Therefore, the time series dimension is used to estimate shifts in the frontier over time, thus providing a measure of technical change. The incorporation of technical efficiency change in the MI provides measure of TFP.

2.5.1 The Malmquist Index of Total Factor Productivity

Malmquist (1953) introduced the MI in a consumer theory context where the notion of proportional scaling factors was used and interpreted as a quantity index. The MI of TFP, was later introduced by Caves *et al.* (1982a) and further developed by Färe *et al.* (1992) is based on the estimation of distance functions. Caves *et al.* (1982a) constructed a MI as a ratio of distance functions and assumed no inefficiency ignoring the direct connection of distance functions and the efficiency measures introduced by Farrell (1957). The assumption of inefficiency was then relaxed by Färe *et al.* (1992); (Färe *et al.*, 1994b) which allowed for inefficient observations. For the purposes of this research an input orientation Malmquist index has been adapted since farmers have more control over the adjustment of inputs rather than the expansion of output (Balcombe *et al.*, 2008a). Specifically the MI between period t and $t+1$ (the latter being the most recent) is defined as the ratio of the distance function for each period relative to a common technology; note that all of the notations in previous sections are used. Therefore, the MI based on an input distance function is defined as:

$$M_I^t = \frac{D_I^t(x^{t+1}, y^{t+1})}{D_I^t(x^t, y^t)}$$

This expresses the ratio between the input-distance function for a farm observed at period $t+1$ and t, respectively, and measured against the technology at period t. Values of the $M_I < 1$ indicate negative changes in TFP, values of the $M_I > 1$ indicate positive changes in TFP while values of $M_I = 1$ indicate no change in productivity.

The input distance function represents the technology at period t, and hence the technology constructed by the observed data for each farm in period t, is defined as

$$D_I^t(x^t, y^t) = max\{\kappa: (x^t/\kappa) \in P^t(y^t)\}$$

where κ is the maximum equiproportional reduction of the input vector without reducing the output.

In a similar way the input distance function representing the technology at period $t+1$ is defined as

$$D_I^{t+1}(x^{t+1}, y^{t+1}) = max\{\kappa: (x^{t+1}/\kappa) \in P^{t+1}(y^{t+1})\}$$

These are called the within period distance functions, the adjacent period distance functions are defined as

$$D_I^t(x^{t+1}, y^{t+1}) = max\{\kappa: (x^{t+1}/\kappa) \in P^t(y^{t+1})\}$$

and

$$D_I^{t+1}(x^t, y^t) = max\{\kappa: (x^t/\kappa) \in P^{t+1}(y^t)\}$$

Note that these adjacent period distance functions are defined for each farm in each period, using the technology constructed for each farm in an adjacent period.

However, since the choice of period t or $t+1$ as the base year is arbitrary (i.e. the base year can be either period t or period $t+1$) Färe *et al.* (1992) defined the MI of TFP as the geometric mean of the t and $t+1$ Malmquist indices. Therefore, for each farm the input orientation Malmquist index is expressed as follows:

$$M_I^{t,t+1} = \left[\frac{D_I^{t+1}(x^{t+1}, y^{t+1})}{D_I^t(x^t, y^t)} \frac{D_I^t(x^{t+1}, y^{t+1})}{D_I^{t+1}(x^t, y^t)}\right]^{1/2}$$

Where $M_I^{t,t+1}$ refers to the MI of TFP from period t to period $t+1$; (x^t, y^t) is the farm input-output vector in the t^{th} period; $D_I^t(x^{t+1}, y^{t+1}) = max\left\{\theta > 0: \left(x^{t+1}/_{\theta}\right) \in P\right\}$ is the input distance from the observation in the $t+1$ period to the technology frontier of the t^{th} period with $P(y^{t+1})$ the input set at the $t+1$ period and θ is a scalar equal to the efficiency score. The indices are calculated with the use of the nonparametric DEA method in order to construct a piecewise frontier that envelopes the data points (Charnes *et al.*, 1978). The technology assumption made to estimate the MI of TFP is CRS. Otherwise, the presence of non-CRS does not accurately measure productivity change (Grifell-Tatjé & Lovell, 1995). The main advantage of the DEA method is that it avoids misspecification errors and it enables the investigation of changes in productivity in a multi-output, multi-input case simultaneously (Balcombe *et al.*, 2008a). Furthermore, the use of the DEA method for the estimation of the MI of TFP makes it easy to compute since DEA does not require information on prices.

In addition, the index is decomposed into two components: efficiency change and technological change

$$M_I^{t,t+1} = \underbrace{\frac{D_I^{t+1}(x^{t+1}, y^{t+1})}{D_I^t(x^t, y^t)}}_{\Delta Eff} * \underbrace{\left[\frac{D_I^t(x^{t+1}, y^{t+1})}{D_I^{t+1}(x^{t+1}, y^{t+1})} \frac{D_I^t(x^t, y^t)}{D_I^{t+1}(x^t, y^t)}\right]^{1/2}}_{\Delta Tech}$$

The first part of equation is an index of relative technical efficiency change (ΔEff) showing how much closer (or farther) a farm gets to the best practice frontier. It measures the "catch up" effect (Färe *et al.*, 1992). The second component is an index of technical change ($\Delta Tech$) and measures how much the frontier shifts. Both components take values more, less or equal to unity as it is the case of the MI of TFP indicating improvement, deterioration and stagnation respectively.

2.5.2 Further decomposition of the Malmquist Index of Total Factor Productivity

In addition, as Färe *et al.* (1994a) demonstrated, the index of ΔEff is further decomposed into two factors, pure technical efficiency ($\Delta PureEff$) and scale efficiency change ($\Delta ScaleEff$).

$$M_I^{t,t+1} = \underbrace{\frac{D_I^{Vt+1}(x^{t+1}, y^{t+1})}{D_I^{Vt}(x^t, y^t)}}_{\Delta PureEff} * \underbrace{\frac{D_I^{t+1}(x^{t+1}, y^{t+1}) \Big/ D_I^{Vt+1}(x^{t+1}, y^{t+1})}{D_I^{t}(x^{t}, y^{t}) \Big/ D_I^{Vt}(x^{t}, y^{t})}}_{\Delta ScaleEff} * \underbrace{\left[\frac{D_I^{t}(x^{t+1}, y^{t+1})}{D_I^{t+1}(x^{t+1}, y^{t+1})} \frac{D_I^{t}(x^{t}, y^{t})}{D_I^{t+1}(x^{t}, y^{t})}\right]^{1/2}}_{\Delta Tech}$$

Where the $D_I^{Vt+1}(x^{t+1}, y^{t+1})$ and $D_I^{Vt}(x^t, y^t)$ corresponds to distance functions estimated under VRS assumption. It must also be noted that $\Delta Eff = \Delta PureEff * \Delta ScaleEff$.

The decomposition of Färe *et al.* (1994a) enables the identification of shifts in the CRS frontier over time ($\Delta Tech$) and changes in pure efficiency and scale efficiency that correspond to VRS frontiers from two different periods.

Moreover, the component distance functions in the technical change index of the MI of TFP provides evidence of the farms responsible for the frontier shift (Färe *et al.*, 1994b). Specifically, if technical change ($\Delta Tech$) of farm i is greater than 1 and the distance function estimates under constant returns to scale for the farm in the period $t + 1$ relative to estimated technology in period t are also greater than 1 and efficiency estimates under constant returns to scale at time $t + 1$ relative to technology at time $t + 1$ equals 1 then that farm has contributed to a shift in the frontier between the two periods. Formally, this is expressed as

$\Delta Tech^i > 1$, $D_I^t(x^{i,t+1}, y^{i,t+1}) > 1$ and $D_I^{i,t+1}(x^{i,t+1}, y^{i,t+1}) = 1$

Simar and Wilson (1998a) proposed a further decomposition of the MI of TFP to estimate changes in technology by changes in the VRS estimate. Specifically, if the position of the farm remains fixed in the periods t and $t + 1$ in the input-output space, and the only change that happens is in the VRS estimate of technology, then the ($\Delta Tech$) will be equal to unity, indicating no change in technology. To indicate therefore a change in technology, the CRS estimate of technology should change. Hence, Simar and Wilson (1998a) proposed the following decomposition, based on the assumptions of Kneip *et al.* (1998b) that the VRS estimator is always consistent:

$$M_I^{t,t+1} = \frac{D_I^{Vt+1}(x^{t+1}, y^{t+1})}{D_I^{Vt}(x^t, y^t)} * \frac{D_I^{t+1}(x^{t+1}, y^{t+1}) \Big/ D_I^{Vt+1}(x^{t+1}, y^{t+1})}{D_I^{t}(x^t, y^t) \Big/ D_I^{Vt}(x^t, y^t)}$$

$$* \left[\frac{D_I^{Vt+1}(x^t, y^t)}{D_I^{Vt+1}(x^{t+1}, y^{t+1})} \frac{D_I^{Vt}(x^t, y^t)}{D_I^{Vt}(x^{t+1}, y^{t+1})}\right]^{1/2}$$

$$* \left[\frac{D_I^{t+1}(x^t, y^t) \Big/ D_I^{Vt+1}(x^t, y^t)}{D_I^{t+1}(x^{t+1}, y^{t+1}) \Big/ D_I^{Vt+1}(x^{t+1}, y^{t+1})} \frac{D_I^{t}(x^t, y^t) \Big/ D_I^{Vt}(x^t, y^t)}{D_I^{t}(x^{t+1}, y^{t+1}) \Big/ D_I^{Vt}(x^{t+1}, y^{t+1})}\right]^{1/2}$$

Where the first two components indicate $\Delta PureEff$ and $\Delta ScaleEff$ and the $\Delta Tech$ is decomposed into pure technical ($\Delta PureTech$) and scale technical change ($\Delta ScaleTech$). Also, $\Delta Tech = \Delta PureTech * \Delta ScaleTech$. The index of pure technical change is the measure of the geometric mean of the two ratios indicating shifts in the VRS frontier between the two periods. Values of $\Delta PureTech$ greater then unity indicate an expansion in pure technology, values less than unity deterioration and values equal to unity indicate stagnation in pure technology. Information derived from the scale technology change index is used to describe the change in returns to scale of the VRS frontier between two time periods. Values of ($\Delta ScaleTech$) greater than unity is an indication that the farms operates either below or above the optimal scale, values less than unity indicate that the technology is moving towards CRS and when it is equal to unity there are no changes in the shape of technology.

2.5.3 Calculating the MI of TFP

According to Färe *et al.* (1994b) the distance functions required for the calculation of the MI of TFP, specifically,

$$D_I^t(x^t, y^t), D_I^{t+1}(x^{t+1}, y^{t+1}), D_I^t(x^{t+1}, y^{t+1}) \; and \; D_I^{t+1}(x^t, y^t)$$

are computed with the use of DEA techniques. Specifically, four different linear programs must be solved. Suppose that for each period $t = 1,2, \cdots, T$ there is $i = \{1, .., n\}$ set of farms which use a set of inputs and outputs representing multiple performance measures. Considering then that each farm i uses J ($j = 1, \cdots, J$) inputs, x_j to produce s outputs y_r ($r = 1, \cdots, s$).

The first Shephard input distance function $D_I^t(x^t, y^t)$ is estimated as follows:

$$[D_I^t(x^t, y^t)]^{-1} = F_I^t\left(x_{ij}^t, y_{is}^t\right) = \min_{\kappa, \lambda^1, \cdots, \lambda^i} \kappa$$

$$st. \kappa x_{ij}^t \geq \sum_{i=1}^{n} \lambda_i x_{ij}^t$$

$$y_{is}^t \leq \sum_{i=1}^{n} \lambda_i y_{is}^t$$

$$\lambda \in \Lambda^{\mathrm{i}}(crs)$$

Where j and s are the $j - vector$ of inputs and the $s - vector$ of outputs defined before as $x^i = \left(x_1^i, \cdots, x_j^i\right) \in \mathbb{R}_+^j$ and $y^i = \left(y_1^i, \cdots, y_s^i\right) \in \mathbb{R}_+^s$ respectively. Further note that the notation has changed and that farms and input or outputs are indicated as subscripts. The value of κ is the technical efficiency for the $i - th$ farm. Also note that D stands for the Shephard distance function and F for the Farrell distance function.

The second input distance function $D_I^{t+1}(x^{t+1}, y^{t+1})$ is estimated as follows:

$$[D_I^{t+1}(x^{t+1}, y^{t+1})]^{-1} = F_I^{t+1}\left(x_{ij}^{t+1}, y_{is}^{t+1}\right) = \min_{\kappa, \lambda^1, \cdots, \lambda^i} \kappa$$

$$st. \kappa x_{ij}^{t+1} \geq \sum_{i=1}^{n} \lambda_i x_{ij}^{t+1}$$

$$y_{is}^{t+1} \leq \sum_{i=1}^{n} \lambda_i y_{is}^{t+1}$$

$$\lambda \in \Lambda^{\mathrm{i}}(crs)$$

The third input distance function required for the MI of TFP $D_I^t(x^{t+1}, y^{t+1})$, considers data from the period $t+1$ relative to technology based on data from period t. Specifically,

$$[D_I^t(x^{t+1}, y^{t+1})]^{-1} = F_I^t\left(x_{ij}^{t+1}, y_{is}^{t+1}\right) = \underset{\kappa, \lambda^1, \cdots, \lambda^i}{min} \quad \kappa$$

$$st. \kappa x_{ij}^{t+1} \geq \sum_{i=1}^{n} \lambda_i x_{ij}^t$$

$$y_{is}^{t+1} \leq \sum_{i=1}^{n} \lambda_i y_{is}^t$$

$$\lambda \in \Lambda^{\mathrm{i}}(crs)$$

Finally, the third input distance function required for the MI of TFP $D_I^{t+1}(x^t, y^t)$, considers data from period t relative to technology based on data from period $t+1$. Specifically

$$[D_I^{t+1}(x^t, y^t)]^{-1} = F_I^{t+1}\left(x_{ij}^t, y_{is}^t\right) = \underset{\kappa, \lambda^1, \cdots, \lambda^i}{min} \quad \kappa$$

$$st. \kappa x_{ij}^t \geq \sum_{i=1}^{n} \lambda_i x_{ij}^{t+1}$$

$$y_{is}^t \leq \sum_{i=1}^{n} \lambda_i y_{is}^{t+1}$$

$$\lambda \in \Lambda^{\mathrm{i}}(crs)$$

Note that each distance function must be calculated for each farm in each period.

2.6 Statistical inference in DEA models

One of the main pitfalls in DEA is that the observed estimates of efficiency may be influenced by sampling variation, implying that the calculated distance functions to the frontier are likely to be underestimated (Balcombe *et al.*, 2008a). In other words, ignoring the noise in the estimation can lead to biased DEA estimates and the results may be misinterpreted. This is due to the estimation of the relative efficiency which is based on an estimate of the PPS from finite samples, rather than the true observed production frontier (Simar & Wilson, 1998b).

Various efforts have been made to provide robust theoretical and empirical statistical properties of DEA estimators. Korostelev *et al.* (1995) has proved the consistency of DEA estimators under very weak general conditions but the rates of convergence were very slow. The same was shown by Banker (1993) but does not provide any information on the rate of convergence. Kneip *et al.* (1998a) provides statistical properties for the multi output, multi input case and has also estimated the rate of convergence. However, Simar and Wilson (1998b; 2000) argue that the most appropriate method to establish statistical properties for the DEA estimators is the use of bootstrap. Although, Lothgren (1998) and Lothgren and Tambour (1999) have used the method of "naive" bootstrapping, this has been criticised by Simar and Wilson (1999) as inappropriate since it does not provide consistent results. This is due to the bounded nature of the distance functions.

Since the estimated distance functions are close to unity, resampling from the original data will provide an inconsistent estimate of the confidence intervals. Simar and Wilson (1998b; 2000) proposed a smoothed bootstrapping procedure in order to correct the bias in DEA estimators, construct confidence intervals and to improve the consistency in the results. The rationale behind bootstrapping is to simulate the true sampling distribution by mimicking the data generation process (DGP) (Balcombe *et al.*, 2008b). Through the DGP a pseudo-data set is constructed which is then used for the re-estimation of the DEA distance functions. Increasing the bootstrapped replicates (more than 2000 (Simar & Wilson, 1998b)) allows for a good approximation of the true distribution of the sampling.

Simar and Wilson (1999) adapted the bootstrapped procedure for the estimation of the MI of TFP in order to account for possible temporal correlation arising from the panel data characteristics (Balcombe *et al.*, 2008a). Specifically, they proposed a consistent method using a bivariate kernel density estimate that accounts for the temporal correlation via the covariance matrix of data from adjustment years. The bootstrapped estimates of the distance functions allows for the calculation of a set of MI of TFP which enables to account for the bias and to construct confidence intervals. The latter are used for statistical inference of the MI of TFP and its components.

In addition, studies measuring productivity and efficiency using DEA to investigate the impact of environmental factors at a second stage analysis have suffered from two problems. 1) serial correlation among the DEA estimates and 2) correlation of the inputs and outputs used in the first stage with second-stage environmental variables (Simar & Wilson, 2007). The serial correlation problem arises because the efficiency estimates of productivity change depending on the performance of the DMUs included in the sample, so efficiency is relative to, and interdependent with, the performance of the operational units in the sample. Regarding the second problem, that is, the correlation between the inputs and outputs of the first stage and the environmental variables in the second stage, it causes correlation between the error terms and the environmental variables, thereby violating one of the basic regression assumptions. A solution to these problems has been proposed by Simar and Wilson (1999; 2007), which consists of bootstrapping the results to obtain confidence intervals for the first stage productivity or efficiency scores.

The significance of the Simar and Wilson (2007) double bootstrap procedure derives from the bias corrected efficiency estimation. These estimates are used as parameters in a truncated regression model. This method is known in the DEA literature as the double bootstrapped procedure by Simar and Wilson (2007).

Presentation of algorithms used to bootstrap in nonparametric models as developed by Simar and Wilson (1998b; 1999; 2007) is based on the notation used to explain the underlying theory for estimating DEA efficiency and the calculation of the MI of TFP as explained in sections 2.3 and 2.5 of this chapter.

2.6.1 Bootstrapping in nonparametric frontier models

The following algorithm proposed by Simar and Wilson (1998b) is used to bootstrap nonparametric frontier models in order to enable statistical inference.

1. Calculate $\hat{\theta}^i$ technical efficiency scores as solutions to $min\{\theta|(\theta x^i, y^i) \in \hat{P}\}$ for $i = 1, \cdots, n$ number of farms. Specifically,

$$\underset{\theta, \lambda^1, \cdots, \lambda^i}{min} \quad \theta$$

$$st. \theta x_j^i \geq \sum_{i=1}^{n} \lambda^i x_j^i$$

$$y^i \leq \sum_{i=1}^{n} \lambda^i y_s^i$$

$$\lambda \in \Lambda^{\mathrm{i}}(\mathrm{crs})$$

Where j and s are the $j - vector$ of inputs and the $s - vector$ of outputs defined as $x^i = (x_1^i, \cdots, x_j^i) \in \mathbb{R}_+^j$ and $y^i = (y_1^i, \cdots, y_s^i) \in \mathbb{R}_+^s$ respectively.

2. Use bootstrap via smooth sampling from $\hat{\theta}^1, \cdots, \hat{\theta}^n$ to obtain a bootstrap replica $\theta^{1*} \cdots \theta^{n*}$ following the following steps

2.1 Let $\beta^1, \cdots \beta^n$ be a simple bootstrap sample from $\hat{\theta}^1, \cdots, \hat{\theta}^n$

2.2 Simulate standard normal independent random variables $\varepsilon^1, \cdots, \varepsilon^n$

2.3 Estimate

$$\tilde{\theta}^i = \begin{cases} \beta^i + h\varepsilon^i & if\ \beta^i + h\varepsilon^i \leq 1 \\ 2 - \beta^i - h\varepsilon^i & otherwise \end{cases}$$

Note that by construction $\widetilde{\theta}^i \leq 1$ and that h is the bandwidth of a standard normal distribution.

2.4 Adjust $\tilde{\theta}^i$ to obtain parameters with asymptotically correct variance, and then estimate the variance $\hat{\sigma}^2 = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{\theta}^1 - \bar{\hat{\theta}}\right)^2$ and calculate

$$\theta^{i*} = \bar{\bar{\beta}} + \frac{1}{\sqrt{1 + h^2/\hat{\sigma}^2}}\left(\tilde{\theta}^i - \bar{\bar{\beta}}\right)$$

where $\bar{\bar{\beta}} = \frac{1}{n}\sum_{i=1}^{n}\beta^i$

Thus the sequence θ^{i*} is obtained by the smoothed bootstrap. It has better properties that the simple bootstrap sequence in the sense that the variance of θ^{i*} is asymptotically correct.

3. Calculate bootstrapped input based on bootstrap efficiency $x^{ib} = \frac{\hat{\theta}^i}{\theta^{i*}}x^i$

4. Solve the DEA program to estimate the new θ^{ib} for each farm by taking the pseudo data as reference.

5. Repeat the steps from 2.1 for B times to yield B new DEA technical efficiency scores θ^{ib}

$$(\theta^{1b}, \cdots, \theta^{ib}) \qquad (b = 1, \cdots B)$$

6. Calculate the bootstrap bias estimate for the original estimator $\hat{\theta}^i$ as

$$\widehat{bias}_B(\hat{\theta}^i) = B^{-1}\sum_{b=1}^{B}\theta^{ib} - \hat{\theta}^i$$

The bias corrected DEA technical efficiency estimator $\hat{\hat{\theta}}^i$ can be computed as

$$\hat{\hat{\theta}}^i = \hat{\theta}^i - \widehat{bias}_B(\hat{\theta}^i) = B^{-1}$$

Finally, the percentile method is involved for the construction of confidence intervals of the DEA estimators. Specifically, confidence interval for the true value $\hat{\theta}^i$ can be established by finding value a_a, b_a such that $Prob(-b_a \leq \theta^{ib} - \hat{\theta}^i \leq a_a) = 1 - a$. Since the distribution of $\theta^{ib} - \hat{\theta}^i$ is unknown the bootstrapped values can be used to find $\hat{a}_a, \hat{b}_a$ such that $Prob(-\hat{b}_a \leq \theta^{ib} - \hat{\theta}^i \leq \hat{a}_a) = 1 - a$. It involves sorting the value of $\theta^{ib} - \hat{\theta}^i$ for $b = 1, \cdots B$ in increasing order and deleting $(a/2) \times 100$ percent of the elements at either end of this sorted array and setting $-\hat{a}_a$ and $-\hat{b}_a$ at the two endpoints, with $\hat{a}_a \leq \hat{b}_a$.

2.6.2 Bootstrapping Malmquist indices

Simar and Wilson (1999) proposed a bootstrapping procedure for Malmquist indices by using the method of a bivariate kernel density estimate via the covariance matrix of data from adjacent years. However, Simar and Wilson (1999) noted that the estimated distance functions are bounded above unity and hence such a bivariate kernel estimator value is biased and asymptotically inconsistent. To solve this issue, they proposed a univariate reflection method first explored by Silverman (1986). Hence the procedure proposed by Simar and Wilson (1999) can be summarised as follows:

1. Calculate the MI of TFP $\widehat{M}_I^{t,t+1}$ for each farm $i = 1, \cdots, n$ in each time (t and $t + 1$) by solving the linear programming models presented in section 2.5.3

2. Construct the pseudo-data set $\{(x_{ij}^{*t}, y_{is}^{*t}); i = 1, \cdots, n, j = 1, \cdots, j, s = 1, \cdots, s, t = 1, \cdots, T\}$ to create the reference bootstrap technology using the bivariate kernel density estimation and adaptation of the reflection method proposed by Silverman (1986)

3. Calculate the bootstrap estimate of the MI of TFP $\widehat{M}_I^{*\,t,t+1}$ for each farm $i = 1, \cdots, n$ by applying the original estimators to the pseudo-sample attained in step 2

4. Repeat steps 2 and 3 for a large number of B times to facilitate B sets estimates for each farm.

5. Construct the confidence intervals for the MI of TFP

To construct confidence intervals of the MI of TFP since the distribution $\widehat{M}_I^{t,t+1} - M_I^{t,t+1}$ is unknown it can be approximated by the bootstrapped estimated of the MI of TFP, hence $\widehat{M}_I^{*\,t,t+1} - M_I^{t,t+1}$, where $M_I^{t,t+1}$ is the true unknown MI of TFP, $\widehat{M}_I^{t,t+1}$ is the estimated index and $\widehat{M}_I^{*\,t,t+1}$ the bootstrapped estimate of the index.

Let a_a, b_a define the $(1 - a)$ confidence interval $Prob(-b_a \leq \widehat{M}_I^{t,t+1} - M_I^{t,t+1} \leq -a_a) = 1 - a$ which can be approximated by estimating the values a_a^* and b_a^* given by $Prob(-b_a^* \leq \widehat{M}_I^{*\,t,t+1} - M_I^{t,t+1} \leq -a_a^*) \approx 1 - a$. Thus, an estimated $(1 - a)$ percentage confidence interval for the i^{th} MI of TFP is given by $\widehat{M}_I^{t,t+1} + a_a^* \leq M_I^{t,t+1} \leq \widehat{M}_I^{t,t+1} + b_a^*$.

We conclude that a MI of TFP for the i^{th}farm is significantly different from unity (which would indicate no productivity change) when the confidence interval does not include unity.

2.6.3 Estimation and statistical inference in a two stage DEA analysis

The efficiency estimates calculated in the research are $\widehat{\theta}^i$, where $1-\hat{\theta}^i$ represents the potential input saving. These estimates are then regressed as the dependent variable in step two, namely the truncated maximum likelihood regression on the following model

$$\hat{\theta}^i = z^i\beta + \varepsilon^i \leq 1$$

Where z^i is a vector of management variables and farm characteristics which is assumed to impact on the choice and use of y and x, β is a vector of parameters to be estimated, and ε^i is a continuous random variable distributed $N(0, \sigma_\varepsilon^2)$ with left-truncation at $1 - z^i\beta$ for each i, and assumed independent of z^i. The significance of the Simar and Wilson (2007) double bootstrap procedure derives from the bias corrected estimation of θ^i for the parameters in the regression model.

The double bootstrap procedure used in this research for the estimation of drivers for Eco-Efficiency is referred to as Algorithm 2 (Simar & Wilson, 2007) and it includes the following seven steps with two sub-routine loops embedded within:

1. Calculate $\hat{\theta}^i$ technical efficiency scores as solutions to $min\{\theta \big| (\theta x^i, y^i) \in \hat{P}\}$ for $i = 1, \cdots, n$ number of farms. Specifically,

$$\underset{\theta, \lambda^1, \cdots, \lambda^i}{min} \quad \theta$$

$$st. \theta x_j^i \geq \sum_{i=1}^{n} \lambda^i x_j^i$$

$$y^i \leq \sum_{i=1}^{n} \lambda^i y_s^i$$

$$\lambda \in \Lambda^{\mathrm{i}}(\mathrm{crs})$$

Where j and s are the $j-vector$ of inputs and the $s-vector$ of outputs defined as $x^i = (x_1^i, \cdots, x_j^i) \in \mathbb{R}_+^j$ and $y^i = (y_1^i, \cdots, y_s^i) \in \mathbb{R}_+^s$ respectively.

2. Employ the method of maximum likelihood to derive an estimate $\hat{\beta}$ of β as well as an estimate $\hat{\sigma}_\varepsilon$ of σ_ε in the truncated regression of $\hat{\theta}^i$ on z^i

3. Loop over the following four steps (a-b) for each farm $i = 1, \cdots, n$ L_1 times to obtain a set of bootstrapped estimates $B_i = \{\hat{\theta}^{*i}\}_{b=1}^{L_1}$:

(a) For each $i = 1, \cdots, n$, draw ε^i from the $N(0, \hat{\sigma}_\varepsilon^2)$ distribution with left truncation at $1 - z^i\beta$

(b) For every $i = 1, \cdots, n$, compute $\theta^{*i} = z^i\beta + \varepsilon^i$

(c) Construct a pseudo-data set (x^{i*}, y^{i*}) where $x^{i*} = x^i$ and $y^{i*} = y^i \left(\frac{\hat{\theta}^i}{\theta^{*i}}\right)$

(d) Calculate $\hat{\theta}^{*i} = \theta(x^i, y^i | \hat{T}^*) \forall i = 1, \cdots, n$, where $\hat{T}^*$ is obtained by using the pseudo-data constructed in the previous step (c)

4. For each farm $i = 1, \cdots, n$, calculate the bias corrected estimator $\hat{\hat{\theta}}^i$ as $\hat{\hat{\theta}}^i = \hat{\theta}^i - Bias(\hat{\theta}^i)$ by using the bootstrapped estimates in B_i obtained in step 3.(b) and the original estimate $\hat{\theta}^i$. The bias term is estimated using the Simar and Wilson (2000) formula $\left(1/L_1 \sum_{b=1}^{L_1} \hat{\theta}_b^{*i}\right) - \hat{\theta}^i$

5. By applying the method of truncated maximum likelihood, estimate the truncated regression of $\hat{\theta}^i$ on z^i to yield estimates $\hat{\hat{\beta}}$ and $\hat{\hat{\sigma}}_\varepsilon$

6. Loop over the following three steps (a-c) L_2 times to access a set of bootstrapped estimates

$$\kappa = \left\{\left(\hat{\beta}^*, \hat{\sigma}_\varepsilon^*\right)_b\right\}_{b=1}^{L_2}$$

(a) For each $i = 1, \cdots, n$, ε^i is drawn from the $N\left(0, \hat{\hat{\sigma}}_\varepsilon^2\right)$ distribution with left truncation at $1 - z^i\hat{\hat{\beta}}$

(b) Compute again for each farm $i = 1, \cdots, n$, the $\theta^{**i} = z^i\hat{\hat{\beta}} + \varepsilon^i$

(c) Employ the maximum likelihood method to estimate the truncated regression of θ^{**i} on z^i to obtain estimates $\hat{\hat{\beta}}^*$ and $\hat{\hat{\sigma}}_\varepsilon^*$

7. Use the bootstrapped values in κ and the original estimates $\hat{\hat{\beta}}$ and $\hat{\hat{\sigma}}_\varepsilon$ estimated in step 5 to construct estimated confidence intervals for each element of β and for σ_ε. The $(1 - a)$ percent confidence interval of the j^{th} element of vector β where α is some small value (i.e. $\alpha = 0.05$) and $0 < a < 1$, is constructed as the $Prob\left(-b_{a/2} \leq \hat{\hat{\beta}}_j^* - \hat{\hat{\beta}}_j \leq -a_{a/2}\right) \approx (1 - a)$ such that the estimated confidence interval is $\left[\hat{\hat{\beta}}_j + a^*{}_{a/2}, \hat{\hat{\beta}}_j + b^*{}_{a/2}\right]$. The same method was used in Simar and Wilson (2000) to construct confidence interval for the efficiency scores.

2.7 Detecting outliers in deterministic non-parametric frontier models with multiple outputs

DEA methods are quite sensitive to the presence of outliers in the data when measuring efficiency (Sexton *et al*., 1986), which can have a strong influence on the construction of the benchmarking frontier, influencing results and interpretation of efficiency scores. Moreover, Johnson and McGinnis (2008) suggest that in the case of two-step contextual analysis where DEA techniques are used to estimate efficiency scores on the first step, outliers that represent very poor performance can be the source of distortion in the second step results.

Furthermore, the deterministic nature of the frontier means that the possible existence of errors (measurement errors, coding errors or other data collection/entry problems) in observation of the DMUs used to define the deterministic frontier may "*severely distort measured efficiency scores for the remaining DMUs in the sample*" (Wilson, 1995). This is analogous to the problem of outliers in classical linear regression models.

Since DEA and generally Linear Programming (LP) – based efficiency models do not yield Ordinary Least Square (OLS) residuals it is not possible to detect outliers using methods based on the classic OLS residuals analysis (Wilson, 1993; 1995). Various detection routines have been developed for this purpose but all of these approaches lack a strong statistical foundation and they fail to detect outliers inside the frontier (inefficient Decision Making Units (DMUs)) (Grosskopf & Valdmanis, 1987; Charnes & Neralić, 1990). A solution to these issues was proposed by Andrews and Pregibon (1978) who developed the AP statistic that does not require OLS residuals and therefore it can be used with LP-based models. A limitation of the AP statistic was that it was developed for the case of only one output. Wilson (1993) proposed an extension of the AP statistic which could be used in the case of multiple outputs. This method allows for a graphical analysis and identification of outliers in the data. The full derivation of the statistic is available in Wilson (1993); (Wilson, 2010). The advantage of this method is that it identifies outliers that have an impact on the efficient frontier. To identify one or more outliers in the dataset the method focuses on changes in the volume of the data cloud when one or more of the observations is removed (Bogetoft & Otto, 2010). In addition, it is emphasised that the technique presented here is used to prioritise observations for checking for potential errors and the deciding if the observations are influential in determining the DEA frontier (Wilson, 1993;1995).

2.7.1 The data cloud method

Let us assume that we observe a set of n farms and each farm $i = \{1, .., n\}$ has a set of j inputs and s outputs representing multiple performance measures. For the i^{th} farm then the $j - vector$ of inputs and the $s - vector$ of outputs are defined as $x^i = (x_1^i, \cdots, x_j^i) \in \mathbb{R}_+^j$ and $y^i = (y_1^i, \cdots, y_s^i) \in \mathbb{R}_+^s$ respectively and $X = (x_1^i, \cdots, x_j^i)$ and $Y = (y_1^i, \cdots, y_s^i)$ be $n \times j$ and $n \times s$ matrices with inputs and outputs for the n farms. The combined matrix $[X\ Y]$ then contains all the observations where the different rows in the combined matrix can be seen as a cloud of points in the $\mathbb{R}_+^j \times \mathbb{R}_+^s$ space, representing a farm. The determinant of the combined matrix $[X\ Y]'[X\ Y]$ is proportional to the cloud of the volume of the cloud:

$$Volume\ of\ data\ cloud\ \simeq D(X,Y)$$

By removing a farm from the data the volume of the data cloud will change. In the case of removing a farm being in the middle of the cloud then the volume of the data will remain unchanged. However, when the farm removed is outside the remaining cloud then the volume will decrease and hence it will give an indication that the farm is an outlier.

For example, let $D^{(i)}$ be the determinant after removing farm i, and consider the ratio (R) of the new volume of the data cloud to the old volume

$$R^{(i)} = \frac{D^i}{D}$$

note that $R^{(i)}$ does not depend on the units in either the inputs (x) or the outputs (y) matrix. If farm i is not an outlier, then D will not change much and $R^{(i)}$ will be close to 1. On the other hand, if farm i is an outlier, the $R^{(i)}$ will be much less than 1. Outliers are therefore identified via small values of $R^{(i)}$.

If there is a group of g outliers and outliers are identified by deleting groups of $1, \ldots, i$ farms, then for $i < g$ it is not common to find an R with a very small value because there will still be outliers in the remaining dataset. However, for $g < i$ we will get an R from which all outliers are deleted, and it can be presumed that this R value will be small. When examining the values of R, the first step is to identify the single isolated small value. If such a value exists, this represents a group of outliers. An isolated small value is an isolated minimum value, or, to fix it on a scale $\frac{R_{min}}{R_{min}} = 1$ should be isolated from other values of $\frac{R^i}{R_{min}}$, or 0 should be isolated from other values of $\log\left(\frac{R^{(i)}}{R_{min}}\right)$. Instead of doing the distributional calculations, we can use a graphical method in which we plot the ordered pairs

$$\left(i, \log\left(\frac{R^{(i)}}{R_{min}}\right)\right)$$

where i is the number of deleted farms. Therefore, in the graph, we look for isolated low points; the i with isolated low points gives an indication of i outliers.

The above are illustrated better if an example is provided. For that purpose, the detection of outliers performed in Chapter 6 is demonstrated.

In particular, 73 farms were tested for outliers using the graphical method of Wilson (1993). Thus a matrix of inputs and outputs of the farms whose efficiency was to be estimated was constructed and the total number of observations to be deleted was set to 12 (i.e. $i = 12$).

In Figure 2.3, outliers are identified at the following groups of farms $i = 3$, $i = 7$, $i = 9$, and $i = 12$. The line connects the second smallest value for each i to illustrate the separation between the smallest ratios for each i.

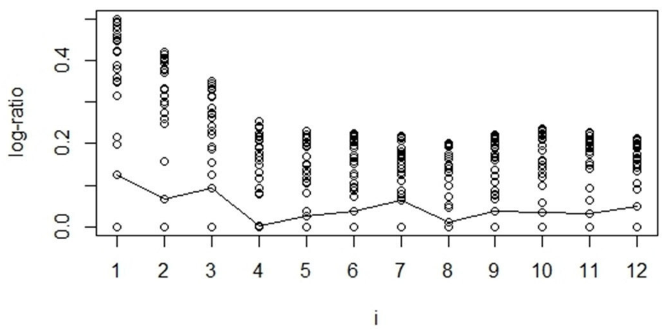

Figure 2.3: Log-ratio plot for detecting outliers in the GCFs data

Table 2.2 presents the values of $R_{min}^{(i)}$ for $i = 1, \cdots 12$. The corresponding log ratio plot in Figure 2.3 suggests 4 groups of outliers for $i = 3,\ i = 7,\ i = 9$ and $i = 12$. Hence observations included in group 12 are the farms identified as outliers in our sample. After the treatment of data and the exclusion of outliers, the remaining 61 farms from the initial 73 were used for the estimation of the Eco-Efficiency ratio and the discussion of the Intensified Production Technology in Chapter 6. As observed by Wilson (1993) this method allows the identification of observations as outliers even if they lie below the frontier set.

Table 2.2: Matrix of deleted observations, 73 observations

i	Deleted observations												$R_{min}^{(i)}$
1	71												0.5552
2	57	71											0.3213
3	**57**	**8**	**71**										0.1972
4	57	18	8	71									0.1318
5	9	15	57	8	71								0.0857
6	9	15	57	18	8	71							0.0556
7	**17**	**9**	**15**	**57**	**18**	**8**	**71**						0.0364
8	50	17	9	15	57	18	8	71					0.0245
9	**26**	**50**	**17**	**9**	**15**	**57**	**18**	**8**	**71**				0.0161
10	26	50	17	9	15	69	57	18	8	71			0.0108
11	25	26	50	17	9	15	69	57	18	8	71		0.0074
12	**23**	**25**	**26**	**50**	**17**	**9**	**15**	**69**	**57**	**18**	**8**	**71**	0.0052

2.7.2 Limitations of the data cloud method

A limitation of the data cloud method is the decision over the stopping point for the outlier analysis – that is the choice of i_{max} – which is arbitrary. Hence, the researcher needs to choose a large enough i in order to allow for masking produced by several observations in the data (i.e. an outlier might be masked by the presence of one or more other nearby outliers in the space containing the data) (Wilson, 1993). Another limitation is that the computation of significance levels for the AP statistic becomes intractable for large data sets with large subset sizes. However, the log ratios used here in the graphical analysis are easily computed and this overcomes the computational burden of the AP statistic.

An alternative method for overcoming this limitations would have been to use the method suggested by Wilson (1995) which is actually solves a super-efficiency DEA model in order to observe influential DMUs and the effect on the frontier when a particular DMU is removed from the peer group.

However, for the purposes of this thesis and since the data sample is small the Wilson data cloud method was used by setting a rather large i ($i = 12$). The computational burden was small and furthermore, the log ratios were used to identify the groups of outliers.

2.8 The EARBC and sources of data

The EARBC covers 27,890 km^2 from Lincolnshire in the north to Essex in the south, and Northamptonshire in the west to the East Anglian coast (Figure 2.4). The landscape ranges from gentle chalk and limestone ridges to the extensive lowlands of the Fens and East Anglian coastal estuaries and marshes. It is in principal a rural area, with almost 1.5 million hectares of land used for agriculture. It is one of the most productive areas in England best known for its cereal crops (wheat and barley production represents more than a quarter of England's total production) and horticultural production (potatoes, carrots, strawberries, salad crops). More than half of the total sugar beet production in England is produced in Cambridgeshire, Lincolnshire, Norfolk and Suffolk[4]. In addition, although sheep flocks, beef and dairy herds located in the area are smaller in size compared with other areas in the country are important for the farming balance of the region (Environment Agency, 2009).

According to the main document of the river basin management plant for the Anglian river basin district (Environment Agency, 2009) the main pressures on the water environment deriving from agriculture are:

- Over abstraction and other artificial flow regulation
- Nitrate and phosphate diffuse pollution – nutrients found in fertilisers used in agriculture that cause eutrophication of waterways.
- Organic pollution – an excess of organic matter such as manure which depletes the oxygen in water available for wildlife
- Physical modification – changes of the structure of water bodies, such as for flood defence especially in the Lincolnshire and Cambridgeshire Fens areas
- Sediment – caused by increased rates of soil erosion from land based activities. Sedimentation can smoother river life and spread pollutants from the land into the water environment

The above mentioned main pressures on the water environment and the high risk of drought associated to climate change are the two reasons that motivated this research to focus on farming systems based on the EARBC.

[4] Information and data published in the DEFRA website under the collection "Structure of the Agricultural Industry. The source of data is the Defra June Survey of Agriculture 2013. Available online at: https://www.gov.uk/government/statistical-data-sets/structure-of-the-agricultural-industry-in-england-and-the-uk-at-june : Accessed on 16.01.2014

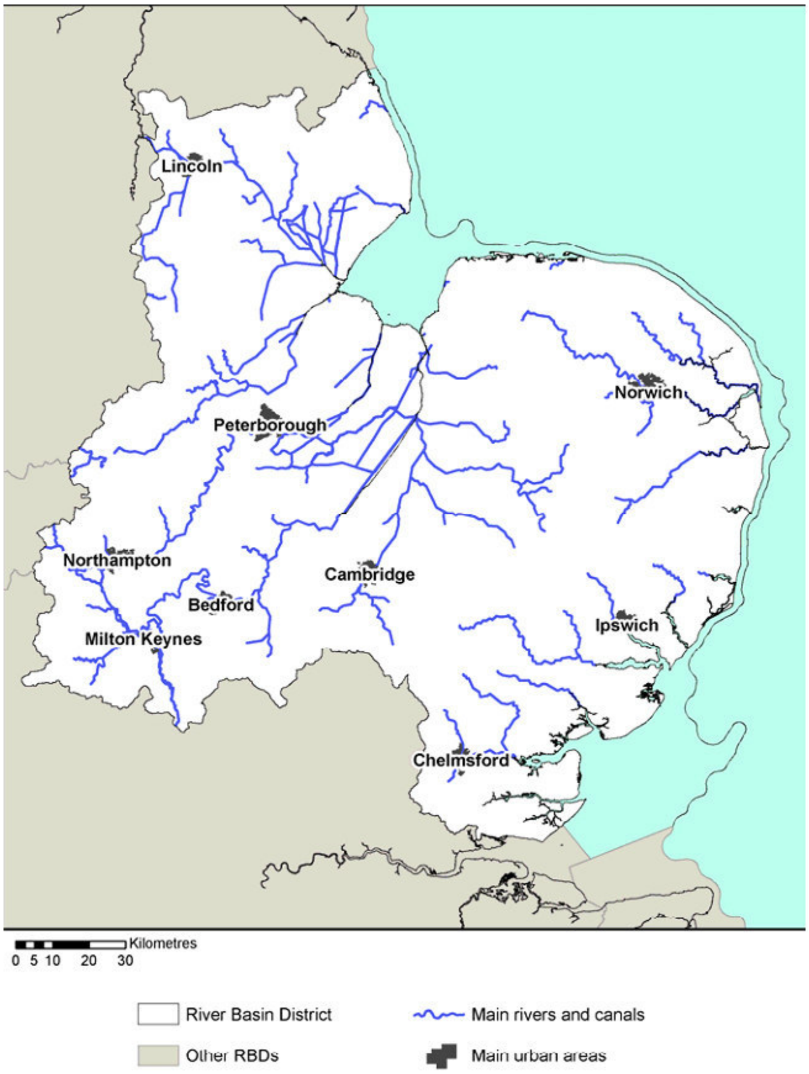

Figure 2.4: Map of the Anglian River Basin District: Source – Environment Agency, Main document, River Basin Management Plan, Anglian River Basin (2009)[5]

The data used to measure changes in TFP, WUE and to estimate a composite index of SI is obtained from the Farm Business Survey (FBS) database. The FBS is widely recognised as the most comprehensive and detailed database providing information on the financial, physical and environmental performance of farm businesses in England. Each empirical chapter (Chapter 4, 5 and 6) includes a data section that presents analytically the main variables used for the input and output sets of the DEA models as well as the relative definitions and descriptive statistics. Further, this research is focusing on the General Cropping Farm systems. The GCF[6] was selected over other agricultural systems in the region mainly because of the mixture

[5] © Environment Agency copyright and/or database right 2009. All rights deserved. This map includes data supplied under licence form: © Crown Copyright and database right 2009. All rights reserved. Ordnance Survey licence number 100026380. Some river features of this map are based on digital spatial data licenced from the Centre for Ecology and Hydrology, © CEH. Licence number 198 version 2.

[6] As GCFs are classified businesses on which arable crops (including field scale vegetables) account for more than two thirds of their total Standard Output (SO) excluding holdings classified as cereals; holdings on which a mixture of

of crops (potatoes, sugar beet, cereals, horticulture), their importance to farmers' incomes, the requirement for supplemented irrigation to secure (under drought conditions) yield and also because it is one of the most representative agricultural systems in the EARBC. Figure 2.5 provides an approximation of the location of the GCF$_s$ in the EARBC based on the 10 km grid reference information available from the FBS.

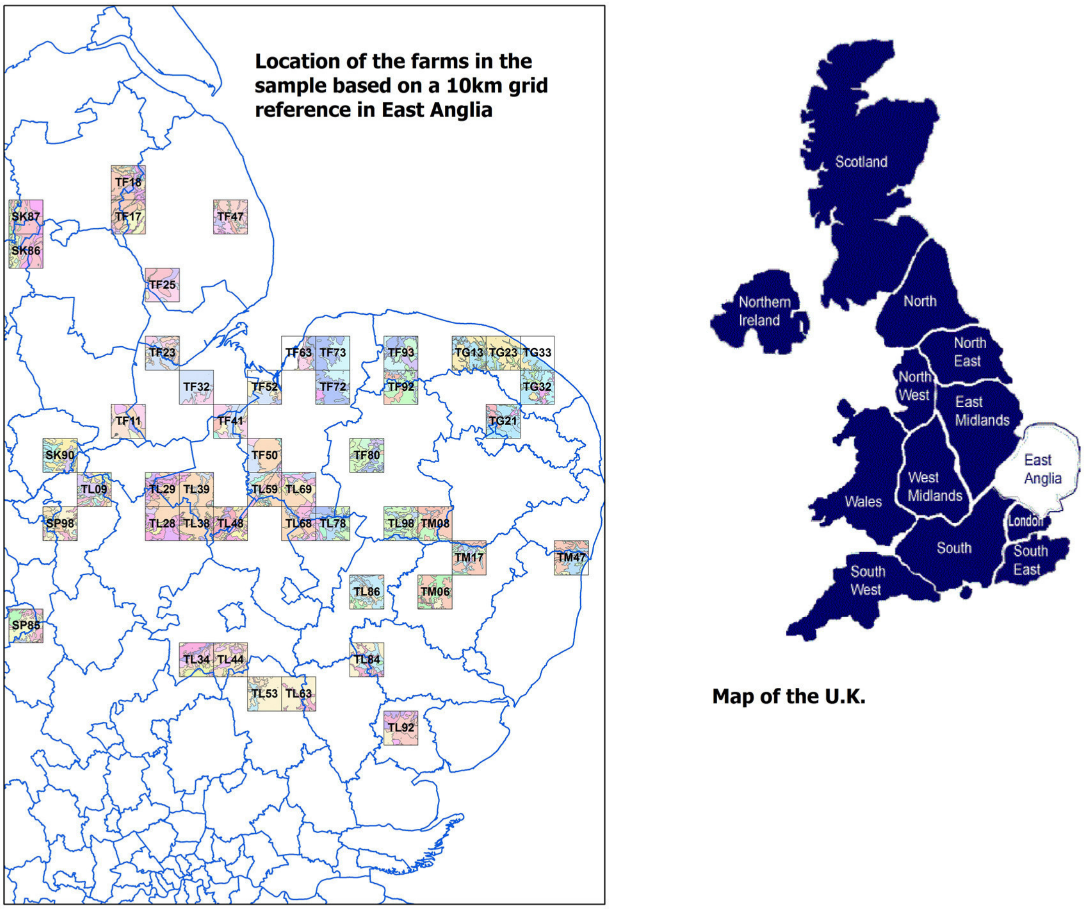

Figure 2.5: Approximate location of the GCF$_s$ in the EARBC based on a 10 km grid reference.

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arable and horticultural crops account for more than two thirds of their total SO excluding holdings classified as horticulture and holdings on which arable crops account for more than one third of their total SO and no other grouping accounts for more than one third. (FBS 2009-2010).

2.9 Summary

To summarise the above, DEA is a well-established non-parametric benchmarking method used in agricultural studies in order to evaluate the performance of farming systems. The flexibility of DEA techniques to account for multiple inputs and outputs and the various model specifications which allow the evaluation of efficiency for specific inputs and the environmental performance of farms are the main reasons to adopt this method for the objectives of this research presented in section 1.3.

However, there are also limitations which have been addressed in this chapter. In particular, the observed estimates of efficiency derived from the DEA models may be influenced by sampling variation, implying that the calculated distance functions to the frontier are likely to be underestimated. Hence the efficiency estimates are biased. In section 2.6.1 the Simar and Wilson (1998) bootstrapped DEA estimates of efficiency are presented. The objective is to estimate the bias and also to obtain confidence intervals for the first stage productivity or efficiency scores. The method is further developed and adapted by Simar and Wilson (1999) for the estimation of the MI of TFP in order to account for possible temporal correlation arising from the panel data characteristics.

Another pitfall of DEA also addressed and presented in section 2.7 is the presence of influential observation in the sample which can have a strong influence on the construction of the benchmarking frontier, influencing results and interpretation of efficiency scores. An appropriate technique has been suggested by Wilson (1993) to detect these outliers and to improve performance estimation of the farms in the sample.

Finally, in this chapter, a comprehensive review of DEA theory was presented in the context of its use within this research and also the different models that are used to evaluate the performance of farms. Moreover, the different technologies in DEA were explained as well as the input and output oriented DEA programs. Since this research also evaluates the performance of farms over time, details of the MI of TFP was also presented, the distance functions required for the calculation of the index were defined and the different linear programs based on DEA methods were presented. Finally, the three algorithms developed by Simar and Wilson (1998b; 1999; 2007) to enable statistical inference in nonparametric models were explained. The main objective of this chapter was to provide the reader with a basic understanding of the DEA methods and efficiency measures in order to provide a theoretical background to the further developments explained in subsequent chapters (Chapters 4, 5 and 6).

Chapter 3

Reviewing DEA studies in the agricultural sector

3.1 Introduction

Parametric and non-parametric methods of economic, production and environmental efficiency are widely applied in evaluating the performance of the agricultural sector. DEA is a nonparametric method which since its introduction by Charnes *et al.* (1978) has undergone thorough theoretical and methodological improvements. The wide application of DEA in a broad range of areas (banking, education, health, agriculture, etc.) and the robustness of the models set the base for DEA to become a popular method for the estimation of technical efficiency of Decision Making Units (DMUs). A number of research studies in the DEA literature focus on the measurement and evaluation of technical efficiency in the agricultural production sector.

The main objective of this chapter is to present a comprehensive review of previous research on the evaluation of sustainability, productivity change and environmental performance of farming systems using DEA. Furthermore, emphasis is given to the literature dealing with the evaluation of composite indicators of sustainability as well as to approaches that combine DEA with other well established methods of farm performance evaluation in the agricultural sector.

The remainder of the chapter is organised as follows. The first section describes the main paths of knowledge dissemination and the DEA models used in agriculture and farm studies. In particular, the section presents in a chronological order studies on technical and economic efficiency estimation in agriculture, water use efficiency estimation, agricultural productivity change at a country, regional and farm level and finally presents studies that assess the impact of policy intervention in the agriculture sector. The second section presents the main methods and the DEA model specifications used to evaluate agricultural systems. Emphasis is given to studies employing sub-vector DEA models, Malmquist productivity indices, bootstrapping methods and second stage regression analysis to evaluate the determinants of efficiency.

3.2 The development of DEA models in agriculture and farm studies

The popularity of DEA in the productivity and efficiency analysis literature lies in its effectiveness to evaluate the performance and efficiency of an individual DMU within a targeted group of homogenous DMUs that operate in a certain industry (banking, health, education, agriculture, energy, transportation, etc.). Detailed literature surveys on the methodological approaches and the recent developments of DEA models for the different industries are available in Liu *et al.* (2013a; 2013b) and Zhou *et al.* (2008).

The main reasons to adopt DEA in an industry such as agriculture are to identify sources of inefficiency for agricultural systems, rank farms relatively to their performance, evaluate management practices, assess the effectiveness of policies and strategies in the agricultural sector and create a monitoring mechanism to quantify current performance for enabling the reallocation of resources. Two distinct development paths of knowledge dissemination and DEA applications in agriculture were identified by Liu *et al.* (2013b). The criterion to identify a common path of knowledge development was based on the dissemination of knowledge between cited and citing documents.

The first development path of knowledge dissemination and DEA applications in agriculture emerges from the work published by Färe *et al.* (1985a), Chavas and Aliber (1993) and Coelli (1995). Färe *et al.* (1985a) applied for the first time the production frontier concept to explore technical efficiency of agriculture. Chavas and Aliber (1993) used DEA to explore technical, allocative, scale, and scope efficiency of agricultural production in a sample of Wisconsin farms emphasising the flexibility of the method in the sense that it does not require the imposition of functional restrictions on the production technology. Coelli (1995) reviewed all developments in frontier modelling and efficiency estimation, both parametric and non-parametric, and suggested a range of possible applications in the agricultural sector. Sharma *et al.* (1997) and Sharma *et al.* (1999) compared measures of production efficiency by estimating a SFA production function and both CRS and VRS output and input oriented DEA models respectively. Further, Sharma *et al.* (1999) explored the determinants affecting the efficiency derived by DEA models using a Shazam's Tobit estimation procedure. Both studies (Sharma *et al.* (1997) and Sharma *et al.* (1999)) concluded that although the DEA production efficiency estimates are believed to be more sensitive in the presence of outliers and noise in the data, the results of the DEA model with and without outliers were more robust when compared with those of the SFA.

The second development path is characterised by the application of DEA models to explore the sources of economic efficiency in the agricultural sector. Particularly, by assessing if scale or scope efficiency[7], and the targets of minimising costs or maximising profits are the main promoters of economic efficiency for agricultural systems.

Lim and Shumway (1992), performed a non-parametric analysis of agricultural production under the join hypothesis of profit maximisation, convex technology and non-regressive technical change. Chavas and Aliber (1993) also used non-parametric techniques and found strong empirical evidence linking the economic efficiency and the financial structure of farms. They also found that most of the farms in their sample could exhibit economies of scope. Ray and Bhadra (1993) linked economic efficiency with the cost minimising behaviour of farming systems and concluded that market imperfections for capital and land are

[7] Economies of scale refers to reductions in the average cost per unit with increasing the scale of operation for a single output type, while economies of scope refer to reduction in the average cost for a farm in producing two or more products (Panzar & Willig, 1977; Panzar & Willig, 1981)

the main reasons for the failures in technical efficiency and cost minimisation. Tauer (1995) and Tauer and Stefanides (1998) used the weak axiom of profit maximisation to evaluate the economic efficiency of dairy farms, and estimated the net output (netput) vector using non-parametric techniques. Furthermore, Tauer and Stefanides (1998) used a Tobit regression to define the characteristics of the farms that could explain the variability in their abilities to select the best net output vectors.

The two development paths merged into the two-step contextual analysis applied by Dhungana *et al.* (2004), Galanopoulos *et al.* (2006), Hansson (2007) and Speelman *et al.* (2008) that used Tobit regression analysis to determine the environmental factors that are correlated to the DEA technical efficiency estimates. Simar and Wilson (2007) argued that most researchers have used the Tobit model based on the observation that several efficiency estimates are equal to unity suggesting a mass probability at one. However, it is emphasised by Simar and Wilson (2007) that the true model describing the relationship between the efficiency estimates and the environmental factors does not have this property. Therefore, Simar and Wilson (2007) suggested that instead of the Tobit model, a double bootstrapped truncated regression should be used in the two-step contextual analysis.

One of the first research studies that used the proposed double bootstrapped procedure (Simar & Wilson, 2007) in a two-stage estimation of the determinants of technical efficiency in agriculture was by Latruffe *et al.* (2008a). As noted by the authors, the method enables statistical inference within models explaining technical efficiency scores, while at the same time producing standard errors and confidence intervals for the estimate of efficiency. Other pieces of research on the method in agricultural systems were by Balcombe *et al.* (2008b) who examined sources of efficiency in Bangladesh rice farming, Fletschner *et al.* (2010) who assessed the financial efficiency of farms in northern Peru and Larsén (2010) who explored the effects of partnerships, in the form of machinery-sharing agreements, for Swedish crop and livestock farms. It can therefore be concluded that the two-step contextual analysis either with the use of Tobit regression or the double bootstrap truncated regression analysis is becoming a more commonly used method in agriculture and farm technical efficiency studies.

Although not identified as an individual path in the development of DEA on the agricultural sector by Liu *et al.* (2013b), the work by Simar and Wilson (1998b) has a significant importance since it enables statistical inference for non-parametric estimates of efficiency as well as its extension by Simar and Wilson (1999) which enables the estimation and statistical inference of Malmquist indices of productivity change with the use of DEA techniques. In agriculture, indicative early pieces of research that based their analysis on the Simar and Wilson (1998b; 1999) methods are by Brümmer (2001), Latruffe *et al.* (2005), Gocht and Balcombe (2006) and Davidova and Latruffe (2007). The above are summarised in Figure 3.1. Note that pieces of research in agriculture following Simar and Wilson (1998b; 1999; 2007) are presented as an individual path since these models enable statistical inference for the technical efficiency estimates.

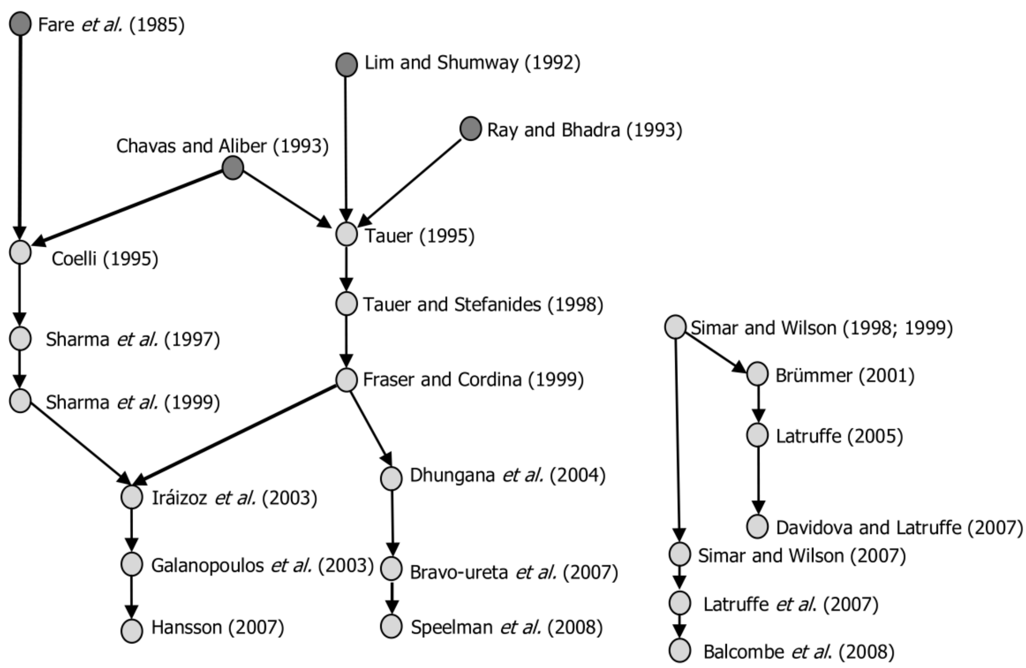

Figure 3.1: Knowledge development paths in agriculture and farm studies. Figure adapted from Liu *et al*. (2013b).

3.3 Fields of interest

Agriculture is a multifunctional process that produces food, biofuels, fibre and other products to sustain and improve human life, provides services related to the maintenance of ecosystems and biodiversity and serves as main source of income for rural areas around the world. Therefore, improving the general performance of an agricultural sector requires change across a number of areas. DEA methods were promoted in agricultural studies due to their flexibility in defining the production technology of farming systems and their ability to incorporate multiple inputs and outputs. Since the first published work by Färe *et al.* (1985a) which examined technical efficiency of farming systems in Philippines, DEA models have been applied to explore efficiency performance in areas such as farming and the environment, productivity change, financial performance, irrigation performance and sustainability both at farm and regional level.

3.3.1 Decomposing economic efficiency of farming systems

Accounting for technical efficiency in agricultural systems incorporates the ability of a farm to achieve the production of maximum output given the limited set of available inputs and technology. Farrell (1957) considers technical efficiency as one of the components of economic efficiency which is the product of technical efficiency and allocative efficiency. The latter is defined as the ability of farming systems to produce a certain level of output using cost minimising input ratios.

Färe *et al.* (1985a) have used a series of programming techniques based on DEA methods to explore and decompose technical efficiency change of the Philippines agricultural sector for a period of 20 years. Technical efficiency was decomposed into scale efficiency, congestion and pure technical efficiency. In respect to this decomposition, the main objective was to identify loss of output resulting from not producing at the optimal scale, which in a mathematical context can be interpreted as producing at the backward bending of the isoquant and in the interior of the upper level set i.e. not on the isoquant. The use of DEA models to estimate technical efficiency in agriculture was further promoted by the work of Coelli (1995) who suggested a series of potential applications of the method to evaluate the performance of farming systems. In addition, Coelli *et al.* (2002) used the same decomposition as Färe *et al.* (1985a) to estimate technical efficiency in Bangladesh rice cultivation and in addition, to account for allocative and cost efficiency. A second stage regression was also used to investigate the impact of farming characteristics on technical efficiency. Coelli *et al.* (2002) conclude that inter-farm performance differentials as identified by DEA methods are of great importance for extension agents helping rice farmers to improve their performance. Graham and Fraser (2003) used an input oriented VRS DEA model to estimate technical and scale efficiency for a sample of dairy farms in all regions of Australia.

Differences in technical efficiency and productivity between farming systems were explored by Lansink *et al.* (2002) in a sample of Finnish crop and livestock farms that participated in the Farm Accountancy Data Network (FADN) in the period between 1994-1997. They used measures of overall input oriented technical efficiency and sub-vector efficiency (input specific efficiency) under the assumption of both CRS and VRS to compare conventional to organic farming systems. According to their findings, organic farms are efficient relative to their own frontier, but use less productive technology when compared to the conventional farms. Specifically, they have identified that productivity of capital, land, and labour are lower for the organic farms. Sipiläinen *et al.* (2008) has extended the above discussion by considering biodiversity as a positive output produced on farms in order to estimate the trade offs in production of market and non market agricultural outputs. In particular, Sipiläinen *et al.* (2008) evaluates the efficiency of Finish crop farms between 1994-2002 in utilising scarce resources in production of both crop yield and crop diversity to compare agricultural systems. For this purpose, efficiency scores for organic and conventional farms are estimated separately with the use of window analysis (Charnes *et al.*, 1985) assuming progressive technical change. The results of Sipiläinen *et al.* (2008) show that there are no differences in technical efficiency between conventional and organic farms when the effect of crop diversity is accounted on the economic performance of the farms. Other similar works are those of Iráizoz *et al.* (2003), D'Haese *et al.* (2009) and Galanopoulos *et al.* (2011).

In addition, Reig-Martínez and Picazo-Tadeo (2004) have used DEA to explore the short term viability of small scale citrus production units in Spain. A VRS DEA model was used to maximise a short-term profit function in order to identify specific features of the best performing farms on the frontier. These features were used to compare the characteristics of the average farms with those on the frontier in order to suggest improvements on the management side of the agricultural systems to eliminate current inefficient practices. According to the results, identifying economic non-viable management practices and removing them from the agricultural systems improves significantly the level of efficiency of the individual farms and their ability to be economic viable in the long term.

Olson and Vu (2007) have used DEA to explore inter-farm differences in efficiency for a sample of Minnesota farm households. In particular, data for the financial and farm characteristics over a period of ten years was used to estimate technical, allocative and scale efficiency measures. A nine input, six output DEA model was estimated assuming VRS. Further, in order to account for the bias in the DEA technical efficiency estimates they used the smoothed bootstrap as suggested by Simar and Wilson (1998b; 2000). In addition, a conventional and a weighted Tobit regression model were used to measure the impact of farm characteristics on technical, allocative and scale efficiency. They concluded that farms have on average improved their technical (by 5%), allocative (by 22%) and scale efficiency (8%) over the study period and that factors such as specialisation of farms, higher current asset share, land to labour and capital to labour ratios have a positive impact on technical efficiency.

Singbo and Lansink (2010) used DEA to estimate directional distance functions to estimate sources of inefficiency in lowland farming in Benin (West Africa). Further, they employed a single truncated bootstrap approach to investigate the determinants of inefficiency. Initially, the DEA dual approach was used to decompose short run profit inefficiency at a farm level into pure technical, allocative and scale inefficiency as well as into input and output inefficiency. They concluded that the main sources of inefficiency are short run, scale, allocative and output inefficiency. Furthermore, their results support the efforts to encourage the adoption of a mixed rice-vegetable farming system to enhance food security in West Africa lowlands.

3.3.2 Environmental performance of farming systems

In the DEA literature, environmental performance of agricultural systems is broadly measured through the inclusion of undesirable outputs in the production function estimation. Undesirable outputs are defined as production outcomes that are socially undesirable and cause negative external impacts to the environment such as pollution of the air (CO_2 emissions) and groundwater (agrochemical leakages). Färe *et al.* (1989) was the first to relax the strong disposability of outputs by modifying the standard Farrell (1957) approach in order to allow for undesirable outputs to be freely disposable and therefore to enable the measurement of the environmental performance of decision making units. A detailed presentation of the literature on the development of the measurements of environmental performance of DMUs from the perspective of production efficiency is available in Tyteca (1996; 1997).

In agriculture, Ball *et al.* (1994) provided empirical application of the proposed linear programming model by Färe *et al.* (1989) to incorporate undesirable outputs into models of agricultural production in the Unites States. Reinhard *et al.* (2000) extended the approach by Reinhard *et al.* (1999) and used both SFA and DEA to compare estimates of environmental efficiency for a set of Dutch dairy farms. They conclude that DEA fulfils all theoretical restrictions (appropriate monotonicity and curvature restrictions) but since it is a deterministic method is unable to identify whether the environmentally detrimental variables fit to the model (Reinhard *et al.*, 2000). In addition, Lansink and Reinhard (2004) investigated technical efficiency and potential technological change in a sample of Dutch pig farms derived from FADN with the use of an input oriented DEA model based on linear programming to compute measures of overall technical and sub vector efficiency. The sub-vector model accounted for undesirable outputs and was therefore used to evaluate the environmental performance of pig farms. Lansink and Reinhard (2004) conclude that the introduction of new technologies at a farm level (such as new feeding techniques, new genetic varieties with increased protein deposition, new housing) have a positive impact on technical efficiency and have higher impact on improving environmental performance.

Studies on the environmental performance of farming systems often discuss the results within the framework of agricultural sustainability. Callens and Tyteca (1999) have used DEA techniques to compute the efficiency of each of their sample farms from a set of surveyed data in order to estimate different partial indicators that measure the sustainable development of the farming systems. Economic, social and environmental efficiency are viewed as a necessary (but not sufficient) step towards sustainability. The indicators were built upon the concepts of cost-benefit analysis and the principles of productive efficiency. The results showed that the developed indicators can be used for detecting the so-called factor of un-sustainability and hence suggest specific actions to improve management practices and to provide recommendations to the design of regulations and incentives for stimulating increased sustainability. de Koeijer *et al.* (2002) presented a conceptual framework for the measurement of sustainability with an environmental perspective based on DEA estimates of efficiency for a sample of Dutch sugar beet growers. Further, de Koeijer *et al.* (2003) evaluate the performance of environmental management and its impact on technical efficiency for Dutch arable farms. Asmild and Hougaard (2006) used a two-step sub-vector DEA approach to demonstrate that only when the improvement potential of technical efficiency is achieved does any additional improvements in environmental efficiency become possible. Hence, Asmild and Hougaard (2006) have used the DEA formulation to model the behavioural assumption that a farmer has sequential preferences. In other words, a farmer will primarily seek to improve the technical efficiency of economic variables and then any environmental variables.

Goncalves Gomes *et al.* (2009) used input-oriented DEA BCC models (two input (farmed area, work force) three output (production of maize, rice and coffee) models) to measure the socio agronomic performance of a farmers group and to assess the sustainability in agriculture in the Brazilian Amazon. In addition, they have used Tiered DEA models to group farmers in sustainability categories and non-parametric regression models to determine the factors with an impact on efficiency measurements. They concluded that there is an evidence of sustainability on the sector based on the fact that farmers have continuously improved their efficiency over a 16 year period. They claim that efficiency variation along time can be used as an indication of sustainability.

Reig-Martínez *et al.* (2011) have used a methodological approach that combines DEA techniques with those of multi-criteria decision making (MCDM) to assign common weights to 12 selected indicators of sustainability in order to rank farms with a composite indicator of sustainability. They observed a positive correlation between the economic and environmental composite sustainability indicators but no correlation with the social indicator. At a second stage they used a double bootstrapped truncated regression to determine factors that influence the sustainable performance of farms. They found that farm size, membership in agricultural cooperatives and agricultural technical education are all factors that positively influence the sustainability of farming systems.

Jan *et al.* (2012) used a joint implementation of Life Cycle Assessment (LCA) and input-oriented DEA in order to investigate the relationship between economic and environmental performance of 56 Swiss dairy firms in the alpine area. The environmental performance of farms was measured by means of an Eco-Efficiency indicator assessed using a DEA approach while the economic performance is measured by the work income per family work indicator. They concluded that a positive relationship existed between economic and environmental performance of the farms in the sample emphasising the importance that this has to policy makers. Specifically, they suggested that incentives to increase environmental resource use productivity could be provided by means of appropriate policy design.

Measuring sustainability of agricultural systems is a complex problem since it requires the synthesis of composite indicators to account for the economic, social and environmental dimensions. Gerdessen and Pascucci (2013) have used DEA to simplify the assessment procedure of sustainability of agricultural systems by partitioning 252 European agricultural regions into efficient and non-efficient regions based on five different scenarios. Two economic, two social and four environmental indicators were used to define the three dimensions of sustainability. Indicators of the type "less is better" (i.e. environmental indicators) were modelled as inputs, while those of type "more is better" are modelled as the outputs (i.e. economic and social indicators). Models under the CRS, VRS assumptions, for both the input and output orientation were estimated. The authors conclude that this multidimensional approach and the use of DEA techniques is valuable for desk based research since it enables policy makers to limit cost and also to expand the use of already available socio-economic and environmental data.

An alternative method to estimate a composite indicator of sustainability for agricultural systems was suggested by Dong *et al.* (2013). They have used a non-negative polychoric Principal Component Analysis to reduce the number of the variables derived from environmental surveys, remove correlation among the variables and to convert categorical variables into continuous variables. These components where then used in a common weighted DEA to evaluate the efficiency levels and hence the overall sustainability for each of their sample farms.

Buckley and Carney (2013) have used a VRS input oriented DEA model to evaluate the efficiency of the EU Nitrates and the Water Framework Directives in managing nutrient transfers into water resources. Managing excessive use of nutrient on agricultural land is an important political challenge. Specifically, the model measured the extent to which application rates of nutrients have exceeded optimum levels concentrating on specialised dairy and tillage farms in Ireland based on data sample derived from the National Farm Survey. Further they have used a second stage bootstrapped truncated regression analysis to identify parameters that could potentially improve the efficiency of nutrient application at a farm level. They concluded that inefficiency is caused mainly due to excess in the use of nitrogen and phosphorous fertilisers and that further cost reductions should also be made for imported feeds for livestock. These reductions have two benefits since it is possible to reduce the risk of diffuse nutrient losses from agricultural systems and also improve the economic performance of farms by increasing gross margin.

3.3.3 Evaluating water use efficiency at farm and regional level

Water is essential to agriculture production not only due to its use for irrigation of crops but also for other uses comprising spraying, drinking for livestock and washing (vegetables, livestock buildings). Water use efficiency both at farm and regional level has therefore attracted the attention of various DEA studies in agricultural production efficiency. Fraser and Cordina (1999) used DEA to assess the technical efficiency of a sample of 50 irrigated dairy farms in Australia for two consecutive years using both input and output orientated models under the CRS and VRS assumption. In their work they compared DEA with the more frequently reported partially indicators of farm efficiency concluding that DEA provides a more consistent measure of farm efficiency. Furthermore, they benchmarked farms in order to identify which inputs and or outputs were being under-utilised. From an extension perspective, this can be very useful information for identifying best practices for the improvement of agricultural productivity.

Rodriguez-Diaz et al. (2004a; 2004b) applied DEA methods in order to assign weights for the calculation of water performance indexes for irrigation districts in Spain. They conclude that this benchmarking method identifies best performances among irrigation districts and hence enables managers to suggest strategies for optimising labour input or water use or to substitute current crops for more profitable ones in an irrigation district.

Lilienfeld and Asmild (2007) used a DEA sub-vector model to estimate excess in water use for irrigating farms in United States. They used a set of panel data of 43 irrigators between 1992 and 1999 to investigate the impact of irrigation system type and other factors such as the size of the farm and the age of the farmer on water use efficiency. The main finding of their study was the identification of a weak relationship between irrigation system type and excess in water use for irrigation. Speelman *et al.* (2008) also used a DEA sub-vector model for the estimation of efficiency of water use in a sample of small-scale irrigation schemes in South Africa. In addition, Speelman *et al.* (2008) used a Tobit regression to determine specific farm characteristics that have an impact on water use efficiency. They conclude that information on specific input reductions (water) as well as defining factors that have a significant impact on the improvement of efficiency is valuable for policy makers and extension services for the design of targeted policies and strategies towards increased efficiency. Along similar lines, Mahdi *et al.* (2008), Frija *et al.* (2009), Wang (2010), Chemak (2012) and (Chebil *et al.*, 2012) estimated technical and sub-vector efficiency and the determinants of technical efficiency using a Tobit model.

Price mechanisms are often used as government policies to control excess water use. Speelman *et al.* (2009) extend their previous research (Speelman *et al.*, 2008) by estimating the impact of water pricing on water use efficiency. The impact on the demand of agricultural inputs in Tunisia of irrigation pricing polices was investigated by Frija *et al.* (2011) with the use of a methodology based on inverse DEA models. By estimating technical efficiency of the individual farms the authors could then derive information to construct individual irrigation water demand functions. The research identified important implications in respect to the objectives of water policy in Tunisia which include water saving, continuity of the irrigation activity and cost saving at a national level.

Shang and Mao (2009) used a CCR input-oriented DEA model for 16 irrigation-fertilisation schemes to assess water use and fertilisation efficiency for winter wheat in north China. The main objective of their research was to study the effect of irrigation and fertiliser on production and water use efficiency to evaluate current schemes of fertilisation and irrigation. They suggested that at low levels of fertiliser use the schemes must avoid irrigation and at high/moderate levels of fertiliser use, irrigation needs to increase in volume.

Yilmaz *et al.* (2009) used an input oriented DEA model with weight restrictions to determine in which regions in Buyuk Menderes Basin of Turkey the use of irrigation methods is most profitable. Weight restrictions were applied in a DEA linear programme to prevent excessive weight flexibility assigned to inputs and outputs. According to their findings, DEA is a very useful method for detecting local inefficiencies and propose possible improvements for irrigation districts. Similarly, Azad and Ancev (2010) used DEA to estimate the component distance functions of an environmental performance index to measure the economic and environmental performance of irrigated farms in Australia. Their findings support the case of segmentation and targeting of policies according to the type of irrigation systems and the specific characteristics of each location.

A joined Cluster and DEA method was employed by Borgia *et al.* (2013) to compare technical efficiency of small and large irrigation schemes in Mauritania. Their main objectives were to assess the performance of farms in order to identify the particular efficient schemes that could serve as best examples for the improvement of irrigation efficiency, land productivity and production efficiency. According to the results four systems were identified as technically efficient and could therefore serve as best practices in Mauritania to improve land productivity and production efficiency.

3.3.4 Evaluating productivity change in agriculture over time at country, region and farm level

Studies on productivity growth in agriculture aim to examine the progress of agricultural systems and their ability to produce at a sufficiently rapid rate to meet the demands for food and raw materials of an increasing population. Further, the decomposition of total factor productivity (TFP) into technical and economic efficiency informs policy makers on the progress or the stagnation of the agricultural sector in terms of technological adaptation and improvements in input use efficiency. In addition, estimating changes in agricultural productivity over a period of time enables the evaluation of implemented development strategies and policy interventions. A common approach to evaluate productivity change during a period of time in agriculture is to estimate Malmquist indices (MI) (Malmquist, 1953; Caves *et al.*, 1982b; Färe *et al.*, 1992) of TFP using DEA methods. The broad use of non-parametric techniques was stimulated by Färe *et al.* (1994b) who showed how to decompose and compute the different components of the MI of TFP. Usually, a MI of TFP and its decomposition into technical and economic efficiency (which is decomposed further into pure economic efficiency and scale efficiency) are used to assess changes in productivity, technology and efficiency of farming systems in different time periods. A considerable amount of studies employ the MI of TFP to assess differences in productivity among countries, regions and at farm level.

Three nonparametric measures including the MI of TFP were used by Bureau *et al.* (1995) to assess differences in productivity growth of the agricultural sector among nine member countries of the EU and the United States. Comparing the results obtained from the three different nonparametric measures, namely the Fisher, Hulten and the Malmquist indices, they conclude that the MI of TFP yields more consistent estimates when compared with the other two. However, the pattern of productivity growth, no matter the computational techniques used, is very similar. The main advantage of the MI of TFP is its ability to account for differences in productivity using only data on quantity of inputs and outputs. Thirtle *et al.* (1995) also used the MI of TFP to assess agricultural productivity change for a sample of 22 sub Saharan African countries among the 1971-1989 period. Although conventional inputs (land, labour, livestock) were used to estimate and compare production levels, at a second stage inputs representing technological change and innovation derived from research and development in agriculture were used to assess productivity change. Lusigi and Thirtle (1997) used a sample of 47 African countries to extend the analysis for the period 1961-1991. An output oriented MI of TFP was used by Fulginiti and Perrin (1997) to explore inter country differences in agricultural productivity growth among 18 developing countries for the period 1961-1985. The main objective was to compare findings from the MI of TFP with other methods presented in Perrin and Fulginiti (1993) which had identified a decline in agricultural productivity for the less developed countries. The results confirm previous findings and reveal that heavy taxation on agriculture had a negative impact on rates of productivity change. Fulginiti and Perrin (1999) extended their research using the same sample and period of time as Fulginiti and Perrin (1997) to explore the impact of price policies on agricultural productivity. Their results support the hypothesis that unfavourable price policies have a negative impact on productivity performance.

Coelli and Rao (2005) used a DEA estimated MI of TFP and examined levels and trends in global agricultural output and productivity for 93 developed and developing countries focusing on evidence of catch up and convergence or possible divergence covering the period 1980-2000. Other research that have employing DEA techniques to measure inter-country differences in agricultural TFP include Piesse and Thirtle (2010b), González (2011) and Zúniga González (2011). In particular, Piesse and Thirtle (2010b) discuss the impact of research and development on agricultural productivity comparing both developed and developing countries.

It is worth remarking that research studies outlined in the above paragraph have all constructed the MI with respect to a contemporaneous frontier technology. In particular, the frontier in year $t + 1$ is compared only with that of the previous year t. A divergence to this approach was adopted by Suhariyanto and Thirtle (2001) who estimated agricultural TFP for 18 Asian countries from 1965 to 1996 by calculating a sequential MI which accumulates the data in order to solve the problem of dimensionality (relatively small number of observations in comparison to many inputs and outputs).

A number of research studies have also used a DEA estimated MI of TFP to assess productivity change at a regional level. Piesse *et al.* (1996) used linear programming techniques to measure efficiency changes in three different regions in South Africa to explore the impact of the 1992 drought on agricultural productivity. The differences in productivity and technical efficiency identified were caused by three main factors: a) the high risks imposed by increased investments in the sector, b) the improved maize varieties which are less resistant in moisture stress than the traditional ones and c) unrecorded regional variations in the severity of impacts due to the drought.

In Spain, 17 regions were compared in terms of agricultural productivity growth by Millan and Aldaz (1998) over the period 1977-1988 is a MI of TFP estimated with non-parametric programming techniques. They conclude that although the average technical change grew during the study period there was considerable regional variation. Moreover, they support that the method is useful to policy makers since it can identify regions with technical progress or regress and therefore help to adapt policies according to specific regional needs.

Son Nghiem and Coelli (2002) have used two modified forms of the standard Malmquist DEA method to evaluate the impact of policy reforms for eight agricultural regions in Vietnam over the period 1976 to 1997. The "three year window" and the "full cumulative" methods were used to deal with degrees of freedom limitations. Results show a strong average growth above 3% per year in TFP in the rice sector emerging from incentive reforms introduced in 1981 and 1987. Similarly, Umetsu *et al.* (2003) explored regional differences in TFP, technological and efficiency change to evaluate the development of the Philippines rice sector for the post Green Revolution era. A MI of TFP and its components – technical and efficiency change – were estimated with non-parametric techniques for the period 1971-1990. The findings show that the introduction of new rice varieties had a positive impact on TFP while declines during the period are likely to have occurred due to the intensification of production in lowland farming systems. Aldaz and Millan (2003) assumed a non-regressive technical change and compared their results on regional agricultural productivity in Spain with the previous work by Millan and Aldaz (1998). Thirtle *et al.* (2003) employed DEA estimated MI indices of TFP to evaluate efficiency changes in agricultural productivity for 18 districts in Botswana during the 1981-1996 period. An important finding of the study is that the gap between productive and poorer regions in Botswana is widened.

Recent studies discussing differences in regional agricultural productivity were undertaken by Zhang *et al.* (2011) who employed a Malmquist-Luenberger productivity index to evaluate productivity change in 30 regions in China among 1989 to 2009; O'Donnell (2012) who explored changes in U.S. agricultural productivity and profitability change over the period 1960-2004; and Mohan and Matsuda (2013) who examined 10 regions in Ghana over the period 2000-2009.

Beyond country and regional level the MI of TFP has also been used to assess productivity change at farm level. The scope of these research studies lies on the need to address specific improvements in farm management not only at individual input level (labour, land productivity etc.) but also on broad measures such as TFP and economic efficiency (both technical and allocative). Fraser and Hone (2001) estimated farm level efficiency and productivity changes for a sample of wool farms in Australia using an 8 year balanced dataset. They used both estimates of annual technical efficiency as well as estimates of the MI of TFP. Zhengfei and Lansink (2006) explored changes in agricultural productivity at a farm level from the perspective of financial performance over the period 1990-1999 for cash crop farms in the Netherlands. The MI was used as an approximation of the performance of farms in order to enable the evaluation of impacts of capital structure (debt) on farm performance and to compare the results with a more traditional approach that uses the return to equity as a performance measure. They conclude that debt has a positive effect on productivity and no effect on return to equity. Latruffe *et al.* (2008b) and Balcombe *et al.* (2008a) used the method suggested by Simar and Wilson (1999) to bootstrap Malmquist indices in order to account for the sampling variation in DEA models. Their work is the first to apply the bootstrap method in agricultural studies to estimate changes in productivity. For the empirical application of the method they used a sample of 250 Polish farms over the period 1996-2000. Further, in Balcombe *et al.* (2008a) a second stage regression using the bias corrected MI of the first stage was used to investigate the factors that had an impact on productivity growth.

In a similar framework, Odeck (2007) used a sample of 19 Norwegian grain growers to measure technical and efficiency change by employing and comparing the methods of SFA and DEA to calculate a MI of TFP over the period 1987-1997. In addition, Odeck (2009) employed the same sample of data and period to provide statistical precision of DEA and Malmquist indices using the bootstrapped methodology. A second stage Tobit regression aimed to explore the impact of farmers' age, experience, climate variability, labour to size and capital to size ratios on the MI and the technical and efficiency change indices. Odeck (2009) suggests that environmental factors such as weather conditions have a significant impact on the variation of efficiency and productivity of farming systems among the study years. The same approach was used by Olson and Vu (2009) to measure productivity growth, technical and efficiency change on Minnesota farms among 1993-2006. More recent studies have extended the use of a bootstrapped Malmquist index for the evaluation of the financial performance of farms (Pedersen & Olsen, 2013) and also to assess the impact of agricultural policies and subsidies in TFP of farming systems (Mary, 2013).

3.3.5 Evaluating agricultural policies

A series of DEA studies focus on the impacts of policies on agricultural efficiency. In particular, the main concern is the impact of subsidies or direct payments on efficiency emerging from the Common Agricultural Policy (CAP) of the EU, which regulates agricultural payments, programmes and directives. Coelli *et al.* (2006) investigate the impact of the 1992 and 2000 CAP reforms on agricultural productivity. In particular, a Malmquist index calculated with DEA techniques was used to estimate changes in total factor productivity of arable farms in Belgium. The CAP reform of 2003 has set specific targets in relation to the improvement of environmental and economic efficiency of farming systems for instance via the direct payments scheme. These payments are not linked to a specific farm output level but rather with the compliance of the farm with baseline requirements relating to the environment, animal welfare and health standards. Kleinhanß *et al.* (2007) modelled these standards using DEA techniques to explore their relationship with the economic efficiency of livestock farming systems in the EU. A production frontier was estimated with and without direct payments and a nonparametric regression was used to address the relationship of relative efficiency on economic size, an approximation of environmental performance and regional dummies[8]. The results show that the direct payment scheme is not sufficient to outweigh negative environmental performance of farming systems and at the same time ensure that farms will become more efficient. The relationship between CAP payments and the management efficiency of farms in France was also investigated by Latruffe *et al.* (2009) using a five stage DEA approach. They concluded that there was a negative relationship between subsidies and managerial ability. In addition, Arfini and Donati (2008) employed DEA techniques to estimate technical efficiency of farming systems. The estimated index of technical efficiency was then used as a proxy for the capacity of farms to use factors of production to their best advantage. The main objective was to assess the impact of the health check of CAP on the competitiveness of farms in different regions of the EU.

Amores and Contreras (2009) proposed an allocation system of agricultural subsidies for olive oil agricultural systems in Spain based on an index of efficiency estimated with DEA methods. In addition, and to comply with the criteria set by the Agenda 2000 as well as with the reformed CAP of 2003 (cross compliance) a set of economic positive and negative externalities were considered in the model. In particular, DEA was used to determine potential differences in efficiency levels between farm typologies, sizes and farm locations in Andalucía. The results revealed a number of insights explaining the variation in effectiveness of farms. In particular, Amores and Contreras (2009) state that "the decomposition of the Overall Efficiency of farms has shown that the efficiency of farms (that which the farm can/should control) would be under-estimated by an overall measurement which considered all farms". In addition, they found that different typologies can potentially limit the efficiency of farms. Thus, Amores and Contreras (2009) suggest that the allocation of subsidies should be made in terms of Farm Efficiency results since society should not demand more from a farm than is possible.

In a recent research study Giannoccaro *et al.* (2013) applied DEA to assess the Eco-Efficiency of water price reform for irrigating farms in Italy. Their research was motivated by the Water Framework Directive of the EU which promotes reforms that improve the environmental performance of farms and also promote the efficient use of water for irrigation. They conclude that the DEA approach is a useful technique for the assessment of water pricing policies where a balance between economic and environmental efficiency is required.

[8] Dummy is a variable used in regression analysis with a value 0 or 1 in order to indicate the absence or presence of some categorical effect (or mutually exclusive events) that may be expected to shift the outcome.

3.4 DEA models and their specifications in agricultural studies

Depending on the objectives of agricultural research, different DEA methodological approaches and model specifications exist. This section reviews the DEA methods widely applied in agricultural efficiency studies as well as the model specifications in regards to the types of DMUs (farm units), the selection of the set of inputs and outputs used and the returns to scale considerations.

3.4.1 Methodological approaches

In terms of DEA applications in the agricultural sector different variations and models are used such as the additive model (Haag *et al.*, 1992), models that estimate allocative input efficiency (Färe *et al.*, 1997), models that account for non-discretionary inputs or outputs (Piot-Lepetit & Vermersch, 1998; Lansink *et al.*, 2002; Asmild & Hougaard, 2006; Lilienfeld & Asmild, 2007), bootstrapped DEA models to enhance statistical inference (Gocht & Balcombe, 2006; Balcombe *et al.*, 2008b; Latruffe *et al.*, 2008a; 2008b), models that apply weight restrictions (Garcia & Shively, 2011) and models that evaluate the performance of farms over a period of time by using the MI of TFP (Balcombe *et al.*, 2008a; Odeck, 2009). In addition, a significant number of studies follow the two-step contextual analysis to estimate the drivers of efficiency (Dhungana *et al.*, 2004; Galanopoulos *et al.*, 2006; Balcombe *et al.*, 2008b; Speelman *et al.*, 2009; Fletschner *et al.*, 2010).

The sub-vector variation of the conventional DEA models enables the researcher to account for variables (inputs or outputs) that are non-discretionary. The variables in the sub-vector model are distinguished into discretionary (the farmer is able to proportionally reduce inputs or expand outputs) and non-discretionary (the farmer has no control over these specific inputs or outputs). Hence, accounting for non-discretionary variables into the DEA model enables the estimation of the proportional input reduction or expansion of outputs only for the set of inputs or outputs that are under the control of the farmer (Lilienfeld & Asmild, 2007). In contrast, in a conventional DEA model, there would be a proportional reduction or expansion of all inputs and outputs simultaneously even for those variables that are out of the control of the farmer (e.g. rainfall – non-discretionary input). The sub-vector technical efficiency model was introduced into the DEA literature by Kopp (1981) and Färe *et al.* (1983). Examples of studies that employ the sub-vector DEA model in agriculture are by Piot-Lepetit *et al.* (1997) where land and labour were considered as non-discretionary inputs, Lansink *et al.* (2002) and Lansink and Silva (2003) also employed the sub-vector variation of DEA model to generate technical efficiency measures for a subset of inputs and to measure energy technical efficiency respectively. Asmild and Hougaard (2006) used a series of models two of which were based on the sub-vector variation to account for the economic versus the environmental performance of Danish pig farms. Revenue and environmental variables were treated as non-discretionary variables alternately into the two sub-vector models.

A common methodological approach to evaluate the performance and productivity change of farming systems over time is the estimation of the MI of TFP with the employment of DEA techniques. As defined by Färe *et al.* (1992), the MI of TFP and its components represent the growth of a DMU (farm) and reflect the progress or regress in efficiency along with the shifts of the frontier over time under the multiple inputs and outputs framework. A detailed presentation of productivity studies in agriculture is presented in section 3.3.4.

In the literature there are broadly two approaches used to obtain efficiency estimates at a farm level; parametric techniques (i.e. Stochastic Frontier Analysis (SFA)) and non-parametric techniques (i.e. Data Envelopment Analysis (DEA)). Parametric techniques are used for the specification and estimation of a parametric production function which is representative of the best available technology (Chavas *et al.*, 2005). The Stochastic Frontier Approach (SFA) was introduced by Aigner *et al.* (1977) and (Meeusen & Vandenbroeck, 1977). In a number of agricultural studies, the SFA and the DEA techniques are used for comparative purposes (Sharma *et al.*, 1999; Reinhard *et al.*, 2000; Iráizoz *et al.*, 2003; Latruffe *et al.*, 2005; Odeck, 2007; Theodoridis & Psychoudakis, 2008).

An increasing number of studies in DEA literature employ the two-step contextual analysis to explore the underlying factors of efficiency or inefficiency of farming systems. For the first step, DEA techniques are used to estimate the efficiency scores for the individual farms while in the second step, the determinants of efficiency or inefficiency are identified through the regression of the efficiency estimates over a set of explanatory variables. Commonly used variables at the second stage regression analysis are;

- the age of the farmer (Lansink & Reinhard, 2004; Olson & Vu, 2007; Speelman *et al.*, 2008; Padilla-Fernandez & Nuthall, 2009; Larsén, 2010; Chebil *et al.*, 2012);
- the education and training qualifications of the farmer (Dhungana *et al.*, 2004; Speelman *et al.*, 2008; Fletschner *et al.*, 2010; Larsén, 2010; Wang, 2010; Picazo-Tadeo *et al.*, 2011; Reig-Martínez *et al.*, 2011; Chebil *et al.*, 2012; Watto & Mugera, 2013);
- the size of the farm (Sharma *et al.*, 1999; Lansink & Reinhard, 2004; Zhengfei & Lansink, 2006; Davidova & Latruffe, 2007; Kleinhanß *et al.*, 2007; Olson & Vu, 2007; Latruffe *et al.*, 2008a; Reig-Martínez *et al.*, 2011), household size (Speelman *et al.*, 2008; Wang, 2010; Watto & Mugera, 2013);
- the years of experience of the farmer or otherwise how many years the farmer has been employed in farming (Lansink & Reinhard, 2004; Olson & Vu, 2007; Huang *et al.*, 2011; Reig-Martínez *et al.*, 2011), access to credit (Chebil *et al.*, 2012; Watto & Mugera, 2013);
- proportion of income derived from agriculture or other sources (Lansink & Reinhard, 2004; Wang, 2010; Picazo-Tadeo *et al.*, 2011; Watto & Mugera, 2013);
- land ownership and share of rented land (Davidova & Latruffe, 2007; Olson & Vu, 2007; Speelman *et al.*, 2008);
- a series of ratios such as capital to labour, land to labour and debt to asset are used as explanatory variables by Davidova and Latruffe (2007), Olson and Vu (2007) and Huang *et al.* (2011);
- the impact of gender on water use efficiency is finally explored by Speelman *et al.* (2008).

A significant number of studies use the Tobit regression (Davidova & Latruffe, 2007; Olson & Vu, 2007; Speelman *et al.*, 2008; Padilla-Fernandez & Nuthall, 2009) and recently the double bootstrapped truncated regression analysis has been introduced into the DEA literature (Simar & Wilson, 2007). Examples of the latter are the studies by Latruffe *et al.* (2008a), Balcombe *et al.* (2008b), Picazo-Tadeo *et al.* (2011) and Gomez-Limon *et al.* (2012).

3.4.2 The type of farming systems and the selection of inputs and outputs

Depending on the type of farming under consideration, DEA research requires the adaption of sets of inputs and outputs of the model in order to successfully reflect the production process and evaluate the technical efficiency of the farming systems under analysis (Cooper *et al*., 2007). An important advantage of the DEA method is that inputs and outputs used for the analysis do not need to be analogous. More specifically, the units of measurement for the different inputs and outputs can be different. For example area farmed might be expressed in hectares, labour in annual working hours, water in cubic meters and farm output either in tonnes per hectare or in monetary terms (Cooper *et al*., 2007). In addition, DEA techniques allow the researcher to account for multiple inputs and outputs which is a common characteristic of farming systems.

A number of studies have used DEA techniques to evaluate the technical efficiency of mixed farming systems such as crop and livestock production (Chavas & Aliber, 1993; Färe *et al*., 1997; Brümmer, 2001; Latruffe *et al*., 2005; Davidova & Latruffe, 2007; Olson & Vu, 2007; Fletschner *et al*., 2010; Larsén, 2010). One of the assumptions of DEA is that the DMUs under evaluation must be homogenous which however, is not the case when analysing livestock and crop farming systems. Hence, in order to account for the non-homogeneity of the farming systems these studies have either used an aggregated monetary output (Brümmer, 2001; Latruffe *et al*., 2005) or they have considered a separate agricultural monetary output for each product (Davidova & Latruffe, 2007). It is very common, especially in the studies accounting for both livestock and crop production and generally in mixed crop production systems, to express the agricultural output in monetary terms (gross margin, sales, market value, etc.). Another common practice used to account for the non-homogeneity of farming systems producing multiple products is to express agricultural output as the separate physical amount of output for each product (tonnes or kg) (Färe *et al*., 1997). On the inputs side of the model the variables used to describe the technology are family or hired labour expressed either in monetary value or hours per year units, running costs (drying and heating energy, salaries, rent), feed and veterinary services costs, seed costs fertilisers and pesticides expressed either into physical units or in monetary value, capital investments into buildings or machinery, energy consumption costs, utilised agricultural area and other miscellaneous costs related to the production of crops or livestock. A similar set of inputs and outputs are used for DEA studies on arable farming systems (de Koeijer *et al*., 1999; de Koeijer *et al*., 2003; Zhengfei & Lansink, 2006) and also for single arable crops such as sugar beet (de Koeijer *et al*., 2002; Padilla-Fernandez & Nuthall, 2009) with the only difference for the latter case that output is measured in product (kg) rather than monetary terms.

The evaluation of technical efficiency for specialist livestock farms has been considered by a series of studies regarding the pig farming (Sharma *et al*., 1997; Sharma *et al*., 1999; Lansink & Reinhard, 2004; Asmild & Hougaard, 2006; Galanopoulos *et al*., 2006) and the beef sector (Latruffe *et al*., 2009).

The evaluation of the technical performance of farming systems producing single type crops such as;

- cereals (Piot-Lepetit *et al.*, 1997; Barnes *et al.*, 2009a);
- rice (Coelli *et al.*, 2002; Dhungana *et al.*, 2004; Balcombe *et al.*, 2008b);
- citrus (Reig-Martínez & Picazo-Tadeo, 2004; Picazo-Tadeo & Reig-Martínez, 2006; 2007);
- olives (Picazo-Tadeo *et al.*, 2011; Gomez-Limon *et al.*, 2012; Picazo-Tadeo *et al.*, 2012);
- and coffee (Garcia & Shively, 2011) was also considered by a number of DEA studies.

Common variables on the inputs side of these DEA models are the utilised agricultural area owned or rented in hectares, the aggregated or disaggregated amounts of fertilisers such as the amount or cost of nitrogen and phosphorous applied, seed costs, energy costs, the capital factor such as hours of used machinery, annual costs of capital, book value of machinery and inventory, depreciated value of total assets and other fixed capital costs. The outputs of these farming systems are expressed either in monetary value or physical amounts of production output (tonnes or kg).

Similar to the case of livestock farming systems, DEA studies evaluating the efficiency of dairy farms, are taking into consideration animal related inputs. Dairy production is commonly measured in hectolitres of milk (hl-100 litres) (Barnes, 2008; Buckley & Carney, 2013) or in milk production per cow (Fraser & Cordina, 1999; Theodoridis & Psychoudakis, 2008; D'Haese *et al.*, 2009). On the input side of the model common variables used are the total number of cows, the number of cows in lactation (D'Haese *et al.*, 2009), labour expressed in monetary terms, units or hours, variable costs of livestock, supplementary feeding including grains and pellets, fertilisers used on forage areas, land expressed in hectares and sometimes expressed as milking area which is equivalent to the perennial pasture land (Fraser & Cordina, 1999).

A number of DEA studies on farming systems focus on the efficient use of specific inputs such as the studies of water use efficiency on irrigation systems (Speelman *et al.*, 2008; Wang, 2010; Frija *et al.*, 2011; Chebil *et al.*, 2012). Most of these studies are based on a mixture of crops (Chemak, 2012) and hence, the agricultural production output is expressed in monetary terms. Water use at a farm level is accounted as an input expressed either in cubic meters or in total irrigation costs or per hectare of irrigated area.

When reviewing the literature, examples of other specialised DEA studies on rain-fed agriculture (Reig-Martínez *et al.*, 2011), organic farming (Lansink *et al.*, 2002; Sipiläinen *et al.*, 2008), greenhouses (Lansink & Silva, 2003; Frija *et al.*, 2009) and horticulture production (Iráizoz *et al.*, 2003) are also available.

The particular set of inputs and outputs identified for DEA studies thus depends on the evaluation context and the scope of the research. Especially in the case of the assessment of the environmental performance of farming systems researchers account for specific environmentally related factors treating them as inputs (e.g. nitrogen used), as desirable outputs (e.g. biodiversity) or as undesirable outputs (e.g. CO_2 emissions) depending on the nature of the variable. The main objective of these studies is to minimise the use of damaging inputs and undesirable outputs and to maintain the desirable outputs such as biodiversity. Examples of specific environmentally related inputs are nitrogen, phosphorus and potassium applied at a farm level (Reinhard *et al.*, 2000; de Koeijer *et al.*, 2002; de Koeijer *et al.*, 2003). In addition indexes of land erosion, biodiversity, pesticides risk, water use, nitrogen and energy used at a farm level are employed to assess the sustainability of farming systems in a range of research (Gomez-Limon & Sanchez-Fernandez, 2010; Picazo-Tadeo *et al.*, 2011; Reig-Martínez *et al.*, 2011; Gomez-Limon *et al.*, 2012; Picazo-Tadeo *et al.*, 2012).

3.4.3 The assumptions made on returns to scale for DEA models in the literature

While using DEA techniques to evaluate the performance of farming systems, two fundamental approaches can be considered based on the assumptions taken by the researchers on returns to scale: constant returns to scale (CRS) (the Charnes, Cooper and Rhodes (CCR) model (Charnes *et al.*, 1978)) and variable returns to scale (VRS) (the Banker, Charnes and Cooper (BCC) model (Banker *et al.*, 1984)). A significant number of DEA studies in agriculture consider both assumptions for the same data. The estimation of efficiency under CRS and VRS enables the decomposition of technical efficiency into pure technical and scale efficiency (Cooper *et al.*, 2007).

VRS (Banker *et al.*, 1984) are considered as the most appropriate assumption in the case of agriculture (Asmild & Hougaard, 2006; Lilienfeld & Asmild, 2007). The alternative CRS method assumes that when doubling all inputs, outputs will also double which is not a reasonable assumption in the case of agriculture. For example, a limiting production input is area farmed which is difficult to increase especially in the short run. However, CRS are used in agriculture when the objective is to estimate measures of scale and pure efficiency or in order to evaluate the change in efficiency and productivity over time with the calculation of the MI of TFP. This is mainly due to the nature of the models applied (Thirtle *et al.*, 2003; Balcombe *et al.*, 2008a; Odeck, 2009). When the objective is to evaluate the environmental performance of farming systems the majority of studies assume VRS since the proportionality between inputs and outputs (under the CRS assumption) is not valid for this context. An exception to the latter is when DEA techniques are used to estimate composite indicators of sustainability where the CRS assumption is more appropriate (Gomez-Limon *et al.*, 2012).

3.5 Critique on DEA techniques and applications in the Agricultural Sector

As it was stated in section 2.1 this research focuses on the application of the following DEA techniques/models i) the conventional DEA VRS and CRS model, ii) the non-discretionary or as it is known in the DEA literature, the sub-vector DEA model, iii) the Slack based DEA model and iv) the use of DEA linear programming techniques for the estimation of the MI of TFP. However, appropriate modifications and additions were considered in this research to overcome limitations of the above mentioned techniques.

In particular, in the case of the conventional DEA model due to the fact that efficiency estimates may be influenced by sampling variation, implying that the calculated distance functions to the frontier are likely to be underestimated we have considered the suggested by Simar and Wilson (1998; 2000) bootstrapped DEA estimates to correct for potential bias in the efficiency estimates of the GCF_s. In addition, this technique is also used in section 4.5.1 and uses the estimate confidence intervals for each estimated efficiency score to compare farms in the sample and also across different time periods. We need to emphasise that the Simar and Wilson (1998; 2000) method is used to develop statistical properties for the DEA efficiency estimates and to correct for any potential bias. However, the Simar and Wilson (1998; 2000) smoothed bootstrapped method is quite often confused in the literature with the Simar and Wilson (2007) double bootstrapped two stage DEA method used to account for the following: 1) serial correlation among the DEA estimates and 2) correlation of the inputs and outputs used in the first stage with second-stage environmental variables. Furthermore, we need to also stress that the double bootstrapped truncated regression model is used for the analysis of the impact of exogenous variables in the efficiency estimates and not to estimate efficiency scores. In addition, most researchers have used the Tobit model based on the observation that several efficiency estimates are equal to unity suggesting a mass probability at one. However, it is emphasised by Simar and Wilson (2007) that the true model describing the relationship between the efficiency estimates and the environmental factors does not have this property. Therefore, Simar and Wilson (2007) suggested that instead of the Tobit model, a double bootstrapped truncated regression should be used in the two-step contextual analysis. Hence for the purposes of this research in section 6.3.3 a truncated regression model has been used. Moreover, it is required to clarify that when the two stage DEA model is mentioned in this research that implies the use of DEA techniques on the first stage to estimate efficiency scores for each farm and a truncated regression model on the second stage to identify the factors influencing the performance of farming systems. Therefore, the latter should not be confused with the two stage DEA model where we first used the DEA linear programme to minimise θ and then having done this to maximise the sum of the slack values given the calculated efficiency level as it is later explained in section 6.3.2.2.

However, the Simar and Wilson (2007) double bootstrapped truncated regression approach is not appropriate when MI of TFP is estimated at the first stage. The reason is that the MI of TFP takes values greater, equal or less than unity. Hence, the assumption that efficiency scores are truncated at zero or unity is not valid at this case. This approach was used in Odeck (2009).

Furthermore, a number of researchers (Lilienfeld and Asmild, 2007); Piesse *et al.*, 1996) have considered rainfall as an input variable in an input orientated DEA model or input orientated MI of TFP. Hence, in this case it is assumed that the farm manager has the ability to decide over the amount of rainfall at the specific period under consideration. An assumption which is not realistic. In this thesis we emphasise that i) rainfall can be used in the input side of the DEA linear programming unless the appropriate constraints are set (rainfall is treated as a non-discretionary (fixed) variable) and ii) the sub-vector model can be used to account for external factors that have an influence on the performance of farming systems (i.e. rainfall on yield).

In addition, a series of studies on agricultural productivity have used the MI of TFP estimated with DEA techniques (Piesse *et al.*, 1996; Coelli and Rao, 2003; Coelli *et al.*, 2006; Rezitis *et al.* 2009) however only few of them have accounted for bias in the data (Odeck, 2009; Olson, 2009). In this thesis, a consistent method using a bivariate kernel density estimate that accounts for the temporal correlation via the covariance matrix of data from adjustment years is used as it is proposed by Simar and Wilson (1999). The bootstrapped estimates of the distance functions allows for the calculation of a set of MI of TFP which enables to account for the bias and to construct confidence intervals. The latter are used for statistical inference of the MI of TFP and its components in section 4.5.2.

Finally, the majority of the studies presented in the literature review ignores the existence of influential DMUs in the sample and thus none has performed any of the diagnostic tests in the literature. Moreover, since few of them have estimated bias and also the presence of outliers is ignored then results on efficiency might be misleading. This was concluded for a number of studies in Wilson (1995). In section, 2.7 a method for detecting outliers in deterministic non-parametric frontier models with multiple outputs is presented and used to identify outliers in the models used in Chapters 5 and 6.

3.6 Foreseen developments of DEA techniques in Agriculture

The use of DEA linear programming models in agriculture to measure performance or productivity of farming systems is becoming more and more popular. The review of the literature revealed that the two-step contextual analysis is gradually becoming a trend in the agriculture and farm area as well as works related to network DEA.

Looking in the future of applications in agriculture, those will be based on the development of DEA methodologies. Recent innovations on methodologies include DEA with streaming data (Dulá & López, 2013) a general two-stage network DEA based on game approach (Li *et al.*, 2012), super-efficiency based on a modified directional distance function (Chen *et al.*, 2013), and a new slack-based super-efficiency model (Fang *et al.*, 2013). On the other hand, there are many innovative applications that adopt new DEA methodologies. These include studies in risk management problems applying three-stage network DEA (Matthews, 2013), and environment issues using latent variable model and range adjusted measure (Bretholt & Pan, 2013). A detailed presentation of the most current trends in DEA literature for the various industries and not only for agriculture is available in (Liu *et al.*, 2013b).

3.7 Summary

In this chapter DEA literature on agriculture has been reviewed in order to provide a further insight in terms of the development paths of the method, the main methodological approaches adopted, the fields of applications and the general model specifications.

The main focus of DEA studies in agriculture has been in identifying sources of inefficiency for farming systems and ranking them relative to their performance, evaluating farm management practices, measuring the impact of agricultural policies and improving the environmental performance of farming systems. Moreover, a series of studies use DEA techniques to evaluate the performance of farms, regions or countries over a period of time. DEA techniques were first adopted in agriculture by Färe *et al.* (1985a) and soon became a popular method for agricultural efficiency studies. The early research studies on the agricultural sector used classical DEA models (CCR and BCC) emphasising the flexibility of the method and its usefulness. After the establishment of the main path of DEA studies by Färe *et al.* (1985a), Chavas and Aliber (1993) and Coelli (1995), researchers started to adopt newly developed approaches and DEA models once they became available and expand their use in agricultural studies. The most recent development path is the adoption of the two-step contextual analysis which first obtains efficiency estimates and then correlates these with various contextual factors through regression analysis (Liu *et al.*, 2013a).

In terms of the general characteristics of the DEA studies, the literature review revealed a broad application of the method in different countries around the world. A common source of data, especially for studies in European countries, is the Farm Accountancy Data Network and its equivalent databases in member states of the EU, such as the Farm Business Survey in England. Other sources of data are databases from ministries of agriculture, statistical institutions and surveys conducted by researchers themselves. The most common field of application of DEA techniques is in the evaluation of the technical efficiency of agricultural systems. Other common fields of interest emphasise the evaluation of productivity, financial management, sustainability and environmental performance of farming systems.

Commonly used DEA models in the agricultural sector are the additive model (Haag *et al.*, 1992), the allocative efficiency models (Färe *et al.*, 1997), the sub-vector model (Piot-Lepetit & Vermersch, 1998; Lansink *et al.*, 2002; Asmild & Hougaard, 2006; Lilienfeld & Asmild, 2007), the bootstrapped DEA models (Gocht & Balcombe, 2006; Balcombe *et al.*, 2008b; Latruffe *et al.*, 2008a; 2008b), weight restricted models (Garcia & Shively, 2011) and the use of DEA techniques to calculate the MI of TFP (Balcombe *et al.*, 2008a; Odeck, 2009). A recent prevailing approach in the DEA literature is the adoption of the two-step contextual analysis to estimate the drivers of efficiency (Dhungana *et al.*, 2004; Galanopoulos *et al.*, 2006; Balcombe *et al.*, 2008b; Speelman *et al.*, 2009; Fletschner *et al.*, 2010).

Finally, although the selection of the set of inputs and outputs depends on the scope of the study and the agricultural sector involved (dairy, cereals, arable, livestock etc.) it is possible to identify some common inputs and outputs taken into consideration for the vast majority of the studies. Agricultural production in DEA models is expressed either in physical units (tonnes, kg, hl, etc.) or in monetary terms. On the input side of the model utilised agricultural area, labour, variable costs and capital are the most commonly used variables.

In conclusion, DEA is a well-established non-parametric method used in agricultural studies in order to evaluate the performance of farming systems. The flexibility of DEA techniques to account for multiple inputs and outputs and the various model specifications which allow the evaluation of efficiency for specific inputs and the environmental performance of farms are the main reasons to adopt this method for the objectives of this research presented in Chapter 1.

In particular, this chapter aimed to review the DEA methods and applications in relation to productivity analysis and the use of DEA techniques to measure the MI of TFP (Chapter 4), the choice of a sub-vector DEA model to assess water use efficiency at a farm level (Chapter 5) and the use of DEA techniques and the importance of the additive model to measure composite indicators in order to assess the environmental performance of farming systems (Chapter 6). The main objective of the chapter was to provide the reader with all the developments of DEA techniques related to the selection of the models in the subsequent chapters in Part II of the thesis and also to present the relative specifications of the methods in agricultural studies.

Part II

Part II consists of three chapters providing empirical evidence on the explanation of agricultural productivity, the excess in water use efficiency and the evaluation of the SI of farming systems.

Chapter 4

Assessing productivity of farming systems over time

4.1 Introduction

As shown in Chapter 1, one of the main objectives of farming systems in the context of SI is to increase agricultural productivity in order to meet the increasing food demand. In the case of GCF_s in the EARBC, the increased risk of summer droughts and higher temperatures due to climate change is also a challenge with a direct impact on farm productivity. In the present Chapter a Malmquist Index (MI) of TFP is used to measure changes in productivity for the period 2007-2011 focusing especially on the component of technical efficiency change in order to discuss the impact of the extreme weather phenomena of 2007 (floods) and 2010-2011 (drought) on agricultural productivity. Furthermore, the importance of exogenous parameters, such as rainfall, on technical efficiency estimation through DEA techniques is also investigated. The DEA linear programming used for the estimation of the MI of TFP, the Sub-Vector DEA model and Scale Efficiency are presented in sections 2.5, 2.3.4, and 2.4 respectively.

4.2 Measuring Total Factor Productivity in the UK

Measurements of Total Factor Productivity (TFP) growth have been widely used in agriculture as a quantitative economic instrument enabling the evaluation of the production performance of farming systems in subsequent periods (Melfou *et al.*, 2013). The decomposition of TFP into the efficiency and technical index components and the observation of the trends in consecutive years, contribute to the design of targeted policies aiming to improve agricultural productivity and sustainable development.

Two of the most important challenges for the future growth of agricultural systems globally are climate change and increased food demand. Global food demand is likely to increase by 70% by 2050 due to both population growth and changes in consumption patterns (Foresight Report, 2011). On the other hand, the impacts of climate change will vary globally and at a national level both in magnitude and nature (positive and negative effects) (Falloon & Betts, 2010).

Changes in rainfall and temperature will have a significant impact on agricultural production for the UK and hence they will influence the way that crops develop, grow and yield (Murphy *et al.*, 2009; Knox *et al.*, 2010). Furthermore, there will also be indirect impacts such as the increased risk and spread of pests and diseases and the suitability of land for agricultural production, especially in parts of East Anglia due to saltwater intrusion and flooding from sea level rise (Knox *et al.*, 2010).

Recent extreme weather phenomena in the UK during the period of 2007-2013, such as the floods of 2007, the drought period of 2010 and 2011 and the subsequent floods of 2012 and 2013, had an impact on TFP[9] recorded by the Department for the Environment, Food and Rural Affairs (Defra). Specifically, TFP in 2007[10] was at its lowest level during the aforementioned period (98.2) and has fallen by 2.9% for the period 2011-2012 (98.7) reaching the levels of 2007. According to Defra (2013b) the main reasons for the variation in TFP estimates between years are factors outside the control of farmers such as extreme weather phenomena and disease outbreaks.

In the case of the EARBC increased temperatures and reduced precipitation will have direct impacts on the hydrological structure of the area (Environment Agency, 2008; Defra, 2009; Environment Agency, 2011) due to increased water abstraction rates for agriculture and decreased water availability. Both climate change and the reduction in natural resources will negatively influence the growth of TFP in the EARBC. Hence the desire for a secure food supply, efficient management of natural resources, resilience to more frequent extreme weather phenomena and development of adaptation strategies for farmers has prioritised the need for the sustainable intensification (SI) of agriculture (FAO, 2011; Foresight Report, 2011). Firbank *et al.* (2013), define SI at farm level as the process of increasing agricultural production per unit of input whilst at the same time ensuring that environmental pressures generated at a farm level are minimised. Thus, the main priority under the framework of SI is the increase in productivity of farming systems.

Productivity is defined as a measure of the rate of output produced given a unit of input used in the production process (partial productivity). However, TFP is a more comprehensive measure relying on the ratio of an index of aggregated outputs to an index of aggregated inputs. According to production theory, the determinants of the rate of output are based on the technology used, the quantity and quality of the production factors and the efficiency with which these factors are employed in the production function (Melfou *et al.*, 2013). Thus, any divergence in TFP growth is the result of the net effect of changes in efficiency, shifts in the production frontier and the scale of production (Färe *et al.*, 1992).

A series of studies have explored the TFP of the agricultural industry in the UK. Defra releases an annual report on TFP of the UK agricultural industry based on the estimation of an ideal Fisher index, which is the geometric mean of the Laspeyres and Paache indices. Thirtle *et al.* (2008) provided a TFP in UK agriculture from 1995-2005 based on a Tornqvist-Theil TFP index (Thirtle *et al.*, 2004) in an effort to explain the decline in TFP as a function of the lag in research and development (public and private) and to returns to scale. This index reveals almost 2% growth in TFP per year up until 1983 and then for the remaining 18 years this fell to 0.2%. Moreover, the level of TFP for the UK post 1983 had fallen behind the EU leading countries (Thirtle *et al.*, 2008). The Tornqvist-Theil TFP index was also used by Barnes (2002) and was modified to include the

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[9] Defra produces an annual publication on the TFP estimate of the UK agricultural industry providing information on output and input volume indices. The estimates of TFP are used to inform policy makers and stakeholders of the economic performance of the agricultural industry and also to measure the impact of government policies and interventions.

[10] Base year 2010=100

environmental and social costs of agricultural productivity for the construction of a social TFP index. Furthermore, Amadi *et al.* (2004) extended the work of Thirtle (1999) by constructing and measuring Tornqvist-Theil TFP indices for potatoes, oilseed rape, winter wheat and spring barley, as well as sugar for the East counties of the UK using data from 1970 to 1997. Renwick *et al.* (2005) also used the Tornqvist-Theil TFP index to measure changes in the productivity of farms in different regions of the UK due to reform of the sugar beet regime. This analysis showed a slight decrease in the productivity of individual farms during 1994-2002.

In addition, Hadley (2006) used farm level data for the estimation of stochastic frontier functions to measure differences in the relative efficiency of 8 different farms types in the UK for the period 1982-2002. The results illustrate that most of the farms are operating close to the technical efficiency frontier and that technical change has played a key role in the increase of efficiency over this 20 year period especially in the most specialised arable farms. In a similar manner, Barnes *et al.* (2010) made comparisons of technical efficiency for different farming systems across England and Wales reporting a general upward trend in technical efficiency throughout the period. English and Welsh general cropping farms have a reported mean of technical efficiency of 0.74 although with considerable variation around the mean (Hadley, 2006). Earlier studies on technical efficiency include Dawson (1985), Wilson *et al.* (1998), and Wilson *et al.* (2001).

4.2.1 Objectives

Agricultural production is sensitive to variations in climate conditions and especially extreme weather phenomena. Changes in yield patterns due to natural causes have an impact on both farmers' incomes and food prices. Therefore, increasing resilience to the extremes requires improvement of technical efficiency, adaptation of management strategies to mitigate the impacts, and improvement of productivity.

Hence, the analysis performed aims to answer the extent to which the recent extreme weather phenomena of 2007 (floods) and 2010, 2011 (drought) had an impact on technical efficiency at a farm level in the EARBC and also to measure changes in agricultural productivity for the same period.

A conventional and a sub-vector Data Envelopment Analysis (DEA) model are used in order to compare technical efficiency estimates at a farm level when the variations in the characteristics of the physical environment (rainfall) are considered or not in the specifications of the linear programming. Not accounting for the physical environment of farming systems is a major pitfall in benchmarking methods like DEA, and biases performance measurements (Dyson *et al.*, 2001). The advantage of the sub-vector model (rainfall variations are considered), is that it ensures the comparison of farms in a homogenous environment where the variation in rainfall levels between different farms is considered. The two models are compared in terms of farm ranking, and to the set of peers assigned for benchmarking for the individual farms in the sample.

Further, a Malmquist Index (MI) of TFP is used to measure changes in productivity for the period 2007-2011. Specifically, attention is drawn to the 2010-2011 period where lower than average levels of rainfall were recorded. The decomposition of the MI into its components and especially the Technical Efficiency change index will allow the estimation of the impact of drought in the EARBC (Piesse *et al.*, 1996). The MI is more robust to the Tornqvist-Theil method used in previous studies in the UK since it is possible to separate technical (the movement of the best practice frontier) and efficiency change (the distance of farms from the frontier). Thus, it is possible to identify if exogenous factors such as research and development or weather phenomena have an impact on the frontier or if technical changes were followed up by similar or not efficiency changes (Piesse & Thirtle, 2010a). For example, it allows estimation of whether an outward shift of the technological frontier was followed up by farms improving their efficiency and hence reducing their distance to the new frontier. Moreover, the MI offers the advantage that multi-input and multi-output technologies can be estimated even in the absence of price data. In addition, we use the methodology proposed by Simar and Wilson (1998b; 1999; 2000) to estimate and bootstrap Malmquist Indices in order to determine whether differences between two or more estimates are statistically significant.

The MI of TFP is further decomposed into technical and efficiency change as proposed by Färe *et al.* (1992). In addition, the index of efficiency change is disaggregated into pure efficiency and scale efficiency change which allows discussion of the importance of farm size and returns to scale over time. Moreover, Simar and Wilson (1998a) have proposed the decomposition of the technical efficiency component of the MI into the pure technical and scale efficiency change that also allows the consideration of returns to scale when shifts of the best performing frontier are accounted for.

4.3 Overview of the EARBC and data requirements

The climate in East Anglia is characterised by an annual rainfall around 620mm per year and includes some of the driest areas in the UK[11]. Furthermore, the EARBC has been characterised as one of the most vulnerable areas in the UK in terms of climate change (Environment Agency, 2008; Defra, 2009; Environment Agency, 2011). This mainly impacts on both land suitability and productivity (yield and crop quality). In addition, projected reduced levels of rainfall and evapotranspiration would increase demand for supplemental irrigation, particularly in high value crops such as potatoes and sugar beet, and hence would increase the demand for water resources in an already over abstracted catchment[12].

Data for the empirical application of the model come from a representative[13] sample of 41 General Cropping Farms (GCF_s)[14] over the period 2007-2011. The data have been obtained from the Farm Business Survey

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[11] Met Office: Regional climate: Eastern England - Climate. Available online at:
http://www.metoffice.gov.uk/climate/uk/ee/ : Accessed on 10.02.2014

[12] The UK Climate Change Risk Assessment 2012: Evidence Report. Available online at:
http://www.defra.gov.uk/environment/climate/government/ : Accessed 10.02.2014

[13] The Farm Business Survey uses a sample of farms that is representative of the national population of farms in terms of farm type, farm size and regional location (FBS – Statistical Information;
http://www.farmbusinesssurvey.co.uk/

[14] As GCF_s are classified holdings on which arable crops (including field scale vegetables) account for more than two thirds of their total Standard Output (SO) excluding holdings classified as cereals; holdings on which a mixture of arable and horticultural crops account for more than two thirds of their total SO excluding holdings classified as

(FBS)[15] which is a comprehensive and detailed database that provides information on the physical and economic performance of farm businesses in England. The selection of this subset of GCF_s ensures that the sample is homogenous in terms of crop mix and environmental conditions and thus makes it possible to compare performances over time. The 41 GCF_s selected over a 5 year period yields a panel dataset with 205 observations available for efficiency assessment. For the evaluation of the MI of TFP this provides 164 observations (since the analysis utilises data from two adjacent years at a time).

The production technology for the estimation of technical and sub-vector efficiency, as well as the MI of TFP, was defined by the area farmed, crop costs (including fertiliser, crop protection, seed and other agricultural costs), other machinery costs[16], total labour input (hours per year), rainfall and water cost per farm including water for irrigation and water used for all agricultural purposes. The outputs identified in the analysis are cash crop and cereal yield. Cash crop production is calculated through the FBS and is equal to the sum of potato and sugar beet production.

Rainfall data from 147 National Flow River Archive (NFRA) gauging stations in the EARBC over the 2007-2011 period and the relevant information on the 10km grid reference for the GCF_s in the sample were used to assign an average rainfall level per year per farm. The use of rainfall as an input in the production function enables the accounting of variations in the environmental conditions between farms in the sample, and also allows assessment of the impacts of the 2011 drought on the technical efficiency of the GCF_s. However, it is treated in the analysis as a variable over which farmers have no management control (a non-discretionary input variable).

All inputs expressed in £/ha for the period 2007-2011 have been deflated, using indices based on 2005 published by the Department for Environment, Food and Rural Affairs (DEFRA) (API – Index of the purchase prices of the means of agricultural production – dataset (2005=100))[17]. Specifically, the following indexes have been used: Fertilisers and soil improvement index, seeds index, plant protection products index, farm machinery and installation index, other costs index. The indexes have been selected according to the relevance of the data aggregated at a farm level through the FBS.

Table 4.1 presents a description of the sample used to build the input and output DEA models for the estimation of the conventional and sub-vector DEA models and the MI of TFP. The final row provides

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horticulture and holdings on which arable crops account for more than one third of their total SO and no other grouping accounts for more than one third. (FBS 2009-2010).

[15] For further information about the Farm Business Survey, including data collection, methodology and Farm Business Survey results, please visit the Defra Farm Business Survey website: http://www.defra.gov.uk/statistics/foodfarm/farmmanage/fbs/

[16] This variable includes, among other costs, equipment related to irrigation, sprayers and equipment related to green technology. It includes costs related to potato boxes, potato graders and other machinery related to production of the specific crops included in the selected outputs.

[17] Index of Producer Prices of Agricultural Products, UK (2005=100), publication date - 18 July 2013. Available online: https://www.gov.uk/government/publications/agricultural-price-indices

information on the average percentage change in volumes of inputs and outputs for the 5 year period. The mean output for both cash crops and cereals grew by 11.33% and by 2.6% respectively. However, it is interesting to note that between 2010 and 2011, cereal yield dropped by 9% while the cash crop yield increased by 22%. The latter is related to the warmer conditions in 2011 which favour sugar beet and potato yield (when irrigation is available). Both cash crops and cereals yields were lowest during 2007 and respectively the maximum during 2009. Farmed area and the annual labour hours have a small variation across the 5 year period recording a 0.4% and 1.1% increase respectively. The input with the highest average increase in £/ha over the years is water; however there is no difference in the variation during the years. The same conclusion can be drawn for machinery and crop costs that recorded an average increase of 5.9% and 3.8% over the years. The only input decreasing during the years is rainfall (-6.3%). The lowest mean of rainfall in the sample is observed in 2011 (453mm) while the highest is observed in 2008 (707mm).

Table 4.1: Descriptive statistics of the inputs and outputs used in the DEA linear programming model for the estimation of efficiency and the MI of TFP

	Farmed area (ha)	Labour (annual hours)	Water cost (£/ha)	Machinery cost (£/ha)	Crop costs (£/ha)	Rainfall[1] (mm)	Cash crops (tonnes/ha)	Cereal (tonnes/ha)
Mean	331	8364	9	70	378	593	57	8
St. Deviation	467	13868	9	51	136	53	15	2
Minimum	23	960	0	5	203	525	20	3
Maximum	2204	67381	35	216	840	763	92	10
Average % change in mean per year	1.1	0.4	7.7	5.9	3.8	-6.3	11.3	2.6

[1] Rainfall is used only for the estimation of the sub-vector efficiency DEA model

4.4 Methodology

In the first part of the analysis a conventional and a sub-vector DEA model are used to explore the importance of exogenous factors such as rainfall in the estimation of technical efficiency of farming systems, while the Malmquist Index (MI) of total factor productivity (TFP) is employed in the second part to explore changes in productivity for the GCF_s in the EARBC.

4.4.1 The input oriented conventional and sub-vector DEA models

The input orientated framework for DEA with Variable Returns to Scale (VRS) is adopted since the focus of the analysis is to estimate impacts of rainfall variability in the technical efficiency of GCF_s in the EARBC. Efficiency scores indicate the total potential reduction for each input level while maintaining individual levels of outputs constant. Rainfall is considered in the input side of the model due to its direct influence on production yields. However, since this is an input variable not under the control of farmers, appropriate adjustments are made to the linear programming in order to account for rainfall as a non-discretionary input.

The VRS approach (Banker *et al*., 1984) was considered as the most appropriate in the case of agriculture (Asmild & Hougaard, 2006; Lilienfeld & Asmild, 2007). The alternative would have been to choose Constant Returns to Scale (CRS) assuming that when doubling all inputs, outputs will also double which is not a reasonable assumption in the case of agriculture. For example, a limiting production input is area farmed which is difficult to increase especially in the short run.

Furthermore, since the purpose of this part of the analysis is to assess differences in technical efficiency estimates when accounting or not for rainfall variation, the results of two DEA models are compared. Therefore, a conventional DEA and a non-discretionary or sub-vector DEA model are used to evaluate and compare input use efficiency estimates for General Cropping Farms (GCF_s) in the EARBC. The linear programming as well as the properties of both the conventional and the non-discretionary DEA model are in detailed described in sections 2.3.3 and 2.3.4 of this thesis. For the purposes of this chapter the general and the sub-vector form of an input oriented DEA linear programming are repeated for the

To formalise the above let us assume that we observe a set of n farms and each farm $i = \{1, .., n\}$ has a set of inputs and outputs representing multiple performance measures. Considering then that each farm i uses J $(j = 1, \cdots, J)$ inputs, x_j to produce s outputs y_r $(r = 1, \cdots, s)$.

The general form of an input oriented DEA linear programming (conventional DEA model) with all inputs variable as it was presented in section 2.3 of this thesis is as follows:

$$
\begin{aligned}
& \min_{\theta,\lambda^i} \theta' \\
& s.t. \quad \theta x'_{ji} \geq \textstyle\sum_{i=1}^{n} \lambda^i x_{ji} && (i) \\
& \qquad y'_{ri} \leq \textstyle\sum_{i=1}^{n} \lambda^i y_{ri} && (ii) \\
& \qquad \lambda^i \geq 0 && (iii) \\
& \qquad \textstyle\sum_{i-1}^{n} \lambda^i = 1 && (iv)
\end{aligned}
\qquad \textbf{(4.1)}
$$

Where θ' is a scalar, representing the efficiency score for each of the n farms. The estimate will satisfy the restriction $\theta_i \leq 1$ with the value $\theta_i = 1$ indicating an efficient farm. This is because the ratio is formed relative to the Euclidean distance from the origin over the production possibility set.

The above linear programming can be then used as it is described in section 2.3.4 to estimate the sub-vector input orientated DEA linear programming.

$$
\begin{aligned}
& \min_{\theta,\lambda^i} \theta' \\
& s.t. \quad \theta x'_{DIji} \geq \textstyle\sum_{i=1}^{n} \lambda^i x_{DIji} && j \in DI \quad (i) \\
& \qquad -x'_{NDIji} \geq \textstyle\sum_{i=1}^{n} \lambda^i (-x_{NDIji}) && j \in NDI \quad (ii) \\
& \qquad y'_{ri} \leq \textstyle\sum_{i=1}^{n} \lambda^i y_{ri} && (iii) \\
& \qquad \lambda^i \geq 0 && (iv) \\
& \qquad \textstyle\sum_{i-1}^{n} \lambda^i = 1 && (v)
\end{aligned}
\qquad \textbf{(4.2)}
$$

Where, x_{DIji} is the j^{th} discretionary input for farm i, x_{NDIji} is the j^{th} non-discretionary input for farm i and y_{ri} is the r^{th} output for farm , $i = (1, \cdots n),\ j = (1, \cdots m)\ and\ r = (1, \cdots s)$. The optimal value θ represents the sub-vector efficiency score for each farm and its values lie between 0 and 1. This efficiency score indicates the degree to which a farm is able to reduce the use of its discretionary inputs without decreasing the level of outputs with reference to the best performers or benchmarking farms in the sample. The first two constraints limit the proportional decrease in both discretionary (equation - $4.2_{(i)}$) and non-discretionary (equation - $4.2_{(ii)}$) inputs, when θ is minimised in relation to the input use achieved by the best observed technology. The third constraint ensures that the output generated by the i^{th} farm is less than that on the frontier. All three constraints ensure that the optimal solution belongs to the production possibility set. The final constraint expressed by the equation $4.2_{(iv)}$, called also the convexity constraint, ensures the VRS assumption of the DEA sub-vector model. The CRS and VRS models differ only in that the former, but not the latter includes the convexity condition described by the equation $4.2_{(iv)}$ and its constrains in $4.2_{(v)}$ (Cooper *et al.*, 2006).

An analysis on returns to scale was also performed in order to determine whether the farms in the sample are operating under Increasing Returns of Scale (IRS), Decreasing Returns of Scale (DRS) and Constant Returns of Scale (CRS). Measures of Scale Efficiency (SE), Pure Technical Efficiency (PTE) and Overall Technical Efficiency were estimated according to the method presented in section 2.4 of this thesis.

The rationale behind using both the sub-vector and the conventional DEA models is to compare technical efficiency estimates at a farm level when the variations in the characteristics of the physical environment (rainfall) are considered or not in the specifications of the linear programming. The assumption behind this is that accounting for environmental variations in DEA models will reduce bias in performance measures where the external environment can potentially have a direct impact on performance (rainfall direct impact to yield).

The advantage of the sub-vector model (rainfall variations are considered), is that it ensures the comparison of farms in a homogenous environment where the variation in rainfall levels between different farms is considered. The two models are compared in terms of farm ranking, and to the set of peers assigned for benchmarking for the individual farms in the sample.

In particular, Spearman's rho correlation test is used to identify the impact of the inclusion of rainfall as a non-discretionary input in the estimation of technical efficiency scores for the farm in the sample. The Spearman's rho correlation test is used here as a non-parametric measure of correlation since the efficiency scores derived from both the conventional and the sub-vector models are skewed.

Spearman's rho is the Pearson's correlation coefficient that would occur if we used the ranks of the scores of the two paired efficiency scores as the data, rather than the scores themselves. For a strong correlation we expect that each farm will receive the same efficiency score on one model as will do on the other. Hence, each farms position (i.e. the rank) on one model will be similar to the position of the other. The rationale for the Spearman correlation coefficient is that differences between all pairs of rank will be small when there is high positive correlation. More specifically, it is expected that farms which have the higher rank on the other model and respectively when they have a low rank. This then means that the difference between each person's pair of ranks should be low or even zero, if there is a strong correlation.

In particular the Spearman rho (ρ) correlation coefficient is measured as follows:

For a sample size of n, the n raw scores X_i, Y_i are converted to ranks x_i, y_i, and ρ is computed from:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

Where $d_i = x_i - y_i$, is the difference between ranks and $\rho \in (1, -1)$.

A number of studies have used Spearman's rho to compare DEA models under different assumptions of returns to scale (i.e. VRS, CRS, DRS) (Giuffrida and Gravelle, 1999; Speelman et al., 2008; Frija et al., 2009; Chemak, 2012). In the present thesis, Spearman's rho is used to conclude on the impact that the inclusion of a fixed (non-discretionary) variable will have on the ranking of the farms and hence to the measurement of their performance. By treating rainfall as a fixed variable on the input side of the DEA model the peer set of each farm is improved. Hence, the two models can be compared under the assumption that the input mix for the conventional and the sub-vector has not changed. Efficiency measures will be used for the equiproportional reductions of the same set of inputs for the two models.

4.4.2 The Malmquist index of total factor productivity

The Malmquist index (MI) of total factor productivity (TFP) (presented in detail in section 2.5 of this thesis), introduced by Caves *et al.* (1982a) and further developed by Färe *et al.* (1992) is based on the estimation of distance functions. For the purposes of the analysis an input orientation Malmquist index is adopted since farmers have more control over the adjustment and efficient use of inputs rather than the expansion of output (Balcombe *et al.*, 2008a). Specifically the MI between period t and $t+1$ is defined as the ratio of the distance function for each period relative to a common technology. Therefore, the MI based on an input distance function is defined as:

$$M_I^t = \frac{D_I^t(x^{t+1}, y^{t+1})}{D_I^t(x^t, y^t)} \quad \textbf{(4.3)}$$

Equation (4.3) is expressing the ratio between the input-distance function for a farm observed at period $t+1$ and t, respectively, and measured against the technology at period t. Values of the $M_I < 1$ indicate negative changes in TFP, values of the $M_I > 1$ indicate positive changes in TFP while values of $M_I = 1$ indicate no change in productivity.

However, since the choice of period t or $t+1$ as the base year is arbitrary (i.e. the base year can be either period t or period $t+1$) Färe *et al.* (1992) defined the MI of TFP as the geometric mean of the t and $t+1$ Malmquist indices. Therefore, for each farm the input orientation Malmquist index is expressed as follows:

$$M_I^{t,t+1} = \left[\frac{D_I^{t+1}(x^{t+1}, y^{t+1})}{D_I^t(x^t, y^t)} \frac{D_I^t(x^{t+1}, y^{t+1})}{D_I^{t+1}(x^t, y^t)}\right]^{1/2} \quad \textbf{(4.4)}$$

Where $M_I^{t,t+1}$ refers to the MI of TFP from period t to period $t+1$; (x^t, y^t) is the farm input-output vector in the t^{th} period; $D_I^t(x^{t+1}, y^{t+1}) = max\left\{\theta > 0{:}\left(x^{t+1}/_{\theta}\right) \in P\right\}$ is the input distance from the observation in the $t+1$ period to the technology frontier of the t^{th} period with $P(y^{t+1})$ the input set at the $t+1$ period and θ is a scalar equal to the efficiency score. The indices are calculated with the use of the nonparametric DEA method in order to construct a piecewise frontier that envelopes the data points (Charnes *et al.*, 1978). The technology assumption made to estimate the MI of TFP is CRS. Otherwise, the presence of non-CRS does not accurately measure productivity change (Grifell-Tatjé & Lovell, 1995). The main advantage of the DEA method is that it avoids misspecification errors and it enables the investigation of changes in productivity in a multi-output, multi-input case simultaneously (Balcombe *et al.*, 2008a). Furthermore, the use of the DEA method for the estimation of the MI of TFP makes it easy to compute since DEA does not require information on prices.

In addition, the index in equation (4.4) can be decomposed into two components: efficiency change and technological change

$$M_I^{t,t+1} = \underbrace{\frac{D_I^{t+1}(x^{t+1}, y^{t+1})}{D_I^t(x^t, y^t)}}_{\Delta Eff} * \underbrace{\left[\frac{D_I^t(x^{t+1}, y^{t+1})}{D_I^{t+1}(x^{t+1}, y^{t+1})} \frac{D_I^t(x^t, y^t)}{D_I^{t+1}(x^t, y^t)}\right]^{1/2}}_{\Delta Tech} \tag{4.5}$$

The first part of equation (4.5) is an index of relative technical efficiency change (ΔEff) showing how much closer (or farther) a farm gets to the best practice frontier. It measures the "catch up" effect (Färe *et al.*, 1992). The second component is an index of technical change ($\Delta Tech$) and measures how much the frontier shifts. Both components take values more, less or equal to unity as it is the case of the MI of TFP indicating improvement, deterioration and stagnation respectively. For a detailed presentation of the estimation of the different components with the aid of DEA and the decomposition of the index please refer to sections 2.5.1, 2.5.2and 2.5.3 respectively.

4.4.3 Statistical inference for MI of TFP and their components

Despite the significant advantages of DEA for the calculation of the MI of TFP we need to consider the fact that the estimates of productivity may be affected by sampling variation. In other words, it is possible to underestimate the distance functions to the frontier if the best performing farms in the population are excluded from the sample (Simar & Wilson, 1999; Balcombe *et al.*, 2008a). To overcome this shortcoming (Simar & Wilson, 1998b; 1999) proposed a bootstrapping method for the construction of confidence intervals for the DEA efficiency estimates relying on smoothing the empirical distribution. The rationale behind bootstrapping is to simulate the true sampling distribution by mimicking the data generation process (DGP) (Balcombe *et al.*, 2008b). Through the DGP a pseudo-data set is constructed which is then used for the re-estimation of the DEA distance functions. Increasing the bootstrapped replicates (more than 2000 (Simar & Wilson, 1998b)) allows for a good approximation of the true distribution of the sampling.

Simar and Wilson (1999) adapted the bootstrapped procedure for the estimation of the MI of TFP in order to account for possible temporal correlation arising from the panel data characteristics (Balcombe *et al.*, 2008a). Specifically, they proposed a consistent method using a bivariate kernel density estimate that accounts for the temporal correlation via the covariance matrix of data from adjustment years. The bootstrapped estimates of the distance functions allow the calculation of a set of MI of TFP which accounts for the bias and enables the estimation of confidence intervals. The latter are used for statistical inference of the MI of the TFP and its components. A detailed presentation for the estimation and bootstrapping of MI is available in Simar and Wilson (1999) and also in Chapter 2 section 2.6.2 of this Thesis.

4.5 Results

4.5.1 Analysis of technical efficiency, scale efficiency and returns to scale

The average technical efficiency over the 5 year period under consideration ranges between 0.84-0.89 for the sub-vector model (rainfall adjusted) and between 0.84-0.87 for the conventional DEA model. Table 4.2 provides information on the distribution of technical efficiency for the two models and the mean efficiency for each year. Comparing the distribution of farms in relation to the frontier it can be noted that the distribution of the farms in the sub-vector model became increasingly skewed towards the higher efficiency rankings. This is presented in Figure 4.2 where the kernel density estimate for the 5-year mean of efficiency scores of the two models is plotted. This is mainly due to the inclusion of rainfall in the model as a non-discretionary input variable which ensures that each farm is only compared with other farms in the sample with the same environmental conditions. The rainfall adjusted model slightly increases the technical efficiency score for the farms that were previously benchmarked within an unfavourable environment (higher rainfall level) but is unchanged for the remaining farms in the sample as has also been observed by Henderson and Kingwell (2005). The overall mean efficiency score for all 5 years is 0.87 and 0.85 for the sub-vector and the conventional model respectively. This implies that when rainfall is accounted in the model, the proportional input potential saving is 13% rather than 15% as it is indicated by the conventional model.

Table 4.2: Distribution of technical efficiency for the conventional and the rainfall adjusted DEA models

	Rainfall adjusted DEA model					Conventional DEA model				
Technical Efficiency Distribution	2007 No of Farms	2008 No of Farms	2009 No of Farms	2010 No of Farms	2011 No of Farms	2007 No of Farms	2008 No of Farms	2009 No of Farms	2010 No of Farms	2011 No of Farms
0.2≤eff<0.5	3	2	2	4	4	3	2	2	4	4
0.5≤eff<0.6	1	1	2	1	1	1	1	2	1	1
0.6≤eff<0.7	3	2	3	2	2	3	2	4	2	2
0.7≤eff<0.8	4	5	4	1	8	5	8	5	2	8
0.8≤eff<0.9	3	5	8	8	3	4	6	8	8	3
0.9≤eff<1	3	5	5	8	2	4	3	4	8	2
Efficiency=1	24	21	17	17	21	21	19	16	16	21
% of farms on the frontier	59	51	41	41	51	51	46	39	39	51
Mean Efficiency	0.88	0.89	0.86	0.87	0.84	0.87	0.86	0.84	0.86	0.84
SD Efficiency	0.19	0.18	0.19	0.20	0.21	0.19	0.19	0.20	0.19	0.21

The drought period of 2010-2012 (Kendon *et al.*, 2013) in East Anglia, had a negative impact on technical efficiency. Technical efficiency in 2011 was reduced by 3.4% for the sub-vector model and by 2.3% for the conventional model in relation to 2010 levels. It is interesting to note that for 2011 both models report the same level of mean technical efficiency (0.84) and also that the distribution of farms in relation to the frontier is nearly the same. The latter is an indication that the same environmental conditions pertain to the farm sample in 2011 causing the two models to converge. Otherwise, the sub-vector model would have accounted for this and thus adjusted the technical efficiency of farms operating in an unfavourable environment as was the case in previous years. Technical efficiency also drops in 2009 for both models, capturing the impact of an increase in input prices for fertilisers and soil improvements[18]. The mean technical efficiency observed in 2009 is 0.84 and 0.86 for the conventional and sub-vector models respectively (Table 4.2).

A Wilcoxon signed-rank test was applied to evaluate differences between the efficiency scores for the two models for each year. Results show that there is statistical significant difference for 2007 (p-value<0.01), 2008 (p-value<0.01), 2009 (p-value<0.01) and 2010 (p-value<0.05). However, using Cohen's criteria (Cohen, 1988; Cohen, 1992), only for 2008 and 2009 there is a large effect where d=-.52 and d=-.55 respectively which represents a change in the levels of efficiency when rainfall is taken into account as a non-discretionary production input. For 2011, there is no statistical significance difference between the efficiency scores of the two models. Figure 4.1, presents the means of efficiency score for each year per model.

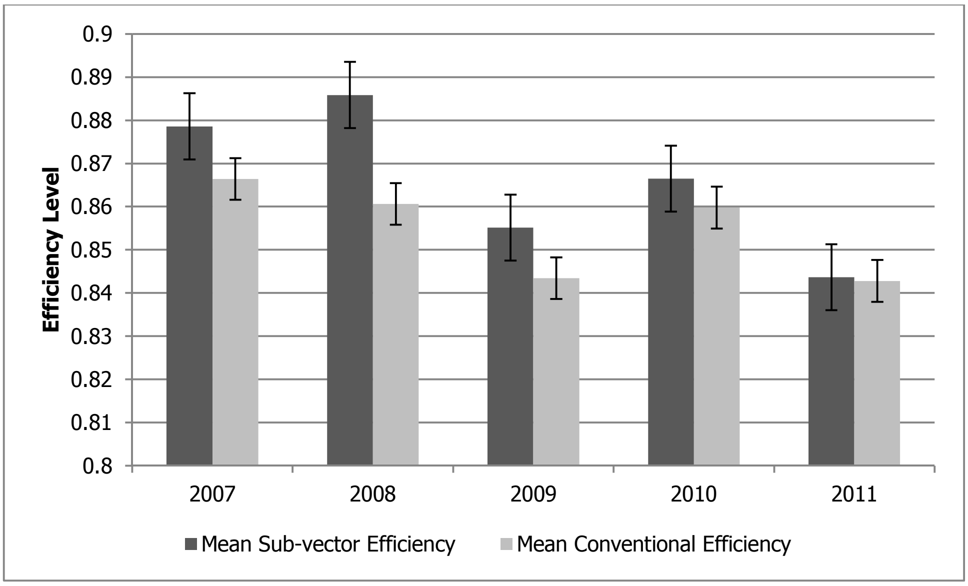

Figure 4.1: Technical efficiency mean per year for the conventional and sub-vector DEA models

In order to better demonstrate the effect on technical efficiency from the inclusion of rainfall as a non-discretionary production input in the DEA model an exemplar is used from the 2009 dataset (specifically farm 39). This farm received 560mm of annual rainfall which is more than 1 SD less than the mean rainfall in the EARBC for 2009 (mean=601, SD=32). Furthermore, when solving the linear programming of the conventional model, the peers of farm 39 (farms 9, 13, 19, 21 and 33) on average received 578mm of rainfall with a maximum of 601mm. Considering the results from the conventional DEA model, farm 39 would need to proportionally reduce its inputs by 22% (technical efficiency=0.78) to be on the technical frontier. However, when the low level of rainfall is accounted for in the sub vector model, the input contraction

[18] This is recorded from the Indicator A4a Input prices (Index 2010=100) based on data from the Agriculture Price Index (API) to monitor changes in input prices for agriculture in UK. Available online: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/285668/agindicator-a4-27feb14.pdf

reported for farm 39 is 13% (technical efficiency=0.87). The new set of benchmarking farms for the adjusted model (farms 7, 9, 13, 19 and 26) received an average of 568mm of annual rainfall and therefore represents a more appropriate set of peers for farm 39 because the environmental conditions are more homogenous. Thus, when environmental conditions such as rainfall are not accounted for in the estimation of technical efficiency of farming systems it could potentially lead to biased estimates and poor management or misinformed extension advice to farmers.

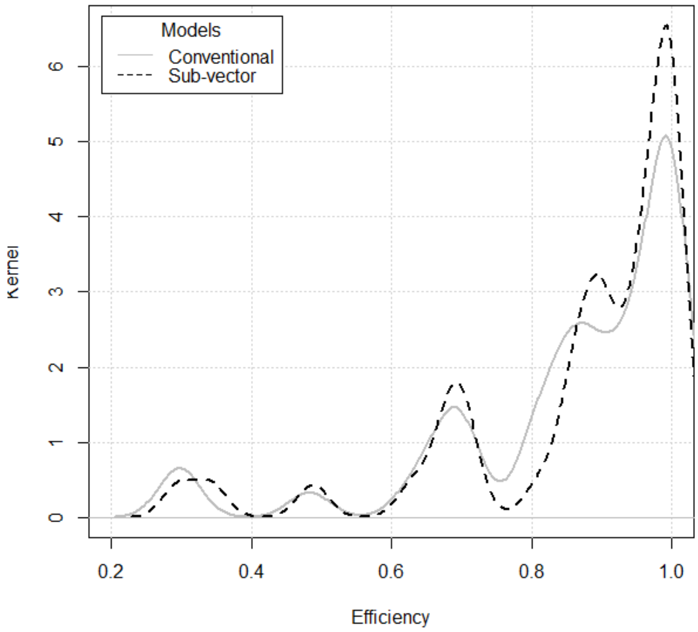

Figure 4.2: Kernel density estimate of the 5 year period for the conventional and sub-vector models

Although changes in the distribution of the efficiency scores between the two models provide useful information when parameters of the environment that are not under the control of the farmer (rainfall) are taken into account, it is more important to consider the changes in the relative rankings between farms (Henderson & Kingwell, 2005; Areal *et al.*, 2012). Differences in the relative ranking of farms between the sub-vector and conventional model indicate a failure to correctly assess the relative performance of each farm and account for the effect of the annual variation of rainfall in production efficiency. For that purpose a Spearman's rank correlation test was performed. The high values of Spearman's *rho* (*rho*>0.9 for each year) and the high level of significance (p-value<0.01) indicate that there is no difference between the relative rankings of the two models.

To further investigate differences between the two models and also to test for significant statistical differences among efficiency scores of different farms we implemented the bootstrapped method of Simar and Wilson (1998b) as it is described in Chapter 2 section 2.6.1.

Table 4.3 shows the standard deviation of the bootstrapped efficiency scores and the relative wide confidence interval (CI) bounds at 5%. It can be seen that there is a significant variation in efficiency scores across the five year period. In addition, CIs are used to test if the mean of the efficiency scores of the two models and the individual efficiency scores across years actually differ. Specifically, if the CIs of the two mean values overlap then there is no statistically significant difference between the two models or the means of different periods. In the case of the conventional and the rainfall adjusted DEA model all mean efficiency scores' CIs overlap which suggests that it is not possible to assert that there are differences between the two models over the five year period. The same was concluded using Spearman's rank correlation test.

Table 4.3: Mean bias corrected technical efficiency for the conventional and sub-vector DEA models

	2007	2008	2009	2010	2011	Mean
Boot. Conventional DEA model						
Mean	0.70	0.68	0.65	0.73	0.66	0.68
Std.Dev	0.22	0.24	0.24	0.21	0.23	0.23
Confidence Intervals, 5%						
Lower Bound	0.65	0.64	0.62	0.66	0.61	0.64
Upper Bound	0.86	0.85	0.83	0.85	0.83	0.85
Boot. Sub-vector DEA model						
Mean	0.72	0.73	0.68	0.73	0.65	0.70
Std.Dev	0.22	0.21	0.22	0.22	0.25	0.22
Confidence Intervals, 5%						
Lower Bound	0.64	0.66	0.62	0.66	0.61	0.64
Upper Bound	0.87	0.88	0.85	0.86	0.84	0.86

Table 4.4, below, provides information on the original and bootstrapped efficiency scores of the sub-vector model across farms and time. This information is used for relative comparisons of the performances among farms based on the DEA estimates of efficiency scores (Simar & Wilson, 1998b). Data relating to farms 6 and 14 from the GCF_s sample are used as exemplars. Farm 6, has a 5-year mean technical efficiency of 0.81 and thus, would need to equiproportional reduce input use by 19% to improve its efficiency while farm 14 would need to equiproportional reduce input use by 33% (5-year mean technical efficiency = 0.67). When testing the CIs for these two estimates it can be noted that they do not overlap and therefore the two farms are significantly different in terms of their technical efficiency. The same can be concluded for example between farms 3 and 37, 1 and 22, 1 and 41, 2 and 36. On the other hand, when CIs overlap then there is no empirical evidence to reject the hypothesis that the two farms are equally efficient. This example demonstrates successfully the use of the CIs derived from the bootstrapped sample for assessing unit performance. However, as it is suggested by Simar and Wilson (1998b) the use of CIs for making performance comparisons requires caution. Although it can certainly be stated that, statistical differences exist between two population means when CIs do not overlap, the reverse is not always the case. i.e. when CIs overlap then statistically significant difference may or may not exist between the two population means. Also, (Simar & Wilson, 1998b), state that extra attention should be paid when making relative comparisons between efficiency scores over different time periods based on the original efficiency scores. To answer if there is difference in performances over a period of time for the case of GCF_s a Total Factor Productivity (TFP) Malmquist Index (MI) is used (Caves *et al.*, 1982a).

Table 4.4: Technical efficiency and bias corrected mean technical efficiency for the sub-vector model

Farm ID	Sub-vector efficiency					5 year period mean	Mean bias	Bias corrected efficiency mean		Confidence Intervals 95%[a]	
	2007	2008	2009	2010	2011				SD	lower	upper
1	1.00	1.00	1.00	1.00	1.00	1.00	0.16	0.84	0.01	0.74	0.99
2	0.63	0.74	0.52	0.61	0.65	0.63	0.16	0.47	0.10	0.52	0.63
3	1.00	1.00	1.00	1.00	1.00	1.00	0.12	0.88	0.03	0.79	0.99
4	0.96	0.89	0.86	0.93	1.00	0.93	0.13	0.80	0.05	0.71	0.92
5[b]	0.38	0.32	0.25	0.28	0.26	0.30	0.30	0.00	0.13	0.25	0.29
6	1.00	0.62	0.78	0.83	0.82	0.81	0.12	0.69	0.17	0.68	0.80
7	1.00	1.00	1.00	1.00	1.00	1.00	0.19	0.81	0.03	0.65	0.99
8	0.72	0.72	1.00	0.86	1.00	0.86	0.17	0.69	0.11	0.62	0.85
9	1.00	1.00	1.00	1.00	1.00	1.00	0.20	0.80	0.02	0.59	0.99
10	1.00	1.00	1.00	1.00	1.00	1.00	0.20	0.80	0.02	0.60	0.99
11	0.32	0.30	0.35	0.39	0.36	0.34	0.30	0.05	0.08	0.27	0.34
12	1.00	1.00	0.97	0.93	0.94	0.97	0.08	0.89	0.02	0.84	0.96
13	1.00	1.00	1.00	1.00	1.00	1.00	0.19	0.81	0.02	0.64	0.99
14	0.62	0.68	0.68	0.87	0.51	0.67	0.16	0.52	0.18	0.55	0.67
15	1.00	1.00	0.82	1.00	1.00	0.96	0.18	0.78	0.06	0.64	0.96
16	0.87	0.98	0.66	1.00	1.00	0.90	0.15	0.75	0.17	0.68	0.90
17	1.00	1.00	1.00	1.00	1.00	1.00	0.19	0.81	0.03	0.66	0.99
18	1.00	1.00	0.80	0.85	0.74	0.88	0.17	0.71	0.12	0.61	0.87
19	1.00	1.00	1.00	1.00	1.00	1.00	0.20	0.80	0.02	0.60	0.99
20	1.00	1.00	1.00	1.00	1.00	1.00	0.19	0.81	0.01	0.63	0.99
21	1.00	1.00	1.00	1.00	1.00	1.00	0.21	0.79	0.02	0.59	0.99
22	0.49	0.74	1.00	0.45	0.77	0.69	0.20	0.49	0.24	0.48	0.68
23	1.00	1.00	0.94	1.00	1.00	0.99	0.17	0.82	0.02	0.67	0.98
24	1.00	0.99	0.74	0.94	0.82	0.90	0.10	0.80	0.13	0.76	0.89
25	1.00	1.00	0.90	0.96	0.87	0.95	0.11	0.83	0.06	0.78	0.94
26	0.95	0.97	1.00	0.96	0.93	0.96	0.12	0.84	0.04	0.76	0.96
27	1.00	1.00	1.00	1.00	1.00	1.00	0.15	0.85	0.04	0.75	0.99
28	1.00	0.87	0.90	0.82	0.71	0.86	0.14	0.72	0.11	0.65	0.85
29	1.00	1.00	0.88	0.89	0.77	0.91	0.14	0.77	0.09	0.69	0.90
30	0.74	0.72	0.63	0.69	0.66	0.69	0.16	0.53	0.06	0.56	0.68
31	0.86	0.98	0.85	0.84	0.73	0.85	0.14	0.72	0.11	0.68	0.85
32	1.00	0.87	0.90	1.00	1.00	0.95	0.18	0.78	0.03	0.63	0.95
33	0.88	1.00	1.00	1.00	1.00	0.98	0.16	0.82	0.05	0.70	0.97
34	0.73	1.00	0.79	0.87	1.00	0.88	0.13	0.75	0.13	0.71	0.87
35	0.94	0.98	0.92	0.92	1.00	0.95	0.11	0.84	0.04	0.77	0.95
36	0.54	0.57	0.53	0.43	0.37	0.49	0.21	0.28	0.14	0.39	0.48
37	0.71	0.82	1.00	0.51	0.48	0.70	0.18	0.52	0.26	0.54	0.70
38	1.00	1.00	0.81	0.96	0.72	0.90	0.13	0.77	0.15	0.71	0.89
39	1.00	0.86	0.87	1.00	0.78	0.90	0.16	0.75	0.09	0.66	0.89
40	1.00	1.00	1.00	0.97	1.00	0.99	0.14	0.85	0.01	0.77	0.98
41	0.68	0.70	0.71	0.78	0.70	0.71	0.15	0.56	0.06	0.59	0.71

[a] Number of bootstrap replication = 2000 ; [b] In some cases, use of Shephard output distance functions can result in bias-corrected distance function estimates that are negative. This will occur whenever the estimated bias is larger than the distance function estimate.

Table 4.5 presents the number of appearances of each farm on the frontier. As can be observed from the results, 26.8% of the farms in the sample remained on the frontier over the 5 year period and 19.5% have never been on the frontier, the remaining 53.7% has appeared on the frontier at least once. Also, comparing the efficiency scores of the sub-vector model between 2007 and 2011, 36.6% of the farms remained on the frontier, 24.4% shifted to the frontier (improved efficiency) of 2011 and 39% received a lower efficiency score compared to the efficiency level on 2007.

Table 4.5: Number of times a farm has been on the frontier during the 5 year period

Times on the frontier	Number of farms	Percentage	Mean efficiency	Minimum efficiency[a]	Maximum efficiency[a]
5	11	26.8%	1.00	1.00	1.00
4	4	9.8%	0.98	0.82	1.00
3	1	2.4%	0.95	0.87	1.00
2	9	22.0%	0.90	0.86	1.00
1	8	19.5%	0.85	0.45	1.00
0	8	19.5%	0.59	0.30	0.98

[a] Minimum and maximum values for the 5 year period for all farms

The mean scale efficiency (SE over the 5 year period is 0.93 with an average of 38% of the farms operating at their optimal scale (SE=1). Comparing PTE and SE for each year it can be noted that there is no difference between the two, implying that both have the same impact on farm efficiency and productivity. Table 4.6 provides information on the distribution of SE for each year. It can be noted that the observed SE for the majority of farms (73%) is between 0.9 and the optimal level (SE=1). This is an indication that generally GCF_s in the EARBC are undertaking appropriate size adjustments in the long run in order to maximise both their efficiency and productivity. The mean pure technical efficiency over the 5 years is 0.87 and the OTE respectively is 0.81 implying that GCF_s could on average reduce their inputs by 13% without any size adjustments in the short run and by 19% when appropriate size adjustments are made in the long run.

Table 4.6: Distribution of scale efficiency for the GCF_s in the 5 year period

Scale Efficiency (SE) Distribution	Number of farms				
	2007	2008	2009	2010	2011
SE <0.6	0	0	0	0	0
0.6 ≤ SE < 0.7	2	1	0	5	2
0.7 ≤ SE < 0.8	2	3	2	6	5
0.8 ≤ SE < 0.9	4	6	5	4	8
09 ≤ SE < 1	16	13	21	13	9
SE = 1	17	18	13	13	17
Mean SE	0.95	0.94	0.96	0.90	0.92
Standard Deviation	0.09	0.10	0.07	0.13	0.10
Mean Optimal Technical Efficiency	0.84	0.84	0.82	0.79	0.78
Mean Pure Technical Efficiency	0.88	0.89	0.86	0.87	0.84

When returns to scale are considered in the analysis, 19.5% of the GCF_s over the 5 year period operated under constant returns to scale indicating that these farms are not required to adjust their scale of operation in order to improve efficiency in the long run. However, 29% of the farms are below the optimal scale level operating under either increasing or decreasing returns to scale and have never managed to adjust their scale of operation during the 5 year period. On the other hand the remaining 51.5% have managed at least once to reach the optimal scale level and to operate under constant returns to scale. Table 4.7 provides information on the relationship between farm size[19] and RTS for the GCF_s between 2007 and 2011. It is interesting to note that a proportion of medium and large farms operate under IRS which implies decreasing marginal costs and rising average cost. The latter indicates that these farms need to shift down their long-run average cost curve and increase their size in order to achieve cost savings. This information, in addition to the results derived from the PTE analysis indicate a need for change in the management of inputs in the short run in order to improve control over the production process.

Table 4.7: Returns to scale per year and per farm size

Farm Size	RTS 2007			RTS 2008			RTS 2009			RTS 2010			RTS 2011		
	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS	IRS
Large	9	5	17	5	6	8	10	6	14	3	2	14	4	1	14
Medium	6	0	1	5	4	7	6	1	1	7	1	8	9	1	6
Small	3	0	0	4	0	2	3	0	0	4	0	2	5	0	1
Total	18	5	18	14	10	17	19	7	15	14	3	24	18	2	21

The FBS classifies farms into Small, Medium and Large based on the Standard Labour Requirements (SLR) which are calculated and then used to approximate the total amount of standard labour used on the farm. Therefore, for the same farm in the 5 year period it is possible to be classified into a different size category based on the calculated SLR index for each specific year. Hence, 64% of the GCF_s were classified under the same size category between 2007 and 2011 while the remaining 36% had either increased or decreased in size. Table 4.8, reports the size classification for each farm in the sample for the 5 year period and compares it with the results in relation to the returns to scale. Shifts of farm size (upward or downward) are also related to changes depicted in the results of returns to scale. For example, farm 1 was classified as a medium size farm and was operating under constant returns to scale (optimal scale) between 2007 and 2008. The downward shift of its size for the years between 2009 and 2011 meant that it was then operating below the optimal scale (increasing returns to scale). It could therefore be suggested that farm 1 should increase its size back to the levels of 2007 and 2008 in order to reach the optimal scale of operation. Furthermore, observing Table 4.8 it is possible to identify periods during which each farm has been operating at its optimal scale and therefore suggest long run strategies to either shift its size or adjust inputs costs to improve productivity and efficiency.

[19] In order to classify farms in the FBS into different sizes the Standard Labour Requirements (SLR) for different enterprises are calculated which are then used to find the total amount of standard labour used on the farm. Once the total annual SLR has been calculated the number of hours can be converted to an equivalent number of full time workers (on the basis that a full-time worker works a 39 hour week and so 1900 hours a year). This leads to the classification of farms by number of full time equivalent (FTE) workers as follows:

Small farms: $1<FTE<2$, Medium farms: $2<FTE<3$, Large farms: $3<FTE<5$

Table 4.8: Farm size classification and returns to scale for each farm in the sample for the 5 year period

Farm ID	Farm size[a]					Returns to scale				
	2007	2008	2009	2010	2011	2007	2008	2009	2010	2011
1	M	M	S	S	S	CRS	CRS	IRS	IRS	IRS
2	L	L	L	L	L	IRS	DRS	IRS	IRS	IRS
3	L	L	L	L	L	IRS	IRS	IRS	IRS	IRS
4	L	L	M	M	M	DRS	DRS	DRS	IRS	CRS
5	L	L	L	L	L	DRS	IRS	CRS	IRS	IRS
6	L	L	L	L	L	IRS	IRS	DRS	IRS	IRS
7	L	M	M	M	M	CRS	CRS	CRS	CRS	CRS
8	L	L	L	L	L	IRS	IRS	CRS	DRS	CRS
9	S	S	S	S	S	CRS	CRS	CRS	CRS	CRS
10	L	L	L	L	L	CRS	CRS	CRS	CRS	CRS
11	L	L	L	L	L	IRS	IRS	IRS	IRS	IRS
12	L	L	L	L	L	IRS	CRS	DRS	IRS	IRS
13	S	S	S	S	S	CRS	CRS	CRS	CRS	CRS
14	L	L	L	L	L	DRS	CRS	IRS	IRS	IRS
15	L	L	M	M	M	CRS	CRS	DRS	IRS	DRS
16	L	L	M	M	L	IRS	IRS	IRS	IRS	CRS
17	M	M	S	S	S	CRS	CRS	CRS	CRS	CRS
18	L	L	L	L	L	CRS	CRS	DRS	DRS	CRS
19	M	M	M	M	M	CRS	CRS	CRS	CRS	CRS
20	S	S	S	S	S	CRS	CRS	CRS	CRS	CRS
21	L	L	M	M	M	CRS	CRS	CRS	CRS	CRS
22	L	L	L	L	L	IRS	DRS	CRS	IRS	DRS
23	M	L	M	M	M	CRS	CRS	DRS	CRS	CRS
24	L	L	L	L	L	IRS	IRS	IRS	IRS	IRS
25	M	M	M	M	M	IRS	IRS	IRS	IRS	IRS
26	M	M	M	M	M	CRS	DRS	IRS	IRS	IRS
27	M	M	M	M	M	CRS	CRS	CRS	DRS	CRS
28	L	L	L	L	L	CRS	DRS	DRS	IRS	IRS
29	L	L	L	L	L	IRS	IRS	IRS	IRS	IRS
30	L	L	M	M	L	DRS	IRS	IRS	CRS	IRS
31	L	L	L	L	L	IRS	IRS	DRS	CRS	IRS
32	L	L	L	L	L	CRS	IRS	DRS	CRS	CRS
33	L	L	M	M	M	IRS	CRS	CRS	CRS	CRS
34	L	L	M	M	M	IRS	CRS	DRS	IRS	IRS
35	L	L	M	M	M	DRS	DRS	IRS	IRS	CRS
36	L	L	L	L	L	IRS	IRS	IRS	IRS	IRS
37	L	L	L	L	L	IRS	DRS	CRS	IRS	IRS
38	L	L	L	L	L	IRS	CRS	IRS	IRS	IRS
39	L	L	M	M	M	IRS	IRS	IRS	CRS	IRS
40	L	M	S	S	M	CRS	CRS	IRS	IRS	CRS
41	L	L	M	M	M	CRS	IRS	IRS	IRS	IRS

[a] L: Large M: Medium ; S: Small

4.5.2 Changes in productivity and efficiency over time and farm and its decompositions into pure technical and scale efficiency change

Focusing only on technical efficiency estimates and their distribution over the study period is not a sufficient method to provide complete information on changes in performance over years (Simar & Wilson, 1999; Odeck, 2009). The estimation of the Malmquist Index (MI) is more appropriate since it enables the explanation of changes in distance functions over years due to movements within the input, output space (efficiency change) and progress or backward movement of the production set over time (technological change).

Table 4.9 reports the MI of Total Factor Productivity (TFP) between 2007 and 2011, and is used to measure changes in productivity, efficiency and technology for the GCF type in the EARBC. Values of the MI above unity indicate improvement, while values below unity indicate deterioration in productivity. In addition, the significance of these changes is reported for each farm. Confidence intervals (CIs) were calculated for 10%, 5% and 1% levels of significance. The majority of the MI estimates are significantly different from unity at the 99% or 95% level. A farm is reported to have experienced significant progress between the two time periods if its confidence interval lower bound is greater than unity, it has significantly regressed during the period if its upper bound is less than unity and there is no statistically significant change if unity is included in its confidence interval.

Only one farm has improved productivity for the period 2007 and 2008 and only 6 farms (15%) have been consistently improving their performance between 2008 and 2011. The most important shift in MI is recorded between 2008 and 2009 where 73% of the farms significantly improved productivity. In the period between 2010 and 2011, the average MI of TFP is below unity indicating deterioration in productivity. Comparing MI of 2010/2011 with the previous period the productivity estimate of 16 farms (39%) has deteriorated, has improved for 9 farms (22%), has continued to improve for 22% and has been less than unity for the remaining 17%. In addition, for the 2010/2011 period 60% of the estimates are significantly different from unity which is the smallest percentage of the study period.

Figure 4.3 presents the changes over the MI of TFP over the five year period per farm size. Year 2007 is considered as the base year for the calculation of the MI. All averages are reported as geometric means. During the period 2007 and 2008 the TFP deteriorated (MI<1) for all farm sizes. On the other hand significant improvement (MI>1) is recorded for the 2008/2009 and 2009/2010 periods for both medium and large farms while for the period between 2010 and 2011 where drought conditions were prevailing the MI is less than unity identifying deterioration in TFP for the two farm sizes. The most affected from the climate conditions in 2010 and 2011 are the small size farms with an average of MI=0.96 for the 2010/2011 period. In addition, the MI for the small size farms is below unity for all paired years with an exception of the period 2009/2010 where a significant improvement in productivity is indicated. This large increase in the MI for the small size farms is mainly due to a single farm (farm 20) which in the period 2009/2010 had MI=5.227 identifying a large improvement in technical efficiency when decomposing the MI into technical and efficiency change. If this farm is excluded from the sample then the curve becomes smoother with an average of MI=1.188.

Table 4.10 provides further information in relation to the TFP change per farm size and time. To explore any statistically significant differences between farm size and productivity changes the Kruskall-Wallis (one way analysis of variance by ranks) test was used. The null hypothesis of samples originating from the same distribution was not rejected for any period. This indicates that no significant differences exist between different farm sizes in the study period in relation to changes in productivity. However, it should be noted that during the two periods of extreme weather phenomena, 2007/2008 floods (Pitt & Britain, 2008) and the 2010/2011 drought, productivity significantly deteriorated, especially during the first period. All farm sizes have an MI value of less than unity. Furthermore, the average MI for the 5 year period for the large, medium and small farms is 0.99, 0.97 and 0.96 respectively indicating a slight deterioration of productivity over the period.

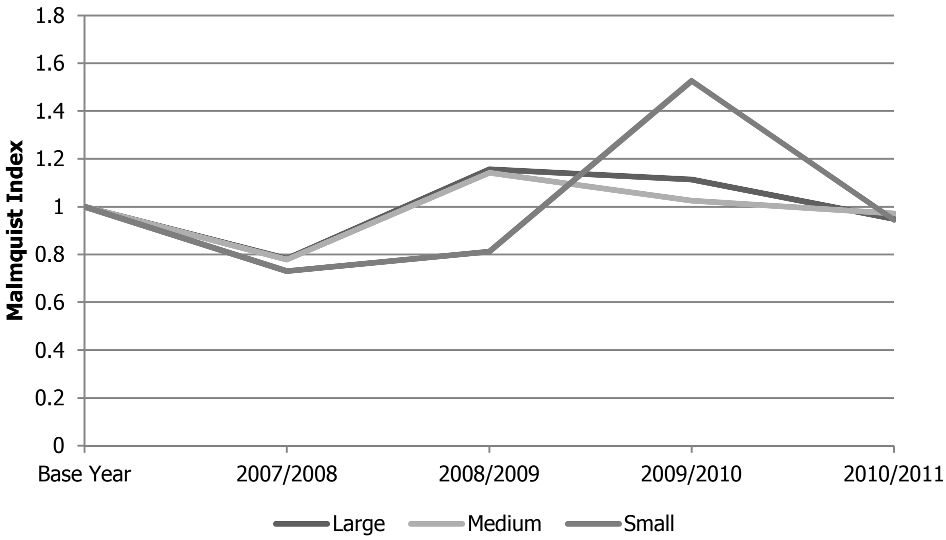

Figure 4.3: Productivity change per year and per farm size

Table 4.9: The MI of TFP per year and per farm size

	Malmquist Index[1]							
Farm Size	**2007/2008**		**2008/2009**		**2009/2010**		**2010/2011**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Large	0.78	0.12	1.16	0.37	1.11	0.32	0.95	0.23
Medium	0.78	0.07	1.14	0.19	1.02	0.19	0.97	0.15
Small	0.73	0.02	0.81	0.40	1.53	1.66	0.94	0.19

[1] Since the Malmquist index is multiplicative, these averages are also multiplicative (i.e. geometric means)

Table 4.10: Statistical significance of the MI of TFP per farm per period

Farm ID	Malmquist total factor productivity index			
	2007-2008	**2008-2009**	**2009-2010**	**2010-2011**
1	0.796***	1.186***	1.249***	0.898
2	0.695***	1.547***	0.880***	1.069**
3	0.679***	0.848***	1.724***	0.769***
4	0.867***	1.205***	0.893***	0.994
5	0.834***	1.608***	1.546***	0.599***
6	1.063***	1.003	1.408***	0.644***
7	0.801***	1.096*	0.983	0.984
8	0.698***	0.543***	1.579*	0.764***
9	0.665***	1.185***	1.071***	1.096***
10	0.819***	2.242	0.497***	0.819***
11	0.840***	0.935***	0.928***	1.008
12	0.669***	1.343***	1.525***	0.859***
13	0.791***	1.235***	0.915	0.696***
14	0.757***	1.278***	0.791***	1.650***
15	0.733***	1.416***	0.924**	1.056**
16	0.796***	1.362***	0.630***	1.156***
17	0.785***	0.560***	1.630**	1.174***
18	0.872***	1.270***	0.946	0.871***
19	0.856***	0.664***	1.547***	0.669***
20	0.743***	0.285***	5.227**	0.934
21	0.631***	1.091***	1.121	1.035
22	0.691***	1.048***	1.117*	1.081***
23	0.871***	1.193***	1.044***	1.111***
24	0.719***	1.452***	1.154***	0.712***
25	0.618***	1.446***	1.062	0.958*
26	0.789***	1.159***	1.175***	0.966
27	0.829***	0.978	1.130**	0.961
28	0.939*	1.098***	1.074***	0.978
29	0.945***	1.034***	1.133***	1.013
30	0.872***	1.115**	0.959***	1.124
31	0.919***	0.938	1.142***	1.007
32	0.930*	1.089*	0.973	0.935**
33	0.689***	0.981	1.226***	0.858***
34	0.560***	1.322***	0.976**	0.988
35	0.728***	1.106**	1.116	0.985
36	0.809***	1.279***	1.104***	1.035
37	0.946	0.920	1.530**	1.157***
38	0.761***	1.444***	0.953	1.202**
39	0.647***	1.144***	0.945	1.320
40	0.782***	1.037*	1.212***	0.779***
41	0.765***	1.271***	0.936***	1.072***

* Significantly different from unity at 0.1 level,
** Significantly different from unity at 0.05 level
*** Significantly different from unity at 0.01 level

The MI consists of two components: a) Efficiency Change (e.g. management change) and b) Technical change (production technology). Detailed presentation of the efficiency and technical change estimates are presented in Table A.1 and Table A.2 in Appendix A. Färe *et al.* (1994b) decomposed efficiency change further into two more components a) Pure efficiency (under the assumption of variable returns to scale) and b) Scale efficiency. Table 4.11 provides further information on the decomposition of the MI for the sample presenting information for the geometric means of the farms for the 5 year period.

Table 4.11: The geometric mean for the 5 year period of the MI of TFP and its components per farm

Farm ID	Malmquist Index	Efficiency Change	Technical Change	Pure Efficiency Change	Scale Efficiency Change	Ranking with respect to MI[1]
1	1.015	1.082	0.937	1.000	1.082	10
2	1.003	1.006	0.997	0.994	1.012	15
3	0.935	0.950	0.984	1.000	0.950	34
4	0.981	0.986	0.995	0.991	0.995	19
5	1.056	1.139	0.927	1.098	1.037	4
6	0.992	1.048	0.946	1.052	0.997	18
7	0.960	1.000	0.960	1.000	1.000	29
8	0.822	0.889	0.925	0.921	0.965	41
9	0.981	1.000	0.981	1.000	1.000	20
10	0.930	1.000	0.930	1.000	1.000	35
11	0.926	0.985	0.940	0.939	1.048	36
12	1.041	1.077	0.967	1.015	1.061	7
13	0.888	1.000	0.888	1.000	1.000	39
14	1.060	1.118	0.948	1.051	1.063	2
15	1.003	1.002	1.001	0.988	1.015	14
16	0.943	0.956	0.986	0.962	0.994	32
17	0.958	1.000	0.958	1.000	1.000	30
18	0.978	1.008	0.969	1.077	0.936	23
19	0.876	1.000	0.876	1.000	1.000	40
20	1.008	1.000	1.008	1.000	1.000	13
21	0.945	1.000	0.945	1.000	1.000	31
22	0.967	0.943	1.025	0.892	1.058	27
23	1.048	1.022	1.025	1.000	1.022	5
24	0.962	1.065	0.903	1.051	1.013	28
25	0.976	0.977	1.000	1.034	0.945	24
26	1.009	1.055	0.957	1.006	1.048	12
27	0.969	1.000	0.969	1.000	1.000	26
28	1.020	1.139	0.895	1.091	1.044	9
29	1.029	1.096	0.939	1.035	1.058	8
30	1.012	1.045	0.968	1.030	1.015	11
31	0.998	1.050	0.950	1.041	1.009	16
32	0.980	1.000	0.980	1.000	1.000	22
33	0.918	0.967	0.950	0.969	0.997	38
34	0.919	0.928	0.991	0.923	1.005	37
35	0.970	0.980	0.990	0.986	0.994	25
36	1.043	1.129	0.924	1.096	1.030	6
37	1.114	1.100	1.013	1.104	0.996	1
38	1.059	1.139	0.930	1.085	1.050	3
39	0.981	1.006	0.975	0.992	1.014	21
40	0.936	1.000	0.936	1.000	1.000	33
41	0.994	1.027	0.968	0.991	1.037	17

[1] MI: Malmquist Index, Note: All indices are geometric means

The efficiency change component of the MI of TFP is related to distance functions measuring shifts of the farms in the sample towards the frontier. It estimates whether a farm is getting closer (catching up effect) or farther from the frontier (Färe *et al.*, 1994b) and is therefore a measure of technical efficiency change. On the other hand the technical change index provides a representation of the shifts to the frontier of the sample based on each farm's observed input mix during the study period. It is therefore possible with this decomposition to isolate the effect of technical efficiency (catching up to the frontier) from outward or inward shifts of the frontier. In addition, the product of efficiency and technical change should by definition be equal to the MI of the period and it is possible that these components are moving in opposite directions. For instance, farm 1 had the capacity to improve productivity over the 5 year period and its geometric mean of MI was 1.015. The index of efficiency change (1.082) indicates an improvement of efficiency and therefore, indicates an improvement in input savings by 8.2% while the index of technological change (0.937) implies that the farm failed to maintain input saving technology. However, this lagging performance in technological change did not outweigh significantly the improvement in efficiency change and thus the overall productivity was improved by 1.5% in the observed period. It is therefore concluded for farm 1 that the improvement in productivity is mainly due to efficiency improvements rather than technological changes. The same is concluded for the majority of the farms in the sample when the geometric means for the MI and its components of efficiency and technical change are considered. Specifically, the geometric mean of the MI of TFP for the 5 year period is 0.98, while for efficiency change is 1.03 and 0.96 for the technical change. Hence, the deterioration in estimated productivity was mainly due to fall back of the frontier rather than a reduction in technical efficiency of the farms. In other words, although farms have improved their management performance in order to shift efficiency upwards, other exogenous factors such as extreme weather phenomena (2007/2008 floods, 2010/2011 drought) and increased input market prices (fertilisers and soil improvements in 2009) resulted in less technological change. Table 4.12 provides further information of the geometric means for the efficiency and technical change per year and per farm size.

Table 4.12: Efficiency and technical change per farm size and per period

	2007/2008		2008-2009		2009-2010		2010-2011	
Farm Size	Efficiency change	Technical change	Efficiency change	Technical change	Efficiency change	Technical change	Efficiency change	Technical change
Large	1.02	0.76	0.99	1.17	1.10	1.01	1.02	0.93
Medium	0.98	0.79	1.11	1.03	0.93	1.10	0.98	0.99
Small	1.00	0.73	1.01	0.81	1.05	1.46	1.02	0.93

In addition, the component distance functions in the technical change index of the MI of TFP provides are used to identify farms responsible for the frontier shift (Färe *et al.*, 1994b). During the period between 2007/2008 no farm caused any shift to the frontier since technical change was less than unity for all farms. The farms that caused the frontier to shift in the remaining three pairs years were farm 13 in the 2008/2009 period, farms 32 and 33 in the 2009/2010 period and farms 4, 16 and 35 in the period 2010/2011. According to Färe *et al.* (1994b) these farms can be identified as the "innovators" of the sample.

The efficiency change index can be further decomposed into pure efficiency and scale efficiency change isolating in that way the impact of farm scale to efficiency change. Table 4.13 reports the distribution of pure and scale efficiency estimates for the consecutive years. Estimates of pure and scale efficiency per farm are presented in Table B.1 and Table B.2 in Appendix B. The results for 2009/2010 indicate that scale efficiency index has improved for more than 71% of the farms however the pure efficiency index deteriorates for the 51% of the farms in the sample. This adjustment in scale might be the reason for the deterioration in efficiency since farms need to adapt their management requirements into the new conditions and scale of operation. Figure 4.4 illustrates these changes, in which scale efficiency deteriorates significantly after the 2008/2009 period. In addition, the improvement in efficiency for the 2007/2008 period is mainly due to improvements in pure efficiency while it has an adverse impact to the next period causing efficiency to deteriorate. However, pure efficiency is the main factor in the improvement of the efficiency change index for the 2010/2011 period.

Table 4.13: Distribution of the efficiency change decomposition

	2007/2008		2008/2009		2009/2010		2010/2011	
Distribution	**Pure**	**Scale**	**Pure**	**Scale**	**Pure**	**Scale**	**Pure**	**Scale**
<0.6	0	0	0	0	0	1	1	0
0.6≤ Eff <0.8	2	1	3	1	5	2	0	2
0.8≤ Eff <1	11	14	7	14	16	4	8	20
Eff=1	16	7	13	2	12	5	15	3
1< Eff <1.2	9	17	11	21	6	20	14	15
1.2≤ Eff <1.4	2	1	6	2	0	5	2	1
Eff>1.4	1	1	1	1	2	4	1	0
Improvement	29%	46%	44%	58.5%	19.5%	71%	41%	39%
Deterioration	32%	36.5%	24%	36.5%	51%	17%	22%	54%
Geometric Mean	1.04	1.02	1.01	1.02	1.03	1.01	1.05	0.98

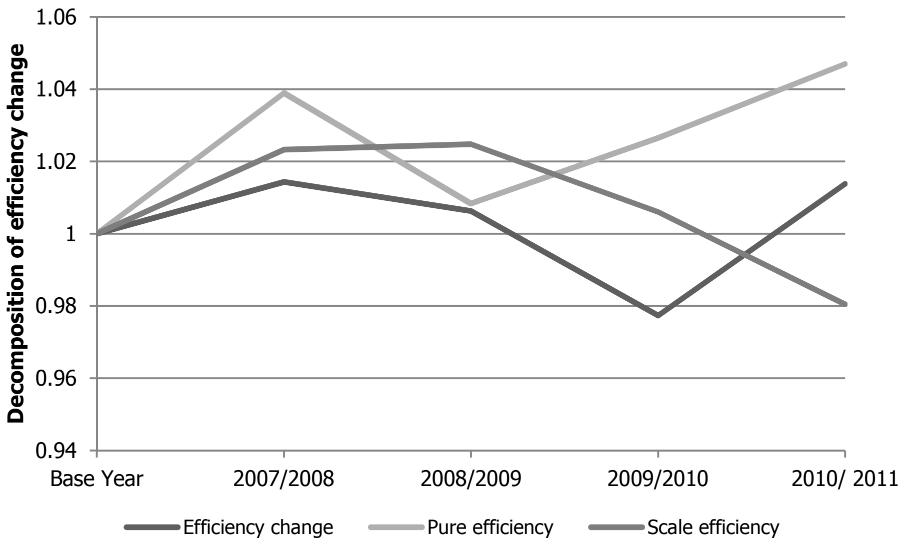

Figure 4.4: Changes in efficiency change index and its components

The decomposition of technical change proposed by Simar and Wilson (1999) was used in order to isolate the impact of farm scale in the technical change component of the MI of TFP. Table C.1 and C.2 in Appendix C provide a detailed presentation of the pure technical, scale technical changes and the product of the latter with the scale efficiency component of efficiency change. However, it should be emphasised that in some cases the computation of pure technical change or scale efficiency based on distance functions between the two time periods is infeasible to compute due to the linear programme constraints. Figure 4.5 illustrates the technical change index. Shifts in the frontier are mainly driven by the pure technical efficiency index rather than the scale of operation of the farms in the sample. Thus, factors affecting the frontier such as the extreme weather phenomena observed in the 2007/2008 and 2010/2011 have a significant impact in technical change and consequently to productivity for the GCF_s in the EARBC. Table 4.14 provides additional information for the distribution of the two components of technical change during the 5 year period.

Table 4.14: Distribution of the technical change decomposition

	2007/2008		2008/2009		2009/2010		2010/2011	
Distribution	**Pure**	**Scale**	**Pure**	**Scale**	**Pure**	**Scale**	**Pure**	**Scale**
<0.6	1	0	1	2	0	0	2	2
0.6≤ Eff<0.8	7	0	2	0	0	3	5	14
0.8≤Eff<1	7	11	4	10	8	23	18	11
1<Eff<1.2	0	3	21	24	21	9	6	5
1.2≤Eff<1.4	0	0	7	1	3	1	2	2
Eff>1.4	0	1	2	0	4	0	1	0
Infeasible to compute	26	26	4	4	5	5	7	7
Improvement	0%	10%	73%	61%	68%	63%	61%	25%
Deterioration	37%	27%	17%	29%	20%	24%	22%	17%
Geometric Mean	0.75	1.00	1.10	0.98	1.13	0.95	0.91	1.05

Considering both pure technical and pure efficiency change in the 2008/2009 period, GCF_s in the EARBC have successfully improved their management performance and were able to maintain this input saving technology during the remaining periods (2009/2010, 2010/2011) (Figure 4.4) while pure technical efficiency drops significantly in the 2010/2011 period pushing productivity below unity.

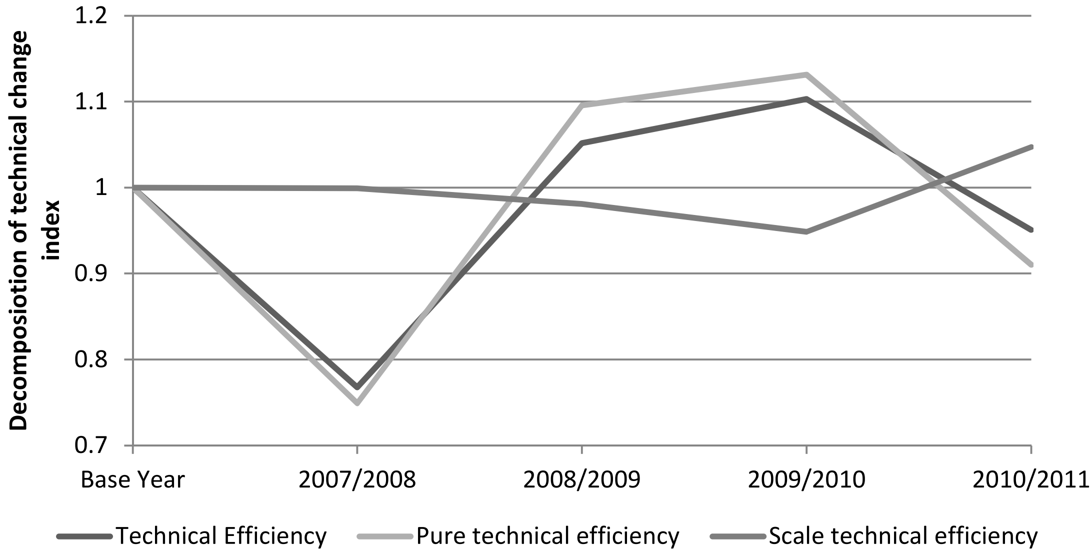

Figure 4.5 Changes in technical change index and its components

4.6 Discussion

Two DEA models, a conventional and a sub-vector (non-discretionary), were used to report farm level technical efficiency estimates for the GCF_s in the EARBC for a 5 year period. The sub-vector model included annual rainfall measurements for each farm in the sample in order to account for variations in precipitation in the EARBC. The non-discretionary model ensures the benchmarking of the farms with those with lower or equal rainfall and therefore, farms are compared in a more homogenous sample. Further, by including rainfall in the model it is possible to capture the impact of variations in annual rainfall on the technical efficiency of the farms. The importance of rainfall in determining technical efficiency of farming systems is also addressed by Makombe *et al.* (2011) where its underlined that their data and hence their performance estimates might have been biased due to the fact that data was derived from a rainy season which was characterised by the Ethiopian Meteorological office as above the average. For the results to be robust they suggest that rainfall variations should be taken into consideration.

Results from the conventional DEA model show that when rainfall variations are ignored, technical efficiency scores are lower and more farms are reported as inefficient. However, the consideration of rainfall as a non-discretionary input increases the number of fully efficient farms and the technical efficiency level of the farms below the frontier. Therefore, in order to reduce biased estimates of technical efficiency and also to improve management advice for farming systems, variations in environmental conditions should be considered to secure a homogenous benchmarking sample.

In addition the two models were compared to test if the ranking of the farms' performance was significantly different. The Spearman's rank correlation test showed that there is no difference between the conventional and sub-vector DEA models. Despite the lack of differences in farm ranking between the two models, the inclusion of rainfall as a non-discretionary input in the production function is suggested to account for variations in exogenous parameters and ensure the homogeneity of the benchmarking sample. This was also the conclusion of Henderson and Kingwell (2005).

Furthermore, results on returns to scale and scale efficiency indicate pathways for the improvement of productivity and maximisation of net benefits. Specifically, the majority of the farms over the 5 year period have a SE value between 0.9 and 1 (optimal scale). This indicates that GCF_s in the EARBC are able to do appropriate scale adjustments in order to achieve the maximisation of both their efficiency and productivity. Moreover, the mean value of optimal technical efficiency (0.81) suggests that it may be possible to reduce inputs by 19% when appropriate size adjustments are also made. Similarly, Hadley (2006) showed that English and Welsh general cropping farms have a reported mean of technical efficiency of 0.74 although with considerable variation around the mean. Concerning the relationship between farm size and returns to scale, a significant proportion of large and medium size farms need to shift down their long-run average cost curve and adjust their size in order to succeed cost saving (operating under IRS). This is further supported by the PTE and OTE results which also suggest a need for change in the management of inputs in the short and long run respectively in order to improve control over the production process. Also, information on returns to scale and farm size over different years are used for the identification of the optimal scale for the GCF_s in the sample and hence, to identify the appropriate strategy for each farm in order to shift its size or adjust inputs costs to improve productivity and efficiency. The positive relationship between farm size and efficiency was also addressed by Dawson (1985).

The TFP measures were calculated using a Malmquist DEA TFP methodology which enables the decomposition of the MI into technical change, technical efficiency change, scale efficiency change and a further decomposition of technical change proposed by Simar and Wilson (1999). Comparison of the results obtained from the MI of TFP revealed deterioration in productivity for the GCF_s in the EARBC over the study period (2007-2011) for all farm sizes. Furthermore, the decomposition of the MI of TFP into its components enabled a disaggregation of the effects of technical efficiency (catching up to the frontier) and outward or inward shifts of the frontier. Hence, deterioration in productivity is mainly due to fall back of the frontier rather than reduction in technical efficiency of the farms. Farms on the efficient frontier are becoming more efficient due to improvements in pure efficiency index rather than technical change. Specifically, productivity falls for the 2007/2008 and the 2010/2011 periods due to a fall in the technical efficiency index which reflects the impact of the extreme weather phenomena for 2007 (floods) and 2011 (drought). Hadley (2006) has similarly showed that technical change is the factor with the most significant role in the increase of efficiency in a period of 20 years (1998-2002). Furthermore, in a more recent work by Barnes *et al.* (2010) a general upward trend in technical efficiency was also reported throughout the period. On the other hand, the most important improvement in MI is recorded between 2008 and 2009 where 73% of the farms are indicated with a significant improvement in TFP. Generally, 15% of the farms have been consistently improving TFP over the study period while the remainder of the sample has been fluctuating above and below unity, thus improving efficiency in some years and decreasing in others.

In addition, scale efficiency change (Figure 4.4) for the years between 2008 and 2009 drops below unity. This is mainly explained by the change in the proportion between large, medium and small farms in the sample compared with previous years. The average farm size in 2011 is lower than 2009 (medium and small size farms have doubled). This is also confirmed by the increased number of farms operating under IRS (Table 4.8). However, Figure 4.5 illustrates that technical scale efficiency change is increasing for the same period implying that farms operate closer to the point of technically optimal scale under the VRS assumption. According to (Coelli *et al.*, 2006) the fall in scale efficiency might be caused from the faster rate that larger farms improve productivity when compared to medium and small farms. Therefore, the performance gap between the different sizes of farms is widening and is depicted by the technical scale efficiency.

4.7 Conclusions

The challenge of sustainable intensification of agricultural production and the need to meet increasing food demand requires farming systems to improve their productivity. In the case of GCF_s in the EARBC, the increased risk of summer droughts and temperatures due to climate change is also a challenge that should be considered.

Conventional and sub-vector DEA models were used to compare differences in the technical efficiency ranking of GCF_s when rainfall is considered in the production technology as a non-discretionary input. Results showed no difference between the two models. However, the inclusion of exogenous parameters with an impact on the productivity of the farms ensures the homogeneity of the sample and therefore better benchmarking results.

The analysis of TFP of the GCF_s in the EARBC, based on the measurement of the MI and its components, has shown that extreme weather phenomena have a negative impact on productivity. During the 5 year study period both efficiency and productivity fell due to the floods in 2007 and the drought period between 2010 and 2011. However, pure efficiency change has been positive indicating that farmers are improving their management skills and are adopting input saving technologies. On the other hand, pure technical efficiency deteriorates and is the main reason for the lowering of productivity of the GCF_s in the EARBC. In addition, the bootstrap of MI of TFP and its components provides a correction for the inherent bias in nonparametric distance functions and allows statistical inference for the results. Hence, it is possible not only to indicate changes in the MI of TFP but also to indicate if these changes are statistically significant.

Finally, the analysis of returns to scale and scale efficiency change allows the identification of farms operating closer to the point of technically optimal scale and also identification of the optimal scale for farms in the sample. Furthermore, distinguishing between PTE and OTE permits the development of strategies for reducing inputs or scale adjustment in the short and long run respectively.

Chapter 5

Water use efficiency in the EARBC

5.1 Introduction

In Chapter 4, the MI of TFP and especially the technical efficiency change component were estimated at a farm level for a period of five years in order to explore the impact of extreme weather phenomena in agricultural productivity. Results have shown that the 2007 floods as well as the 2010-2011 drought periods had a significant negative impact on the technical efficiency change index. Since GCF system is the main farming system using supplementary irrigation in the EARBC for securing yield and farmers' income, the sustainable management of water resources is of considerable importance, especially when drier summers and higher temperatures are predicted for the area. Furthermore, in the context of SI of farming systems, the improvement of management of limited natural resources, such as water and land, is a priority. Thus, a conventional and a sub-vector DEA model are used in this Chapter to measure technical efficiency and WUE respectively for GCF_s in the EARBC to suggest specific strategies towards the improvement of productivity and management of water resources at a farm level. A detailed presentation of the sub-vector DEA model is available in section 2.3.4 of the methodology Chapter.

5.2 The importance of irrigation in the UK

Water is essential to agriculture production with uses comprising irrigation, spraying, drinking for livestock and washing (vegetables, livestock buildings). In the UK water for agriculture is obtained either directly from rivers and boreholes, or from the supply of mains waters as well as a combination of both (Defra, 2011). The effect of extreme weather phenomena associated with climate change on water availability has been studied (Knox *et al.*; Environment Agency, 2008; Defra, 2009; Jenkins *et al.*, 2009; Daccache *et al.*, 2011). Most of these studies conclude that the availability of water for agriculture is under threat. The impacts for England in particular will be spatially and temporally variable (Defra, 2009). Therefore, future projections for reduced rainfall during spring and summer time and the increase in the average temperature will lead to more frequent and extensive drought[20] periods (Charlton *et al.*, 2010). The recent dry periods of 2011 and 2012 caused increased pressures in UK water resources. In various catchments across the country, there was little or no water available for abstraction (FAS, 2013). Focusing on water use for irrigated root and vegetable

[20] "Drought is a nature produced but temporary imbalance of water availability, consisting of a persistent lower than average precipitation, of uncertain frequency, duration and severity, the occurrence of which is difficult to predict, resulting in diminished water resources availability and carrying capacity of the eco-systems". (Pereira et al., 2002)

crops, the continued production in the south and east of England will be dependent on the provision of adequate sources of water for irrigation. In addition, harvesting in wetter autumns could also be problematic (Charlton *et al.*, 2010).

The main region within England for which water is crucial for agriculture production is the Anglian region where the main use of water is for irrigation. The average abstraction of water (excluding tidal) in the Anglian region for spray irrigation between 2000 and 2012 was 50.5 million m^3 accounting for the 59% of the average total water used in agriculture for England. In terms of number of abstraction licences in force for spray irrigation in 2012, the Anglian region accounts for the 38% of total licences in England[21]. Irrigation in the EARBC is mainly concentrated on cash-crop production (potatoes and sugar beet) and therefore it is considered as a major production input to secure yield and income for the farmers, especially during dry periods. Irrigated production delivers substantial economic benefits in the EARBC not only at the farm gate but also beyond that point since it supports a number of related businesses that provide equipment and farm supplies and are also responsible for the promotion and distribution of production. It can therefore be considered as an important factor for the development of the rural economy in East Anglia (Knox *et al.*, 2009). The EARBC may face high pressures in future due to both a) an increase in water abstraction rates for agriculture due to increased water demand and increased number of abstraction licences and b) a decrease in water availability associated with changing weather conditions. The main climate threats are temperature increase and reduced precipitation (Environment Agency, 2008; Defra, 2009; Environment Agency, 2011) with direct impacts on the hydrology structure of the area.

The Environment Agency (EA) is the water regulatory authority for England and is also responsible for the authorisation of abstraction licences (Environment Agency, 2013). Its primary responsibility is to balance the water needs of all abstractors (all industries involved in water abstraction including agriculture) with that of the natural environment. Moreover, the EA is responsible for the assessment of the Catchment Abstraction Management Strategies (CAMS) and the assessment of the water resources that are available for abstraction. Each CAMS estimates how much freshwater is required in a given environment and the amount of water already licensed for abstraction (Environment Agency 2008). The EA considers WUE as a need to save and manage water efficiently whilst at the same time promoting environmental sustainability.

Irrigated agriculture in the EARBC has therefore to achieve two goals in order to secure the future growth and the economic sustainability of the sector. The first objective is to maintain and improve productivity in order to meet increasing future food demand (FAO, 2011) but at the same time to preserve the associated natural environment. Intensive agricultural practices combined with the probability of more frequent dry periods in the area may increase the competition for water resources in an already over-abstracted and over-licensed catchment (Knox *et al.*, 2009). The SI of agricultural production is promoted as a mechanism that

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[21] Data comes from the "Water quality and abstraction statistics" published in the DEFRA website. The source of data is the Environment Agency. Available online at: https://www.gov.uk/government/statistical-data-sets/env15-water-abstraction-tables : Accessed on 26.12.2013

can balance the two objectives and at the same time mitigate any conflicts between these two objectives. More specifically, the SI of agriculture requires farmers to simultaneously increase their yields in order to meet the future demand for food, but also to reduce environmental pressures generated by the production process (Garnett & Godfray, 2012).

In this sense, agricultural productivity and WUE should be considered together when evaluating the sustainability of farming systems. However, the social aim of sustainable farming systems (i.e. increase productivity, being water use efficient) does not necessarily match with farmers private aims (i.e. increase profitability). In order to close this gap between social and private objectives, farmers, need to demonstrate efficient water use for renewing an irrigation abstraction licence (Knox *et al.*, 2012). For instance, a farmer may seek to maximise production and profit per unit of water (financial sustainability) while the goal of an environmentally sustainable system could be to minimise the use of water per value or volume of production (Knox *et al.*, 2012). These contrasting approaches to efficiency and also between increasing agricultural productivity and environmental preservation require a management approach that simultaneously takes into consideration sustainability, productivity, and profitability (Vico & Porporato, 2011).

For most farmers in England involved in high value crop production water use for irrigation is driven by the need to produce a high quality product and hence obtain contracts and high prices from their customers, particularly supermarkets (Knox *et al.*, 2012). Therefore, economic incentives can play a critical role in irrigation decisions (Oster & Wichelns, 2003). Knox *et al.* (2012) suggests that an economically rational farmer, when there are unlimited water resources, would aim to use water until the marginal benefit no longer exceeded the marginal cost. If the farmer fears that the water resources may be inadequate, irrigation is restricted to the most (financially) responsive crops. WUE is therefore considered as an economically driven parameter strongly related to the production and marginal profit of a farm. The Farm Business Survey in England 2009/2010 also recorded financial or customer reasons as the primary reasons (55%) for farmers carrying out management practices for efficient water use in irrigation (Defra, 2011).

In addition, Knox *et al.* (2012) suggest that excess irrigation is avoided when the farmer is aware of the risk of increased crop disease, has difficult land access and/or has concerns about the risk of fertiliser leaching. Most farmers therefore sensibly aim for best (or reasonable) use of a potentially limited water supply, aiming not to over or under irrigate (especially in the case of dry summers), whilst minimising any non-beneficial losses (e.g. run-off, leaching). This is often described as “applying the right amount of water at the right time in the right place”.

Water demanded for irrigation at a farm level depends on farmers’ decisions on when and which crop to produce, the volume and the frequency of irrigation and also the selection of irrigation method and technology (Marques *et al.*, 2005). It is therefore a decision related to the production technology and the management ability of the farmer. Vico and Porporato (2011), note that there are a number of uncertainties in relation to both the economic and productivity goals of a farmer that increase the complexity of the choice of a sustainable and efficient water management strategy. These uncertainties are related to pests and diseases, temperature extremes, rainfall variability and timing in relation to crop growth stages, crop physiological properties and response to water availability. Further, they are confounded by differences in soil properties that determine water runoff and percolation (English *et al.*, 2002). Among the above, rainfall variability (especially increased frequency of drought periods during the growing season) can significantly impact productivity and profitability (Vico & Porporato, 2011).

5.2.1 Measuring water use efficiency at a farm level

The vast majority of published research papers and reports on measuring WUE focus on engineering and agronomic techniques. Under this framework, WUE can be defined as the yield of harvested crop product achieved from the water available to the crop through rainfall, irrigation and the contribution of soil storage (Singh *et al.*, 2010).

However, these approaches do not consider water as an economic good and therefore they do not allow the evaluation of the economic level of WUE (Wang, 2010). The economic approach to defining and measuring WUE is based on the concept of input specific technical efficiency (Kaneko *et al.*, 2004). Thus, water use at a farm level is used in combination with other inputs (land, labour, fertilisers, etc.) to estimate a production frontier which represents an optimal allowance of the inputs used. This methodology aims to assess farmers' managerial capability to implement technological processes (Karagiannis *et al.*, 2003). In addition to management decisions, special regional characteristics (i.e. soil type and its available water capacity) can play a crucial role in influencing water application at farm level and therefore efficiency (Lilienfeld & Asmild, 2007; Knox *et al.*, 2012).

In the literature there are broadly two approaches used to obtain efficiency estimates at a farm level; parametric techniques (i.e. Stochastic Frontier Analysis (SFA)) and non-parametric techniques (i.e. Data Envelopment Analysis (DEA)). Parametric techniques are used for the specification and estimation of a parametric production function which is representative of the best available technology (Chavas *et al.*, 2005). The SFA was introduced by Aigner *et al.* (1977) and Meeusen and Vandenbroeck (1977). The advantage of this technique is that it provides the researcher with a robust framework for performing hypothesis testing, and the construction of confidence intervals. However, its drawbacks lie in the *a priori* assumptions in relation to the functional form of the frontier technology and the distribution of the technical inefficiency term, in addition to the results being sensitive to the parametric form chosen (Wadud & White, 2000).

Karagiannis *et al.* (2003) and Dhehibi *et al.* (2007) have proposed a non-radial, input oriented measure of input specific technical efficiency based on SFA to obtain estimates of technical and irrigation efficiency for out of season vegetable growing farms. These authors used a second stage regression approach to identify the determinants of WUE differentials. However, Lansink *et al.* (2002) stressed that the estimation of input specific technical efficiency is problematic when using SFA. The main reason is that the curvature conditions (e.g. concavity in inputs) cannot be globally satisfied when a translog specification is used[22].

Due to the flexibility of DEA, in avoiding a parametric specification of technology and assumptions about the distribution efficiency but at the same time allowing for curvature conditions to be imposed, it is the preferred method for the analysis of technical and specific input (water use) efficiency in the EARBC over SFA. DEA is used to evaluate the performance efficiency of various Decision Making Units (DMU's) which convert multiple inputs into multiple outputs. It is a technique that provides a straightforward approach to measure the gap between each farmer's behaviour from best productive practices, which can be estimated from actual observations of the inputs and outputs of efficient firms (Lansink *et al.*, 2002; Wang, 2010). The production frontier is constructed as a piecewise linear envelopment of the observed data points. This means that the best performing farms are identified as those using the least amounts of inputs to produce their individual levels of output. Linear, or convex, combinations of those best performers constitute the production frontier. The efficiency of the farms is then measured relative to this estimated frontier of best performers (Lilienfeld & Asmild, 2007).

Various research projects have used DEA for measuring WUE at a farm level (Lilienfeld & Asmild, 2007; Mahdi *et al.*, 2008; Speelman *et al.*, 2008; Frija *et al.*, 2009; Wang, 2010; Veettil *et al.*, 2011; Chebil *et al.*, 2012; Chemak, 2012; Borgia *et al.*, 2013). The majority has used a sub-vector DEA model to estimate excess water use as proposed by Färe *et al.* (1994a).

5.2.2 Determinants of efficiency

WUE in agriculture can be influenced by various factors which have been identified in the literature. Wang (2010) suggests that age, income, education level, farm size and the irrigation methods used are factors influencing WUE. Moreover, Wang (2010) identified that exclusive water property rights as well as the competitive price mechanism had a strong influence on efficiency. The same regression parameters as Wang (2010) were tested at a second stage by Mahdi *et al.* (2008), Lilienfeld and Asmild (2007) and Speelman *et al.* (2008). The latter, in addition, took into consideration as influencing parameters the choice of crop, the landownership and the total cultivated area. The same approach was adapted by Wambui (2011) in the assessment of WUE and its influencing parameters in the Naivasha lake basin. Structural and managerial characteristics were also proven to influence the technical performance of farms by Van Passel *et al.* (2007) who concluded that the same factors as mentioned above, as well as the prospect of succession and dependency on subsidies, are influencing efficiency.

In the case of the agriculture sector in England, Hadley (2006), suggests that factors constantly appearing to have a statistically significant effect on the difference in technical efficiency among farms are farm size, farm debt ratios, farmer age, levels of specialisation and ownership status. Moreover, Wilson *et al.* (2001),

[22] More details can be found in Lansink et al. (2000, 2001) where generalised maximum entropy was used to estimate farm specific production frontier that satisfies curvature conditions and avoids distributional assumptions about the efficiency term.

estimated technical efficiency of farmers in Eastern England and explained the variation in efficiency by using a number of managerial biographical details, managerial drives, motivations, practices and procedures with respect to business planning.

5.2.3 Objectives

There are two main objectives 1) to assess the technical efficiency of irrigating GCF_s in the EARBC and 2) to provide an estimate of excess water use at farm level. For these we use a benchmarking technique with a sample of farms derived from the Farm Business Survey of 2009/2010. The identification of excessive water use at farm level can then be used to provide recommendations for improvements of management practices and policy interventions. Excess water use has an economic impact (increased production costs) at a farm level but also can be a source of environmental degradation. In particular it not only reduces available water resources but also involves short and long term damage caused by surface runoff as a result of over application and deep percolation losses of water below the root zone which cannot be utilised by crops (Pimentel *et al*., 2004). Further, farmers that over abstract and overuse surface or ground water from an aquifer that is not adequately recharging due to drought imposes an opportunity cost on future generations (Oster & Wichelns, 2003) and threatens the sustainability of the ecosystem.

For the purposes of the analysis, WUE is defined as the ratio of the minimum feasible water use to the observed water use at a farm level for irrigation and general agricultural purposes, subject to the available production technology, the observed level of outputs and the use of other inputs. It is therefore an input oriented measure of technical efficiency which allows for a radial reduction of water use at farm level (Wang, 2010). This approach allows for a specific input reduction (water) without altering the production output and the quantities of other inputs used. In this sense, WUE has an economic rather than an engineering meaning (Kaneko *et al*., 2004; Wang, 2010).

By considering the importance of the human factor in decision making and the use of specific management practices, technical efficiency scores are used to discuss the determinants of efficiency. Various attributes of the farmers and also management practices for efficient water use practised at a farm level are related to the benchmarking farms in the sample in order to identify areas for management improvement and thus can provide a focus for policy makers.

The development and implementation of integrated water management strategies and policies becomes a crucial decision to secure the sustainability of agricultural sector in specific parts of the UK. This suggests a need to develop guidance on what should be measured and how data might be interpreted to demonstrate efficient use of water in agriculture (Knox et al. 2012). Considering this the chapter concludes on specific recommendations for the data requirements necessary to measure WUE at a farm level, based on the sub-vector efficiency approach. These are discussed in the context of the SI of agriculture and climatic change.

5.3 Overview of the EARBC and data requirements

Data for the empirical application of the model have been obtained from the FBS[23] which is a comprehensive and detailed database that provides information on the physical and economic performance of farm businesses in England. A representative farm sample of 61 GCF_s was selected based on the EARBC from the FBS 2009/2010 database. Since DEA methods are quite sensitive to the presence of outliers in the data when measuring efficiency (Sexton *et al.*, 1986), four farms were omitted from the initial sample, being identified as outliers based on the method described in Wilson (1993); (Wilson, 2010). These outlier farms would have had a strong influence on the construction of the benchmarking frontier and therefore could influence the results and the interpretation of the efficiency scores. The final number of farms in the research sample was 57.

The production technology for the estimation of technical and sub-vector efficiency was defined by the area farmed, total agricultural costs (including fertiliser, crop protection, seed and other agricultural costs), other machinery costs[24], total labour hours per year and water use per farm including irrigation and the total amount of water in cubic meters used for all agricultural purposes. The outputs used in the DEA model were cash crop and cereal yield. Cash crop production was calculated through the FBS and was defined as the sum of potato and sugar beet production.

However, not all farms in the sample were using water for irrigation. Therefore, in order to keep the assumption of homogeneity of the sample required in the DEA method the dataset was split into two groups, i.e. irrigating farms were defined as those that use water for irrigation while the remaining farms form the second group of using water for various agricultural purposes other than irrigation (washing, spraying, etc.). Table 5.1 presents a description of the sample used to build the input and output DEA model.

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[23] For further information about the Farm Business Survey, including data collection, methodology and Farm Business Survey results, please visit the Defra Farm Business Survey website: http://www.defra.gov.uk/statistics/foodfarm/farmmanage/fbs/

[24] This variable among other costs it includes equipment related to irrigation, sprayers and equipment related to green technology. It includes costs related to potato boxes, potato graders and other machinery related to production of the specific crops included in the selected outputs

Table 5.1: Descriptive statistics of the inputs and the outputs used in the DEA linear programming model

Inputs and outputs for the DEA model	Group 1: Irrigating Farms		Group 2: Water used for various agricultural purposes	
	Mean	St. Deviation	Mean	St. Deviation
Area farmed (ha)	287	226	193	193
Total agricultural costs (£/ha)	510	187	427	140
Water use (m^3/ha)	79	58	2.19	1.73
Machinery cost (£/ha)	70	57	56	49
Total labour (hours/ha)	25	14	24	16
Cash crop yield (tonnes/ha)	37	20	40	19
Cereal crop yield (tonnes/ha)	8	1	8	2

5.4 Methodology: Data Envelopment Analysis

In an input orientated framework for DEA, the best performing farms are identified as those that manage to produce the individual levels of output with the least amounts of inputs. Linear, or convex, combinations of those best performers constitute the production frontier. Since DEA is a benchmarking technique, the efficiency of the remaining farms is then measured relative to this estimated frontier of the best performers in the sample. A more detailed discussion of the different DEA models and the development of the techniques is available in Cooper *et al.* (2006).

DEA models can be either input or output orientated assuming different types of returns to scale. For the purposes of this analysis an input orientated model with Variable Returns to Scale (VRS) was selected where efficiency scores indicate the total potential reduction for each input level while maintaining individual levels of outputs unchanged. VRS (Banker *et al.*, 1984) are considered as the most appropriate in the case of agriculture (Asmild & Hougaard, 2006; Lilienfeld & Asmild, 2007). The alternative would have been to choose Constant Returns to Scale (CRS) assuming that when doubling all inputs, outputs will also double which is not a reasonable assumption in the case of agriculture. For example, a limiting production input is area farmed which is difficult to increase especially in the short run.

Furthermore, since the purposes of this research is to assess the inefficiency of water use for General Cropping Farms (GCF_s) in the EARBC, a non-discretionary or sub-vector variation of the model for DEA was used. Model specifications and assumptions have been presented in detail in sections 2.3.3 and 2.3.4 of this thesis. We repeat the linear programming here in order to enable the understanding of the concept of water use efficiency and excess in water use.

$$
\begin{aligned}
&\min_{\theta,\lambda^i} \theta' \\
&s.t. \quad \theta x'_{DIji} \geq \sum_{i=1}^{n} \lambda^i x_{DIji} && j \in DI \quad (i) \\
&\quad -x'_{NDIji} \geq \sum_{i=1}^{n} \lambda^i (-x_{NDIji}) && j \in NDI \quad (ii) \\
&\quad\quad y'_{ri} \leq \sum_{i=1}^{n} \lambda^i y_{ri} && (iii) \\
&\quad\quad \lambda^i \geq 0 && (iv) \\
&\quad \sum_{i-1}^{n} \lambda^i = 1 && (v)
\end{aligned}
\qquad \textbf{(5.1)}
$$

Where, x_{DIji} is the j^{th}discretionary input for farm i , x_{NDIji} is the j^{th} non-discretionary input for farm i and y_{ri} is the r^{th} output for farm i, $i = (1, \cdots n),\ j = (1, \cdots m)\ and\ r = (1, \cdots s)$. The optimal value θ represents the sub-vector efficiency score for each farm and its values lie between 0 and 1. This efficiency score indicates how much a farm is able to reduce the use of its discretionary inputs (water use) without decreasing the level of outputs with reference to the best performers or benchmarking farms in the sample. The first two constraints limit the proportional decrease in both discretionary (equation $(5.1)_{(i)}$) and non-discretionary (equation -$(5.1)_{(ii)}$) inputs, when θ is minimised in relation to the input use achieved by the best observed technology. The third constraint ensures that the output generated by the i^{th} farm is less than that on the frontier. All three constraints ensure that the optimal solution belongs to the production possibility set. The final constraint expressed by the equation $(5.1)_{(iv)}$, called also the convexity constraint, ensures the VRS assumption of the DEA sub-vector model. Therefore, the non-discretionary inputs can be treated in the DEA model as negative outputs (Bogetoft & Otto, 2010). The CRS and VRS models differ only in that the former, but not the latter includes the convexity condition described by equation $(5.1)_{(iv)}$ and its constraints in $(5.1)_{(v)}$ (Cooper *et al.*, 2006).

Considering the above, a farm that receives a sub-vector efficiency score equal to 1 is therefore a best performer located on the production frontier and has no reduction potential for water use. Any other score less than $\theta = 1$ however indicates a potential reduction in water use, i.e. excess water is used at a farm level, thus this farm is considered as water use inefficient. To illustrate this with a numerical example let us assume that the optimal θ for a farm is 0.75 which means that this farm is able to produce the same level of output by using 75% of its current level of water when compared to the best performing technology in the sample. The excess water use can be calculated as:

$$(1 - \theta)x_{DIji} \qquad \textbf{(5.2)}$$

An analysis on returns to scale was also performed in order to determine whether the farms in the sample are operating under Increasing Returns of Scale (IRS), Decreasing Returns of Scale (DRS) and Constant Returns of Scale (CRS). Measures of Scale Efficiency (SE), Pure Technical Efficiency (PTE) and Overall Technical Efficiency were estimated according to the method presented in section 2.4 of this thesis.

5.5 Results

The estimated mean technical efficiency under the two different assumptions of VRS (PTE) and CRS (OTE) for the group of irrigating farms was 0.97 (STD=0.02) and 0.95 (STD=0.02) respectively. This implies that irrigating farms could on average reduce their inputs by 3% without any size adjustments (PTE is considered) and by 5% when size adjustments are made (OTE is considered), maintaining in both cases the same level of output. For the group of non-irrigating farms, the mean technical efficiency under the VRS and CRS assumptions is 0.94 and 0.89 respectively indicating a 6% reduction in inputs without any size adjustments and an 11% reduction when size adjustments are made. Table 5.2 presents statistical information and the distribution of PTE and OTE for the sample. In terms of PTE there is no statistical difference between the two groups of farms (Welch Two Sample t-test, $t=1.44$, $p\text{-value}>0.10$).

The mean SE for the irrigating farms is 0.97 (STD=0.01) with 73% of the farms operating at their optimal scale (SE=1). The figures for the non-irrigating farms are 0.95 (STD=0.01) and 71% respectively. When comparing PTE and SE for both groups there is no difference between the two implying that both have the same impact on farm efficiency and productivity.

The mean sub-vector efficiency for the irrigating farms is 0.87 (STD=0.07), indicating that the observed value of outputs (cash crop and cereal yield) could have been maintained by keeping the level of other inputs constant whilst reducing water requirements by 13%. Specifically, only three irrigating farms have been identified as water use inefficient. The majority of the farms (80%) are characterised as water use efficient. In the case of non-irrigating farms, the mean sub-vector efficiency is 0.81 (STD=0.05) indicating that water requirements could potentially be reduced by 19%. Fourteen farms are identified as water use inefficient with the remaining 67% of the farms being on the frontier. There is no statistical difference in terms of sub-vector efficiency for the two groups (Welch Two Sample t-test, $t=0.64$, $p\text{-value}=0.53$). Table 5.3 presents the estimated savings in water use through expression (5.6) for the inefficient farms in both groups. In addition technical and sub-vector WUE are positively correlated (Kendall's Tau=0.93, $p\text{-value}<0.01$).

Table 5.2: Frequency distribution of technical and WUE under the assumptions of CRS and VRS, and mean of SE.

Irrigating farms				
	Technical efficiency		WUE	
Efficiency level (%)	CRS	VRS	CRS	VRS
	Number of farms	Number of farms	Number of farms	Number of farms
0<Eff<25	0	0	1	2
25<Eff<50	0	0	4	1
50<Eff<75	2	0	0	0
75<Eff<100	4	3	1	0
Eff=100	9	12	9	12
Mean Efficiency	**0.95**	**0.97**	**0.76**	**0.87**
Mean Scale Efficiency	**0.97**		**0.88**	
Non-Irrigating farms				
Efficiency level (%)	Technical efficiency		WUE	
	CRS	VRS	CRS	VRS
	Number of farms	Number of farms	Number of farms	Number of farms
0<Eff<25	0	0	8	5
25<Eff<50	0	0	10	2
50<Eff<75	6	5	3	6
75<Eff<100	17	9	2	1
Eff=100	19	28	19	28
Mean Efficiency	**0.89**	**0.94**	**0.64**	**0.81**
Mean Scale Efficiency	**0.95**		**0.78**	

Table 5.3: Estimated technical efficiency, sub-vector efficiency and water excess for both farm groups

	Farm	Technical Efficiency	Sub-Vector Efficiency	Excess in Water use (m^3/ha)
Irrigating	1	0.83	0.44	49.45
	7	0.81	0.26	96.43
	10	0.93	0.29	130.08
Non-irrigating	17	0.94	0.52	0.39
	20	0.74	0.19	2.52
	26	0.99	0.87	0.19
	27	0.73	0.52	0.71
	30	0.60	0.22	1.57
	34	0.78	0.35	1.39
	35	0.84	0.57	0.64
	36	0.82	0.33	0.67
	44	0.58	0.16	2.26
	46	0.89	0.68	0.75
	47	0.92	0.74	0.81
	49	0.79	0.21	1.44
	50	0.83	0.62	0.49
	52	0.69	0.06	6.98

When returns to scale are considered in the analysis, 60% of the irrigating and 45% of the non-irrigating farms operate under constant returns to scale indicating that these farms are not required to adjust their scale of operation in order to improve efficiency in the long run. However, in the case of irrigating farms, two are operating under DRS which implies a reduction in scale of operation in order to achieve input use efficiency and four are operating under IRS. The latter indicates that these farms need to shift down their long-run average cost curve and increase their size in order to save costs. Similarly in the group of non-irrigating farms, ten are operating under DRS and 13 under IRS. Table 5.4 presents information in relation to the returns to scale and farm size[25] in the sample. It is interesting to note that for the non-irrigating group a significant proportion of medium and large farms operate under DRS which implies increasing marginal cost and rising average cost.

[25] In order to classify farms in the FBS into different sizes the Standard Labour Requirements (SLR) for different enterprises are calculated which are then used to find the total amount of standard labour used on the farm. Once the total annual SLR has been calculated the number of hours can be converted to an equivalent number of full time workers (on the basis that a full-time worker works a 39 hour week and so 1900 hours a year). This leads to the classification of farms by number of full time equivalent (FTE) workers as follows:
Small farms: 1<FTE<2, Medium farms: 2<FTE<3, Large farms: 3<FTE<5

Table 5.4: Returns to scale in relation to farm size for both groups in the sample

Group	Returns to Scale	Farm Size			%
		Large	Medium	Small	
Irrigating	CRS	5	3	1	60
	DRS	2	0	0	13
	IRS	2	2	0	27
Non-Irrigating	CRS	6	9	4	45
	DRS	3	7	0	24
	IRS	5	6	2	31

5.5.1 The profile of water use efficient irrigating and non-irrigating farms

Since DEA is a benchmarking technique it is interesting to examine the characteristics of farms serving as peers in the sample. Graphically this is illustrated as the farms on the technological frontier that the farm under optimisation in the DEA model is projected onto. The reference set of farms is the set of units that span the part of the frontier where the reference unit is located. For both irrigating and non-irrigating farms a group of peers has been identified based on the frequency that these have served as benchmarking units in the sample based on the idea that they are the most influential and the most efficient in terms of water use (Cooper *et al.*, 2006).

For the irrigating group four farms have been identified as the most frequently appearing peers, specifically farms 2, 6, 12 and 14. Information on specific water management practices, irrigation system used and reasons for taking measures to reduce or prevent pollution or for carrying out water efficient methods is presented in Table 5.5. It is interesting to notice that water balance calculations, the use of a decision support tool and the ownership of a weather station or forecast records are common practices amongst these farms. In-field soil moisture measurement (including assessing the soil and crop inspection) is also practised by two of the farms. Furthermore, the major reason for adopting these management practices is driven by the need to protect the environment. It should also be noted that all four farms are following a guidance system for managing nutrient input, test soil nutrient levels and are calibrating fertiliser spreaders. Also, farm 2 is taking measures in order to reduce pollution of surface water by farm operations.

In the case of non-irrigating farms, as expected, the water use management profile is different. The most frequently appearing peers are farms 13, 16, 17, 23 and 38. Only one of these farms is using in-field soil moisture measurement, while none is following the water balance approach. These two practices although important for scheduling irrigation are also essential to account for all water additions and subtractions from the soil root zone and therefore useful to improve productivity. Moreover, four of the farms are using either their own weather forecast or they are using published data from other weather forecast agents such, for instance the Meteorological Office. Farm 17 is not using any weather records or forecast information. As in the case of irrigating farms, all farms are using agronomic advice. The main reasons behind the adaptation of any practice related to prevention of pollution or for carrying out water efficient methods is compliance to legislation (farms 13, 16, 17, 23) and financial reasons (farm 38). The non-irrigating peer group matches the irrigating group in terms of management practices adapted to reduce or prevent water pollution. All farms follow a guidance system for managing nutrient input, testing of soil nutrients and are calibrating their fertiliser spreaders. Farms 16, 13, 23 and 38 are also using tramlines which allow accurate and efficient fertilising and spraying of crops while also reducing losses of runoff and total phosphorus by a significant amount (Deasy *et al.*, 2010). In addition, farms 16 and 38 are using six metre buffer strips, ponds and wetlands to reduce run-off and to store water. The latter can be an effective strategy to trap sediment and nutrients from runoff pathways and significantly contribute to the reduction of diffuse pollution according to the findings of the MOPS2 project (Deasy *et al.*, 2010). Such practices will improve water quality and also enable UK agriculture to meet the requirements of the EU water framework directive. Finally, farm 38 is the only farm that practises minimum tillage as a method of soil manipulation to improve crop production efficiency. The detailed profile of the non-irrigating peer farms is presented in Table 5.6.

Table 5.5: Management practices for efficient water use: Irrigating farms

Farm ID	2	6	12	14
High tech spray nozzles				✓
Optimised irrigation systems	✓		✓	
Decision Support tool	✓		✓	✓
Agronomic advice	✓	✓	✓	✓
Own weather forecast/records	✓	✓		✓
Other weather forecast/records	✓		✓	✓
Water balance calculations	✓		✓	✓
In-field soil moisture measurement (including feeling soil, crop inspection)	✓			✓
Primary reasons for taking measures to reduce or prevent pollution or for carrying out water efficient methods	Environmental	Environmental	Environmental	Financial

Table 5.6: Management practices for efficient water use: Non-irrigating farms

Farm ID	17	16	13	23	38
High tech spray nozzles	✓	✓		✓	✓
Optimised irrigation systems					
Decision Support tool					
Agronomic advice	✓	✓	✓	✓	✓
Own weather forecast/records				✓	✓
Other weather forecast/records		✓	✓		
Water balance calculations					
In-field soil moisture measurement (including feeling soil, crop inspection)				✓	
Primary reasons for taking measures to reduce or prevent pollution or for carrying out water efficient methods	Legislation	Legislation	Legislation	Financial	Legislation

5.6 Discussion

The increased frequency of extreme weather phenomena (drought and flood periods) in the future for the UK will result to a higher risk with regards to securing yield and farm income. This, in addition to increased food demand, has raised the need for agricultural production systems to adapt in a challenging and insecure environment. Agriculture in the EARBC is vulnerable to water shortages due to the increasing risk of drought and over abstraction of water resources. Therefore the efficient use of water resources becomes a joint priority within a framework of SI of agriculture. Furthermore, the average technical efficiency score is for the GCF_s in the sample for the CRS and VRS model assumptions is 0.95 and 0.97 respectively. Similar findings and efficiency levels are reported by Wilson *et al.* (1999) in a study measuring and explaining technical efficiency in UK potato industry.

Our results on the average sub-vector WUE 0.87 and 0.81 for both irrigating and non-irrigating farms respectively suggest that improvements can be made towards the management of water resources in agriculture.

Regarding returns to scale, pathways for the improvement of productivity and maximisation of net benefits given the limited land and water resources are suggested. Specifically, 27% of the irrigating and 31% of the non-irrigating GCF_s operate on the downward sloping part of the long run average cost curve. There is a potential therefore to increase production and hence profitability. This information, in addition to the results derived from the PTE analysis; indicate also a need for change in the management of inputs in the short run in order to improve control over the production process. On the other hand 13% of the irrigating and 24% of the non-irrigating GCF_s are either producing above their profit maximising level of outputs or using excessive amounts of inputs per unit of output. The latter is confirmed by the level of inefficiency of water use based on the sub-vector model (Table 5.2).

The majority of irrigating farms in the sample (86.7%) are abstracting water directly from bore holes, river streams, ponds, lakes and reservoirs. In order to renew their abstraction licences farmers are required to demonstrate efficient use of water resources to the regulator (Environment Agency, 2013). The results from the sub-vector model confirm that most of the irrigating farms (80%) are on the frontier and hence are water use efficient. Knox *et al.* (2012) refers to the "Save water, save money[26]" booklet produced in 2007 and distributed to 2500 farmers across England to promote the "pathway to efficiency". The main components of the pathway include that farmers understand their system of production, make efforts to optimise the use of their irrigation systems, ensure appropriate soil and water management and demonstrate best practices that have proved over time to lead to more efficient irrigation (Knox *et al.*, 2012).

The profile of the best performing irrigating farms in our sample can be used as a good practice example to promote WUE in England. Specifically, farmers are managing their irrigation systems to ensure the right

[26] The information booklet is available for download from the UK Irrigation Association website: http://www.ukia.org/pdfs/Save%20water%20save%20money.pdf

water pressure, water use and irrigation uniformity. That involves regular checks on the distribution network and equipment performance to enable the right application of water on crops and thus improving yield and quality. In addition, in-field soil moisture measurement (including assessing the soil and crop inspection) and water balance calculations are management practices applied by the peer farms which enable them to schedule irrigation better and hence provide the optimal application of water at the right time and volume. Further to these, the majority of the peers use a decision support tool for short and long term irrigation planning and monitoring. Such a tool provides farmers with options to support management decisions to improve economic and water efficiency as well as the environmental performance (reducing wastage) of the farming system (Khan *et al.*, 2010). An important finding derived from the benchmarking analysis of the irrigating farms is that the reason for adopting irrigation management practices is to improve WUE and to protect the environment.

Although the non-irrigating farms in the sample have a different profile in terms of water management practices it is necessary to emphasise the common methods used between the two groups to reduce or prevent water pollution. Both follow a guidance system for managing nutrient input, test soil nutrients and calibrate fertiliser spreaders. Multiple benefits arise from these practices both for the farmer and the environment. From the perspective of the farmer, this means best value from fertilisers and manures used reduced input costs and also enhanced crop yield and quality. In addition, there are reduced environmental risks due to leakages and excess of nutrients which could damage biodiversity and water quality. Both groups use tramlines, buffer strips, ponds and wetlands to reduce run-off and store water. However, the difference between the two groups in this regard is that the main reason for non-irrigating farms to adopt these practices is compliance with legislation rather than for direct economic or environmental benefit.

5.7 Conclusions

Water for agriculture in the EARBC may be becoming scarcer and more variable due to the increased abstraction rates and the increased occurrence of drought phenomena during the crop development period. Nationally there is a need to secure production in order to meet increasing food demand and thus supplementary irrigation of crops increases the pressure on water resources in the catchment. To ensure the sustainability of farming systems in the area, farmers need to both maximise economic productivity and efficiency while directing their strategies towards minimising excess of water for irrigation and other agricultural uses (washing, spraying).

A benchmarking technique such as DEA can provide a useful tool to identify excess water use when comparing farms with others in the same region and with the same characteristics and therefore help to improve WUE at farm level. Such a tool could also be available to farmers through the FBS farm business online benchmarking tool[27] in order to enable them to improve WUE and compare their performance with other farms in the sector. Moreover, peer farms can provide useful information in respect of operational and management changes that can be made to improve irrigation system performance and water productivity.

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[27]Available at: http://www.farmbusinesssurvey.co.uk/benchmarking/

In addition, the analysis on returns to scale provides pathways for long term improvements and planning which could be used to strategically position a farm in relation to the long term average cost curve and hence improve economic efficiency and productivity of the GCF_s.

From a policy perspective, the current water abstraction regulation in the UK is under reform. The main pillars of the reform are based on the need to face challenges in water availability due to changing weather conditions, the increased demand for water from growing population and the need to enable trading of water rights (Defra, 2013a). The results presented here suggest that the new legislation should incentivise farmers to improve management practices for efficient water use not only for irrigation but also for other agricultural purposes and also improve water storage at farm level through rain harvesting and on farm reservoirs. Furthermore, it is essential that any reform accounts for the importance of supplementary irrigation for cash crops (potatoes, sugar beet) and the need to secure yield. Any restriction on water abstraction during the growth period due to water shortages or drought conditions would result in a failure to meet quality standards and consequently income loss to farmers. Therefore, it is important that the new regime considers the economic significance off irrigated agriculture not only for the farming systems but also for the local jobs and local economies.

Finally, this research highlights the importance of using a well-established and coherent database such as the FBS for this type of analysis. The detailed information on production elements of farming and the collection of data related to management practices can potentially be used for a consistent benchmarking tool for assessing WUE and best management practices to ensure the continued improvement in the environmental performance of farms.

Chapter 6

Evaluating SI of farming systems

6.1 Introduction

The analysis presented in Chapter 4 and Chapter 5 outlined strategies for the improvement of agricultural productivity and the management of natural resources (water) in the context of SI of farming systems. However, these are not the only requirements. According to the definition of SI by Firbank *et al.* (2013) farms are also required to reduce the environmental pressures generated by the production process at a farm level. This Chapter uses DEA techniques to evaluate the SI of farming systems based on the estimation of an Eco-Efficiency index. The assignment of weights to environmental pressures through linear programming techniques, when optimising the relative Eco-Efficiency score, allows the identification of appropriate production technologies for each farm and therefore indicates specific improvements that can be undertaken towards SI. The results of the analysis are used to suggest strategies for the integration of farming practices and environmental policies in the framework of SI of agriculture. Paths for improving the index of Eco-Efficiency and therefore reducing environmental pressures are also outlined in the discussion section of this Chapter.

6.2 The sustainable intensification of farming systems

Climate change and increased food demand are two of the most important challenges for the future growth of agricultural systems. Global food demand is likely to increase by 70% by 2050 due to both population growth and changes in consumption patterns (Foresight Report, 2011). The need for securing food supply, managing natural resources efficiently, building resilience to more frequent extreme weather phenomena and developing adaptation strategies for farmers has prioritised the need for a sustainable intensification (SI) of agriculture (FAO, 2011; Foresight Report, 2011).

Firbank *et al.* (2013), define SI at a farm level as the process of increasing agricultural production per unit of input whilst at the same time ensuring that environmental pressures generated at a farm level are minimised. SI of agriculture can therefore be considered not only as a practice but also as a mechanism of farm management that serves the balance between sustainability and intensification of production. This relies on the engagement of integrated methods and technologies to manage limited natural resources (soil and water), pests and nutrients (Pretty, 1997). Garnett *et al.* (2013) suggest that food security requires as much attention to be focussed on increasing environmental sustainability as to raising productivity. This means that, farmers, not only need to simultaneously increase yields to meet food demand, but also need to reduce environmental pressures generated by the production process. Therefore, from an environmental perspective this means reducing any additional conversion of land to agriculture (maintain existing land ecosystems and biodiversity), increasing productivity and improving input use efficiency (e.g. water, energy, agrochemicals) (Garnett & Godfray, 2012; Garnett *et al.*, 2013).

Agriculture in the UK is a major contributor in determining and enhancing the viability of rural economies and preserving rural landscapes but also is the main source of degradation in a range of ecosystem services (Firbank *et al.*, 2008). Sustainable farming systems therefore, are characterised as those that are able to be productive and to maintain their contribution to society in the long term. These agricultural systems by definition will be using natural resources efficiently, be competitive in the commercial market and environmentally protective (Rigby & Caceres, 1997).

For UK agriculture to meet the future challenges of food demand and climate change, SI can therefore be a management option especially for areas that are experiencing a stasis in productivity growth, where a more efficient use of natural resources, production inputs and new technologies may be able to move production onto an upward trajectory and at the same time reduce the negative environmental impacts (Firbank *et al.*, 2013; Garnett *et al.*, 2013; Barnes & Thomson, 2014).

Recent research has sought evidence of SI among farming systems in the UK (Areal *et al.*, 2012; Barnes & Poole, 2012; Firbank *et al.*, 2013; Barnes & Thomson, 2014). Firbank *et al.* (2013) suggest that a farm is practising SI when it has managed to increase the food production per unit area in the study period and at the same time none of the environmental indicators selected has deteriorated. They sampled 20 farms of different types (arable, mixed, dairy, upland livestock farms) characterised and selected as being innovative by their peers. Results from the selected indicators and the outputs of the focus groups show that there is evidence of SI among British farms over the recent period. The motivation of farmers towards SI has mainly been financially driven via increased input use efficiency (reducing waste and pollution) and by allocating resources through agri-environment schemes to enhance biodiversity at farm level (Firbank *et al.*, 2013).

Barnes and Thomson (2014) have used a balanced panel of 42 beef farms within Scotland to consider the relationship between sustainability and intensification in the context of Scottish agriculture and the use of possible indicators for measuring SI. Further, they have conceptualised the link between the technology frontier and sustainable intensification by identifying the need for reallocating inputs to increase efficiency and productivity, and hence to cause an upward shift into the technology frontier.

6.2.1 Using Eco-Efficiency to measure sustainable intensification

One of the challenges in measuring SI is to find appropriate measures of the environmental dimensions. One variable that may give some indication of change in supply of ecosystem services is the level of rough grazing area to total area used, a criterion for identifying Higher Nature Value farming systems (Barnes *et al.*, 2011), and also as a proxy for environmental outputs (Areal *et al.*, 2012). Firbank *et al.* (2013) underlines the need for the development of metrics that can simultaneously account for both environmental pressures and economic output of farming systems in order to evaluate SI at farm level in temperate regions. As an example, composite indicators have been used to assess sustainability and production efficiency (Gomez-Limon & Riesgo, 2009) in the agricultural sector since it is possible, with the appropriate weighting of the different dimensions of the indicator, to assess progress on the three common dimensions of sustainability (economic, social and environmental) in order to produce an integrated performance output for evaluation. According to Barnes and Thomson (2014), most composite indicators have focused on country or regional level while only a few focus specifically on the agricultural sector. However, there is no evidence for the existence of an agreed set of indicators or a composite indicator for evaluating and measuring SI (Westbury *et al.*, 2011; Firbank *et al.*, 2013; Barnes & Thomson, 2014).

As such a composite indicator, the Economic-Ecological Efficiency, frequently known as Eco-Efficiency, emerged as a practical approach for evaluating progress towards sustainability and economic efficiency (Schaltegger *et al.*, 1996). The concept was introduced by Schaltegger and Sturm (1990) and was then adopted and popularised by the World Business Council for Sustainable Development (2000). The OECD (1998) defines Eco-Efficiency as a ratio of an output (value of products) over the inputs used (the sum of environmental pressures generated by the firm, the sector or the economy) which measures the efficiency with which ecological resources are used to meet human needs. Using Eco-Efficiency as a measure of the economic value added over the environmental pressure generated is a potential method of evaluating progress towards the SI of agricultural systems. Therefore, an improvement in the Eco-Efficiency index can be translated as a decrease in environmental impact while the value of production is maintained or increased (de Jonge, 2004; European Environment Agency (EEA) 2010; Gomez-Limon *et al.*, 2012) and the reverse in the case of deterioration.

However, as emphasised by the WBCSD (2000), improvements in the index of Eco-Efficiency do not automatically lead to improvements in sustainability. Given that sustainability is usually concerned with the absolute pressure that an economic activity is generating rather than the relative pressure, the main pitfall in the Eco-Efficiency ratio is that high levels of environmental pressures (e.g. soil erosion, pesticides risk, water use, fertiliser risk, CO_2 emissions) generated at a farm level can be interpreted as an eco-efficient activity if compensated by high levels of Net Farm Income (Kuosmanen & Kortelainen, 2005; Picazo-Tadeo *et al.*, 2011; Gomez-Limon *et al.*, 2012). Any advance of Eco-Efficiency in relative terms (economic value added per environmental pressure) may still indicate an increase in the environmental pressures generated by the economic activity and therefore cause unacceptable harm or irreversible damage to the ecosystem.

These shortcomings, however, do not invalidate the use of Eco-Efficiency as a concept to stimulate innovation and enhance the SI of farming systems. Kuosmanen and Kortelainen (2005) suggest at least two basic reasons for using an Eco-Efficiency index for assessing the impacts of production systems. First, in the context of trying to reduce environmental pressures, improvements in Eco-Efficiency can be shown to be cost-effective and second, from a policy perspective, improvements in the efficient use of inputs are more attractive and easier to adopt than other more radical policies that directly restrict the level of economic activity. This win-win outcome of policies promoting efficient use of inputs encourages sustainable agriculture without the need for even greater environmental regulation as it leads to a reduction in the level of damaging inputs, such as fertilisers, pesticides, fossil fuels etc., will increase environmental efficiency and also improve net cost savings (de Jonge, 2004).

Therefore SI can be viewed as a trade-off between economic and ecological performance characterised by an Eco-Efficient frontier (Mahlberg & Luptacik, 2014) that aims to reduce environmental pressures in agriculture. In other words, a farm lying on the frontier cannot increase output without increasing the intensity of production which results in increasing waste and emissions. Eco-Efficiency frontiers can be estimated with the use of the Data Envelopment Analysis (DEA) method, a non-parametric frontier based modelling approach. This is a method based on production efficiency models that are used to estimate frontier functions and measure the efficiency of farms in relation to the estimated frontiers (Coelli *et al.*, 2005). A detailed literature review on integrated ecological-economic analysis in a production context is presented in Lauwers (2009).

Modelling and assessing Eco-Efficiency in a DEA based modelling framework can be approached in two different ways according to Korhonen and Luptacik (2004). The first approach decomposes the problem into two parts by initially measuring both technical efficiency (the relationship between desirable outputs to the inputs) and ecological efficiency (the relationship between the desirable outputs to the undesirable outputs) and then combining them in a DEA model. The second approach suggests accounting simultaneously for economic and ecological performance given that the objective is to increase the desirable outputs and minimise the environmental pressure generated by the production process. According to Picazo-Tadeo *et al.* (2012) the latter can provide a base for developing a broad range of models depending on the treatment of the economic output and/or the environmental pressures.

Various research papers have used DEA techniques to discuss the notion of Eco-Efficiency in different industries (Korhonen & Luptacik, 2004; Kuosmanen & Kortelainen, 2005; Hua *et al.*, 2007; Zhang *et al.*, 2008; Lauwers, 2009). Although DEA techniques have been widely used for the assessment of the environmental performance of farms (de Koeijer *et al.*, 2002; Asmild & Hougaard, 2006; D'Haese *et al.*, 2009; Buckley & Carney, 2013) and the agricultural sector (Barnes *et al.*, 2009b) only a few research papers have applied the method for the assessment of farming Eco-Efficiency defined as the ratio of economic value added over the environmental pressure generated (Gomez-Limon *et al.*, 2012). Picazo-Tadeo *et al.* (2011) have used DEA techniques for the assessment of potential environmental pressure reductions in a set of 171 farms in rain-fed agriculture systems of Valencia, Spain. Picazo-Tadeo *et al.* (2012) have also assessed the Eco-Efficiency of a set of 55 olive farms belonging to the traditional plain grove system in Andalusia, Spain by using directional distance functions and DEA techniques. Additionally, Gomez-Limon *et al.* (2012), following Kuosmanen and Kortelainen (2005) and Picazo-Tadeo *et al.* (2011), have used DEA techniques to estimate pressure distance functions which contribute to a farm level assessment of Eco-Efficiency in 292 Andalusian olive farms. Iribarren *et al.* (2011) have used a joined implementation of the Life Cycle Assessment (LCA) and DEA approach to assess 72 dairy farms in Galicia (Spain) in order to identify farms with an efficient operation by using Eco-Efficiency criteria.

Here, it is suggested that environmental pressures generated at a farm level, as defined by Picazo-Tadeo *et al.* (2011), can be interpreted as an indication of the level of intensification of agricultural production in an effort to secure yields and maximise profit. Higher levels of inputs (fertilisers, crop protection costs, water, fuel, etc.) for individual farms in a benchmarked sample indicate that these farmers are using more intensive production methods when compared with others in the same sample. The objective of this chapter to measure the SI of farming systems, which can be used by both farmers and policy makers to identify excess input use and explore the different levels of intensification between farms of the same type. Little, if any, previously published research has so far applied DEA estimates of Eco-Efficiency for the assessment of SI in agricultural systems.

The research focuses on the Eco-Efficiency of General Cropping Farms (GCF_s) in the EARBC of England, as a case study, and evaluates how these farms perform in the context of the SI of agriculture. Additionally a double bootstrap truncated regression analysis (Simar & Wilson, 2007) is used to analyse the characteristics of the farming systems (e.g. farm size, farmer's education level, membership in environmental schemes, agri-environmental payments and costs) that may have an impact on Eco-Efficiency and subsequently to the balance between sustainable production and intensification.

6.3 Material and methods

6.3.1 Dataset and variables

Data for the empirical application of the model was obtained from the Farm Business Survey (FBS) which is a comprehensive and detailed database that provides information on the physical and economic performance of farm businesses in England[28].

Initially data for 83 General Cropping Farms (GCF_s)[29] were extracted from the FBS. These GCF_s, geographically located in the EARBC were surveyed for the FBS in 2011. Ten farms were excluded due to missing data or zero values. Because DEA methods are quite sensitive to the presence of outliers in the data when measuring efficiency (Sexton *et al.*, 1986), the remaining 73 farms were tested for outliers using the graphical method of Wilson (1993).

[28] For further information about the Farm Business Survey, including data collection, methodology and Farm Business Survey results, please visit the Defra Farm Business Survey website: http://www.defra.gov.uk/statistics/foodfarm/farmmanage/fbs/

[29] As GCF_s are classified holdings on which arable crops (including field scale vegetables) account for more than two thirds of their total Standard Output (SO) excluding holdings classified as cereals; holdings on which a mixture of arable and horticultural crops account for more than two thirds of their total SO excluding holdings classified as horticulture and holdings on which arable crops account for more than one third of their total SO and no other grouping accounts for more than one third. (FBS 2009-2010).

This resulted in a representative[30] sample of 61 General Cropping Farms (GCF_s) after detecting and excluding outliers, based on the EARBC from the FBS 2011/2012 database. The GCF type was selected because of the mixture of crops (potatoes, sugar beet, cereals, horticulture) that requires intensive use of machinery (especially potatoes and sugar beet), irrigation of the crops to secure (under drought conditions) yield and also because it is one of the most representative agricultural systems in the EARBC.

The selection of the area was based on a) the importance of the EARBC in terms of agricultural production in England and b) the projected vulnerability of the area under the UKCP09 climate projections in terms of reduced rainfall and increased temperature (Jenkins *et al.*, 2009).

More than half of the EARBC land surface is used for agriculture and horticulture (approximately 1.5 million hectares). Also, it is recognised as one of the most productive agricultural landscapes in England, known for its cereal crops and the production of potatoes and sugar beet. In particular, in the counties of Cambridgeshire, Lincolnshire, Norfolk and Suffolk over half of the total sugar production in England is harvested.

When discussing sustainability and especially the intensification of the production process, the high risk of drought in the EARBC as well as the increased demand for direct abstraction of water is an important environmental pressure generated from the GCF system. More specifically reduced summer rainfall could lead to irrigation water shortages and associated conflicts over water use, insufficient water flow to dilute pollution, inability of soil to absorb rainfall, reduced crop yield and increased fire risk (Charlton *et al.*, 2010).

The production technology in the case of GCF_s in the EARBC is described through the economic costs of fertilisers, crop protection, water use, and machinery fuel and energy requirements. Each variable is expressed on a per hectare basis when used as input in the model. These are described in detail by the Farm Business Survey Instructions for data collection (Farm Business Survey, 2011).

In the model;

Fertilisers costs include all straight compounds and organic manures together with farmyard manure, lime and chalk, peat, soil composts and combined fertiliser/insecticides, sewage, soot, and all waste products.

Crop protection costs include all herbicides, fungicides, insecticides, slug pellets and dusts.

Water costs: include costs of water for irrigation, drinking, cleaning, cooling, etc on the farm. It also includes all charges and licences payable for connection to a water supply and for abstraction of water for irrigation where they relate to the farm business.

Machinery and vehicle fuels and oil covers the gross cost (before any subsidy) of petrol, diesel, oil, gas, paraffin and lubricating oils and greases for agriculture at farm level.

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[30] The Farm Business Survey uses a sample of farms that is representative of the national population of farms in terms of farm type, farm size and regional location (FBS – Statistical Information; http://www.farmbusinesssurvey.co.uk/

Energy costs are the sum of costs for electricity and heating fuel. More specifically, electricity costs cover all electricity used in the farm business including that used for drying cereals, etc. It also covers the cost of electricity generated on the farm by means of green technologies which is costed in as a contra item at the same rate of buying in from the national grid. Heating fuel includes all the heating fuels except electricity for all farm purposes. Any fuel used for chilling produce on farm is also recorded in this variable.

Economic value added per farm is calculated as the Farm Business Gross Margin per hectare. The calculation of farm output took into consideration the adjustment for disposal of previous crops, the main crop enterprise output excluding set aside payments, the by-products and forage output and the set aside payments. Output from integrated non-agricultural activities was excluded. All variable costs recorded from the FBS related to agricultural production were subtracted. The remaining value is the economic value added at a farm level. Table 6.1 presents a description of the sample used to build the input and output DEA model.

Table 6.1: Descriptive statistics of the inputs and the outputs used in the DEA linear programming model

No of farms 61	Fertiliser cost (£/ha)	Crop protection Cost (£/ha)	Water cost (£/ha)	Machinery fuel cost (£/ha)	Energy cost (£/ha)	Economic value added (£/ha)
Mean	142	133	7	70	18	1,231
St. Deviation	46	61	5	42	14	386
Minimum	15	6	1	5	1	491
Maximum	241	293	21	194	75	2,724

6.3.2 Assessing sustainable intensification of agriculture with Data Envelopment Analysis

6.3.2.1 DEA approach[31]

The DEA method (Charnes *et al.*, 1978; 1979; 1981; Charnes *et al.*, 1985) was used to assess the SI of the GCF_s in the EARBC. DEA is a linear-programming method which calculates the most efficient Decision Making Units (DMUs) or the best-practice frontier in a given set of firms, here in relation to GCF_s. DEA is a non-parametric method in the sense that it requires only a limited number of *a-priori* assumptions regarding the functional relationship between inputs and outputs. Instead, the production frontier is constructed as a piecewise linear envelopment of the observed data points. Different units of measurement can be used for the various inputs and outputs and knowledge of their relative prices is not required. The DMUs enclosed by the envelope are the ones considered to be inefficient and, depending on the model of DEA used (either

[31] For the purposes of this paper and to keep consistent with the previous literature, symbols and formulations of the model are adapted and appropriate adjusted from Picazo-Tadeo *et al.* (2011)

input or output oriented), should adjust their inputs or outputs to move on the frontier. Output oriented DEA maximizes output for a given level of the inputs used, while input-oriented DEA minimizes inputs for a given level of output. While using DEA two different approaches can be considered based on the assumptions taken on returns to scale: constant returns to scale (the Charnes, Cooper and Rhodes (CCR) model (Charnes *et al.*, 1978)) and variable returns to scale (the Banker, Charnes and Cooper (BCC) model (Banker *et al.*, 1984)).

DEA, as opposed to adopting weighing schemes for indicators estimation, does not use subjective judgement, which may be considered an advantage (Kuosmanen & Kortelainen, 2005; Cooper *et al.*, 2006). DEA techniques has been used to assess the environmental impacts associated with agricultural production process (de Koeijer *et al.*, 2002; Asmild & Hougaard, 2006; Gerdessen & Pascucci, 2013; Aldanondo-Ochoa *et al.*, 2014). In particular, DEA has been used to jointly evaluate the economic and environmental potential improvement of production systems by incorporating environmentally undesirable or unwanted outputs such as, nutrient leaching from the soil, emissions and diffuse pollution.

The approach adopted in this research was developed by Kuosmanen and Kortelainen (2005) which deals jointly with the economic and ecological performance of firms

Here, Eco-Efficiency is defined as the ratio of economic value added over the environmental pressures generated. Let us assume that we observe a set of $k = 1, 2, \dots, K$ homogenous farms and that this set of farms is generating economic value denoted by variable $v = (v_k)(k = 1, \cdots, K)$. Furthermore, the agricultural production process generates a set of $n = 1, \cdots, N$ damaging environmental pressures similarly observed at a farm level which are denoted by the matrix $\boldsymbol{p} = \begin{bmatrix} p11 & \dots & p1n \\ \vdots & \ddots & \vdots \\ pk1 & \dots & pkn \end{bmatrix}$. The *Intensified Production Technology*[32] set (IPT) representing all the feasible combinations of value added (v_k), and environmental pressures p_{kn} , is defined as:

$$IPT = [(v_k, p_{kn}) \in R_+^{1+N} |\ \text{value added } v \text{ can be generated with pressures } p\ ] \qquad \textbf{(6.1)}$$

Following Kuosmanen and Kortelainen (2005) and Picazo-Tadeo *et al.* (2011) Eco-Efficiency of farm k is formally defined as:

$$Eco - efficiency^k = \frac{v_k}{P(p_k)} \qquad \textbf{(6.2)}$$

where P is the pressure function that aggregates the n environmental pressures into a single environmental pressure score.

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[32] The term Intensified Production Technology is preferred in this paper rather than the Pressure Generating Technology (PGT) introduced by Picazo-Tadeo et al. (2011) since in this research is argued that excessive use of inputs is related to the effort of farming systems to intensify the production process.

The economic value added v_k is calculated as follows:

$$v^k = Value\ Added^k = \frac{Farm\ Gross\ Margin\ NFI\ basis^{\ k}}{Area\ Farmed^k} = \frac{£}{ha} \qquad \textbf{(6.3)}$$

The value added on the numerator of the Eco-Efficiency ratio can be calculated either through direct primary data collection or indirectly by using published information (secondary data) on prices and quantities of outputs. Secondary data obtained from consistent and robust databases, such as the UK's Farm Business Survey (FBS) or the Farm Accountancy Network (FADN) of the European Union, can provide a reliable source of information (Barnes & Thomson, 2014). An advantage of the use of secondary data, from a policy-making view point, is that it provides a cost-effective approach for the metrics of SI. The difficulty in the assessment of Eco-Efficiency arises in the calculation of the aggregated composite indicator of environmental pressures (i.e. the denominator).

The various dimensions of an environmental pressure composite indicator require the adoption of a weighting scheme to assign relative importance to each pressure. Common practices for this purpose are the use of workshops, expert panels, arbitrary equal weighting schemes and also weightings based on a selection of subjective valuations or judgements. Workshops have been used by Ripoll-Bosch *et al.* (2012) to generate a weighting scheme on a farm by farm basis with respect to intensification. However, the use of a subjective weighting scheme can lead to bias and conflicting weights assigned to the different dimensions within the framework of SI strategies (Barnes & Thomson, 2014). In order to avoid this bias resulting from a subjective choice of weights, Picazo-Tadeo *et al*. (2011) and Kuosmanen and Kortelainen (2005) are suggesting the use of DEA[33] as the preferred aggregation method. Instead of assigning a common scheme of weights for each input in the sample, the solution of the Linear Programme (LP) through DEA techniques allows the identification of a set of optimal weights to be determined at a farm level. Specifically, a set of weights for farm k is chosen so that it maximises the relative Eco-Efficiency score of this farm when it is benchmarked with the other farms in the sample (Picazo-Tadeo *et al.*, 2011).

To compute the composite environmental pressure indicator of farm k, a weighted sum of the environmental pressures generated by farm k to the environment is required. This is expressed as:

$$p_k = \sum_{n=1}^{N} w_{nk}\, p_{kn} \qquad \textbf{(6.4)}$$

where w_{nk} is the weight with which pressure n enters into the computation of the composite environmental pressure indicator for farm k.

More specifically, and according to expression (6.4)

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[33] DEA techniques are widely used in the area of environmental performance assessment and efficiency. A detailed presentation of different DEA models is contained in Zhou *et al.* (2008)

$$P(p_{kn}) = w_{1k}Fertiliser\ Costs_k + w_{2k}Crop\ Protection\ Costs_k + w_{3k}Water\ Costs_k \qquad \textbf{(6.5)}$$

$$+w_{4k}Machinery\ Fuels\ Costs_k + w_{5k}Energy\ Costs_k$$

At this point it is useful to emphasize that the optimal weight assigned for each environmental pressure can differ among different farms under evaluation. This can be overcome by assigning a restriction to weights through linear programming techniques. For the purpose of this research it was decided not to use any weight restrictions and to use DEA to assign the optimal weights for the environmental pressures in each farm as suggested in the literature (Kuosmanen & Kortelainen, 2005; Picazo-Tadeo *et al.*, 2011).

The Eco-Efficiency score for each farm k' belonging to the benchmarking sample of $k = 1, \cdots, K$ farms is computed from the following fractional programme to obtain values for the aggregated environmental pressure weights $(w_{nk})(n = 1, \cdots, N)(k = 1, \cdots K)$. Eco-Efficiency for the $k - th$ farm is maximised subject to the constraint that all efficiency measures must be less than or equal to one. This is because the ratio is formed relative to the Euclidean distance from the origin over the production possibility set.

Maximize$_{w_{nk'}}$ Eco-Efficiency$_{k'} = v_{k'}/\sum_{n=1}^{N} w_{nk'}p_{nk'}$

Subject to: **(6.6)**

$v_k/\sum_{n=1}^{N} w_{nk'}p_{nk'} \leq 1\ k = 1, \cdots, K \quad (i)$

$w_{nk'} \geq 0\ n = 1, \cdots, N \quad (ii)$

Since the above formulation yields infinite solutions, it is necessary to reformulate the calculation and express the DEA problem using duality. Therefore, the fractional programme (6.6) has an equivalent envelopment form, which is expressed as:

Minimize$_{\theta k', zk'}$ Eco-Efficiency$_{k'} = \theta_{k'}$

Subject to:

$v_{k'} \leq \sum_{k=1}^{K} z_k v_k \quad (i)$ **(6.7)**

$\theta_{k'}p_{nk'} \geq \sum_{k=1}^{K} z_k p_{nk}\ n = 1, \cdots, N \quad (ii)$

$z_k \geq 0\ k = 1, \cdots, K \quad (iii)$

Where $\theta_{k'}$ is a scalar, representing the Eco-Efficiency score for each of the k farms. The estimate will satisfy the restriction $\theta_{k'} \leq 1$ with the value $\theta_{k'} = 1$ indicating an Eco-Efficient farm. Moreover, a set of intensity variables z_k[34] representing the weighting of each observed farm k in the composition of the eco-efficient frontier, is introduced.

The interpretation of the envelopment model results can be summarized as:

[34] Symbols w_{nk} and z_k are used for notation purposes in order to distinguish between the weights in a) fractional and b) envelopment form of the DEA model

a) If $\theta_{k'} = 1$, then the farm under evaluation is on the frontier (100% efficient) and therefore there are no other farms operating more efficiently. This farm has achieved a balance between intensified production technology and economic value added. There are no reductions required in the environmental pressure generated at a farm level. Otherwise, if $\theta_{k'} < 1$ then the farm under evaluation is less than 100% efficient i.e. there is a potential proportional reduction of environmental pressures which will decrease the intensification of production and will improve the balance between environmental pressures and economic value added generated at a farm level.

b) The left hand side of the envelopment model is the reference set while the right hand side represents the specific farm under evaluation. The non-zero optimal z_k represents the benchmarks for a specific farm. The reference set will provide coefficients for the z_k to define the hypothetically efficient farm. The reference set or the efficient target reveals how environmental pressures can be reduced to make the farm more efficient where the sustainable intensification of agriculture, (as defined by a balance between environmental pressure and economic value added) is seen as a desirable outcome.

6.3.2.2 Slack considerations within DEA models

The CCR model (Charnes *et al.*, 1978) implemented Farrell's efficiency (Farrell, 1957) in the linear programming of DEA techniques. A drawback of this approach is that a farm can have an efficiency score of one ($\theta_k^* = 1$) and still be Pareto-Koopmans inefficient (Koopmans, 1951) in the sense that some inputs could be reduced or some outputs could be expanded without affecting the need for other inputs or the production of other outputs. This excess in inputs and shortfall in outputs that exists even after the proportional change in the inputs or the outputs is defined in DEA literature as "slack".

The efficiency scores derived from expression (6.7) assess the radial reductions of environmental pressures required for a farm to attain Eco-Efficiency based on Farrell's efficiency approach. However, additional reductions might be feasible in some pressure directions, while the economic value added is maintained. A solution to this drawback is to penalise "slack" in the DEA model formulation. Following the traditional DEA framework (Tone, 2001; Cooper *et al.*, 2006) these pressure-specific reductions, or pressure slacks, can be obtained from the following optimising program (Ali A. & Seiford L. M., 1993; Picazo-Tadeo *et al.*, 2011).

$$Maximise_{s_{k'}^v, s_{k'}^p, z_k} S_{k'} = s_{k'}^v + \sum_{n=1}^{N} s_{nk'}^p$$

$$subject\ to:$$

$$v_{k'} + s_{k'}^v = \sum_{k=1}^{K} z_k v_k \qquad (i) \qquad \textbf{(6.8)}$$

$$\theta_{k'}^* p_{nk'} - s_{nk'}^p = \sum_{k=1}^{K} z_k\, p_{nk}\ n = 1, \cdots, N \qquad (ii)$$

$$s_{k'}^v s_{nk'}^p \geq 0\ n = 1, \cdots, N \qquad (iii)$$

$$z_k \geq 0\ k = 1, \cdots, K \qquad (iv)$$

The slack variables s^v and s^p represent the shortfalls in economic value added and the excess in environmental pressures generated, respectively. The objective of expression (6.8) is to maximise the sum of pressure excess and value added shortfalls at a farm level while keeping their radial Eco-Efficiency scores at the level calculated from expression (6.7) (Picazo-Tadeo *et al.*, 2011). If there is positive slack, we can say that the farm is Farrell efficient but that there is additional saving potential associated with some inputs and/or the opportunity for expansion associated with some outputs.

Thus, expression (6.8) is used to assess the economic inefficiency of a farm k by a slacks based efficiency score after environmental pressures are adjusted to their minimum level.

Additionally, slacks can be used to identify and estimate the causes of economic inefficiency (Zhou *et al.*, 2006). In this sense, any excess in environmental pressures identifies an intensified agricultural production unit that could reduce its environmentally-damaging inputs. In the framework of SI, identifying slacks, or as defined by Picazo-Tadeo *et al.* (2011) pressure specific reductions, stimulates inefficient farmers to further improve their productivity while simultaneously focusing on the reduction of excess in the use of environmentally-damaging inputs.

Torgersen *et al.* (1996) proposed a methodology which can be used to estimate potential reductions of environmental pressures in addition to pressure excess. Therefore, for the purposes of this research, Torgersen's methodology was applied in order to estimate the potential reductions in the intensified production technology towards the improvement of the economic and environmental efficiency of the farm in the framework of SI.

The aggregate reduction of pressure n needed to bring farm k' into a Pareto – Koopmans efficient status is computed by adding together radial reductions and pressure specific excess.

$$p_{nk}{}^{reduction} = (1-\theta_k^*)_{pnk'} + s_{nk'}^{p} \qquad \textbf{(6.9)}$$

s^p is representing pressure slacks (excesses)

The left side of the equation is the proportional reduction of pressure n while the right side is the pressure specific excess.

In order to measure the pressure specific Eco-Efficiency it is necessary to also measure the Pareto-Koopman efficient level of pressure n.

$$p_{nk^i}^{Pareto-Koopmans\ efficient} = p_{nk'} - \left[(1-\theta_{k'}^*)p_{nk'} + s_{nk'}^{p}\right] \qquad \textbf{(6.10)}$$

$$= \theta_{k'}^* p_{nk'} - s_{nk'}^{p}$$

Finally the pressure specific measure of Eco-Efficiency for farm k' and pressure n is computed as the ratio between the eco-efficient level of that pressure and its actually observed level.

$$\textit{Pressure specific eco-efficiency} = \frac{p_{nk'}^{Pareto-Koopmans\ efficient}}{p_{nk'}} = \theta_{k'}^* - \frac{s_{nk'}^{p}}{p_{nk'}} \qquad \textbf{(6.11)}$$

The importance of slacks in explaining pressure specific Eco-Efficiency can be assessed by computing the weighting of potential pressure reductions due to slacks, on total pressure potential reductions. The above relationship can be expressed formally for pressure n as:

$$\sigma_n = \frac{\sum_{k=1}^{K}\left(p_{nk}^{radial} - p_{nk}^{Pareto-Koopmans\ efficienct}\right)}{\sum_{k=1}^{K}\left(p_{nk} - p_{nk}^{Pareto-Koopmans\ efficient}\right)} = \frac{\sum_{k=1}^{K}\left(s_{nk}^{p}\right)}{\sum_{k=1}^{K}\left[(1-\theta_k^*)p_{nk} + s_{nk}^{p}\right]} \qquad \textbf{(6.12)}$$

$p_{nk}^{radial} = \theta_{nk}^* p_{nk}$ being the pressure n that would result from the radial contraction of all environmental pressures of farm k towards its eco-efficient reference on the frontier.

6.3.3 Econometric estimation of drivers of Eco-Efficiency

Beyond the analysis of specific environmental pressures for each farm, a regression model at a second stage was used to assess the impact of various managerial and farm characteristics on the level of Eco-Efficiency. Studies measuring productivity and efficiency using DEA to investigate the impact of environmental factors at a second stage analysis have suffered from two problems. 1) serial correlation among the DEA estimates and 2) correlation of the inputs and outputs used in the first stage with second-stage environmental variables (Simar & Wilson, 2007). The serial correlation problem arises because the efficiency estimates of productivity change depending on the performance of the DMUs included in the sample, so efficiency is relative to, and interdependent with, the performance of the operational units in the sample. Regarding the second problem, that is, the correlation between the inputs and outputs of the first stage and the environmental variables in the second stage, it causes correlation between the error terms and the environmental variables, thereby violating one of the basic regression assumptions. A solution to these problems has been proposed by Simar and Wilson (1999; 2007), which consists of bootstrapping the results to obtain confidence intervals for the first stage productivity or efficiency scores.

The significance of the Simar and Wilson (2007) double bootstrap procedure derives from the bias corrected efficiency estimation of θ_k (estimated by expression (6.7)). These estimates are used as parameters in a truncated regression model. A detailed presentation of the double bootstrapped procedure and the Algorithm 2 used in this chapter is available in Simar and Wilson (2007) and the adaptation of this methodology for explaining Eco-Efficiency in Picazo-Tadeo *et al.* (2011). The procedure is also presented in Chapter 2 section 0 of this Thesis.

6.4 Results

6.4.1 Measuring Eco-Efficiency in the East Anglian River Basin Catchment

6.4.1.1 Summary of Eco-Efficiency

In relation to radial Eco-Efficiency - 18% of the farms are on the frontier with the remaining 82% of the farms being characterised as Eco-Inefficient. This means that there is a potential for a proportional reduction of environmental pressures in the EARBC area and therefore improvement of the Eco-Efficiency of the GCF. In terms of the intensified production technology, this reveals the potential for a reduction in the use of environmentally-damaging inputs for the farms in the benchmarking sample which thus improves their performance towards SI (i.e. farms can maintain the level of production but simultaneously reduce the negative impact to the ecosystem).

Additionally, from the 61 farms in the sample, 47 farms were identified as having input slacks (i.e. there is additional saving potential associated with some of the environmental pressures) while there were no output slacks (i.e. there is no opportunity for expansion associated the economic value added). Inputs slacks in the model can be used to measure the specific input excess in order to direct farm management towards the improvement of efficiency and SI. Table 6.2 presents a summary of the radial Eco-Efficiency scores as they have been calculated from expression (6.7)[35].

Table 6.2: Summary of Eco-Efficiency scores for the farms in the sample

Eco-Efficiency range	Number of farms	%	Descriptive Statistics	
0.1<= E < 0.2	3	4.9	Min	0.183
0.2<= E <0.3	8	13.1	1st Qu.	0.342
0.3<= E <0.4	11	18	Median	0.500
0.4<= E <0.5	8	13.1	Mean	0.562
0.5<= E <0.6	6	9.8	3rd Qu.	0.772
0.6<= E <0.7	7	11.5	Max.	1
0.7<= E <0.8	5	8.2	No of farms with input slacks	47
0.8<= E <0.9	2	3.3	No of farms with output slacks	0
0.9<= E <1	0	0	Total No of Farms	61
E ==1	11	18		

The optimal DEA weights assigned for each environmental pressure provide insights into the performance of the farms in the sample. More specifically, as stressed by Kuosmanen and Kortelainen (2005), the weight profiles for each farm reveal the strengths and weaknesses in terms of the environmental performance criteria and consequently the intensified production technology. A low assigned optimal DEA weight for a specific environmental pressure signifies an excess in use whereas a high optimal weight indicates good management of inputs in the intensified production technology framework.

Comparing optimal weights between the farms on the frontier (fully efficient) and those inside (eco-inefficient) provides information in the difference between the balance of inputs and also indicates areas for improvement. The average optimal weights assigned for each environmental pressure for the 11 farms on the frontier indicate relatively high weights for water costs (36.17%), machinery fuels costs (31.02%) and crop protection costs (16.88%) and low scores for fertiliser costs (8.58%) and energy costs (7.35%). For the remaining farms characterised as eco-inefficient, the optimal weight for water costs (71.99%) indicates a

[35] To solve the DEA linear programme both in expression (6.7) and (6.8) the package Benchmarking 0.23 (Bogetoft & Otto, 2010) in R 2.15.3 is used.

strong performance in water use management while poor performance is revealed through the optimal weights for machinery fuels (13.97%), energy costs (7.23%), fertiliser costs (4.87%) and crop protection (1.95%).

6.4.1.2 Pressure specific Eco-Efficiency

Figure 6.1 provides a visualisation of the slack values in relation to the specific environmental pressure generated. Costs related to crop protection, machinery fuel and energy are the three environmental pressures that require the highest extra proportional reduction per farm. That is the reduction in excess of specific inputs whilst keeping efficiency at its maximum level. Information on radial Eco-Efficiency and slack values for each farm are then used through expressions (6.11) and (6.12) in order to reveal the aggregated reduction in each environmental pressure to achieve Eco-Efficiency and consequently to improve the performance of the farm towards SI.

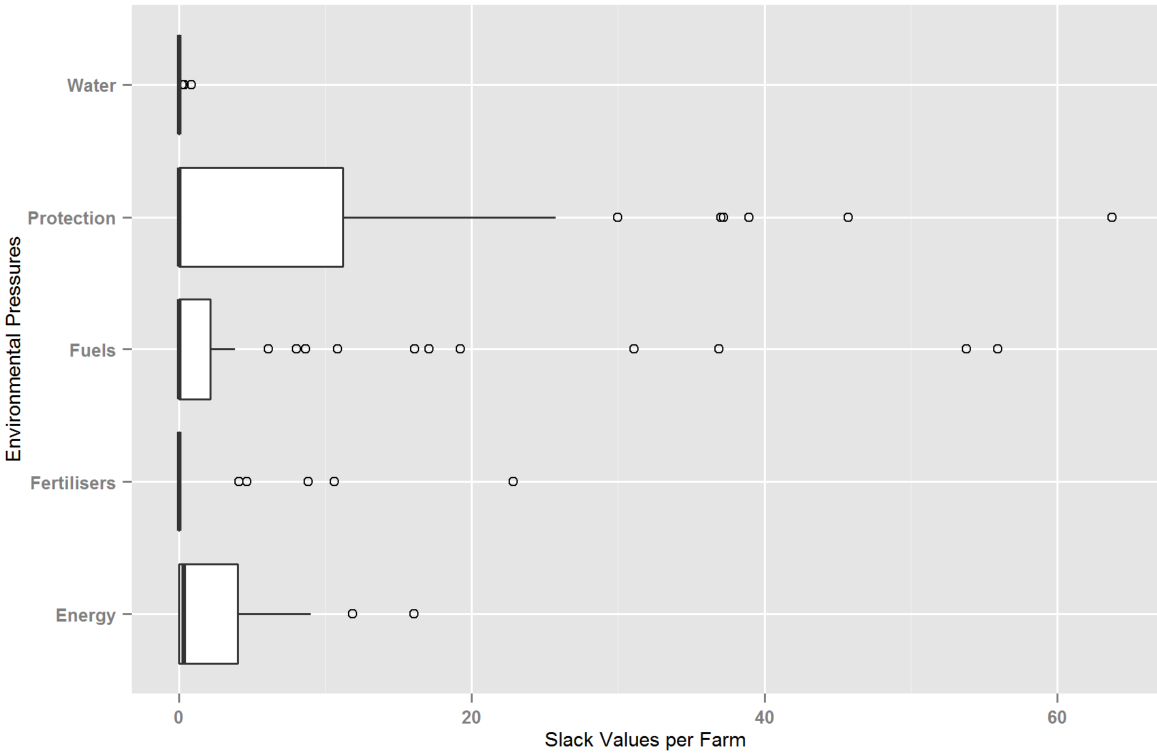

Figure 6.1: Slack values for each individual farm per environmental pressure category

To illustrate the interpretation of radial Eco-Efficiency, and pressure specific Eco-Efficiency generated by each component of the intensified production technology set, the case of farm ID 22, is considered in more detail as an example.

Farm 22 has initially p_n = fertiliser costs (£170) + crop protection costs (£144.7) + water costs (£1.1) + machinery fuel costs (£49.8) + energy costs (£5.5) = £371.2 per ha and its radial Eco-Efficiency score is θ_{22}=0.7787. Therefore, it could reach the frontier if the input values are reduced radially by the ratio θ_{22} and the input excess recorded (slack) (Cooper *et al.*, 2006). If we only consider the radial Eco-Efficiency each environmental pressure must be reduced by 22.13% (1-0.7787) while maintaining value added which implies a total £82.1 cost reduction per ha. Using the information of slacks in DEA, the computed excess for specific pressures for this farm would allow for further reductions. Specifically, crop protection costs and machinery fuels costs have slack values equal to £8.9 and £8.7 respectively. That allows the farm to reduce further the cost by £17.6. Therefore, adding together radial reduction and pressure specific excess, the aggregate reduction in cost necessary to achieve Eco-Efficiency amounts to £99.7 per ha, such that the efficient pressure would be £271.5 per ha. Accordingly, the pressure specific score of Eco-Efficiency for this farm on crop protection costs is 0.7172, and 0.6064 for machinery fuel costs which stems from the comparison of eco-efficient pressure to actually observed environmental pressure. Table 6.3 presents a summary of the pressure specific Eco-Efficiency scores for the GCF_s in the EARBC. For the measurement of pressure specific Eco-Efficiency expression (6.11) has been used.

Table 6.3: Mean pressure specific Eco-Efficiency

	Mean Pressure specific Eco-efficiency	St. Deviation	Minimum	Maximum	Percentage of farms with slack
Fertiliser Cost	0.556	0.264	0.183	1	8.20%
Crop Protection	0.514	0.289	0.126	1	40.98%
Water Cost	0.561	0.269	0.178	1	4.92%
Machinery Fuels	0.511	0.278	0.180	1	26.23%
Energy Costs	0.481	0.317	0.033	1	50.82%

When solving for maximum efficiency, the non-binding environmental pressures constraints indicate that the amount of slack in inputs is the unnecessary expenditure and can be avoided without sacrificing efficiency. Table 6.4 shows the weights of importance of slacks in explaining the aggregate potential reduction of environmental pressures goes from 19% in the case of energy costs to 0.63% for water use costs at a farm level. For instance farmers can avoid unnecessary crop protection costs by 11.21% to reduce the intensified production technology and improve their performance towards SI.

Table 6.4: Importance of slack values in the total proportional reduction of environmental pressures

Environmental Pressure	Importance of slacks	Number of farms with slack	Mean	St. Deviation	Min	Max
Fertilisers	1.23%	5	0.84	3.44	0.00	22.86
Crop Protection	11.21%	25	8.07	13.90	0.00	63.75
Water Cost	0.63%	3	0.02	0.12	0.00	0.85
Fuels	11.57%	16	4.58	11.79	0.00	55.94
Energy Cost	18.79%	31	2.31	3.45	0.00	16.04

6.4.2 Explaining Eco-Efficiency

The selection of potential determinants of farm Eco-Efficiency was based in the consideration of previously published literature (Van Passel *et al.*, 2007; Barnes, 2008; Meul *et al.*, 2008; Basset-Mens *et al.*, 2009; Gomez-Limon & Sanchez-Fernandez, 2010; Picazo-Tadeo *et al.*, 2011; Barnes & Thomson, 2014)

A second – stage regression analysis is used to explore the impact of environmental variables of the Eco-Efficiency scores for each farm.

The hypotheses to be tested via these variables are the following:

- Farm size: It is expected that larger farms operate more efficiently since they have developed economies of scale that improve productivity and efficiency.
- Farmer's education level and experience: It is expected that farmers with higher educational levels and experience, manage and allocate resources more efficiently. That is farmers are able to allocate inputs and manage excess better through innovative management techniques on the field (precision agriculture). Moreover, it is expected that farms with better ratios between inputs and outputs have better managerial skills and can allocate resources better in the production process and therefore potentially improve the ratio between economic value added and the environmental pressures generated at farm level.
- In addition the participation of the farmer in the Linking Environment and Farming (LEAF) organisation as well as in Agri-Environmental payment schemes (Entry Level Stewardship, Higher Level Stewardship, Countryside Stewardship Scheme, etc) promotes sustainable food and farming with high environmental standards and therefore enhances Eco-Efficiency, (Agri-Environmental payments and cost variables in the model).

Following the above description of the variables, the following econometric model is estimated:

$$Ecoeff_{it} = \beta_0 + \beta_1 * Dsmall_{it} + \beta_2 * Dmedium_{it} + \beta_3 * AgriEnP_{it} + \beta_4 * AgrEnC_{it} + \beta_5 * Edu_{it} + \beta_6 * FarmerAge_{it} + \beta_7 * LEAFMemb_{it} + \varepsilon_{it}$$

Where, EcoEff is the biased corrected Eco-Efficiency, Dsmall and Dmedium are dummy variables (1=Small, 0=Otherwise and 1=Medium, 0=Otherwise respectively) for the small and medium farm sizes respectively

[36], Edu is a dummy variable defining the level of education (1=Higher (eg college or above and 0=Basic (eg Only school, A level, etc), LeafMemb is a variable indicating the membership of a farmer in the LEAF organisation, (1=Membership and 0 otherwise), the AgriEnP and AgriEnC define the environmental payments received and the costs related to these (all measured in £) by each individual farm and finally, the age of the farmer is indicated by the variable FarmerAge. The descriptive statistics of the explanatory variables are presented in Table 6.5.

Table 6.5: Descriptive statistics of the variables used in the truncated regression model

	Mean/No of cases	St. Deviation
Bias Corrected Eco - Efficiency	0.449	0.192
Agri-Environmental Payments £'000	22.64	41.26
Agri-Environmental Costs £'000	6.58	16.24
Farmer Age	55.23	9.51
Large Farm Size	33	
Medium Farm Size	22	
Small Farm Size	6	
LEAF Membership	13	
No LEAF Membership	48	
Basic Education	18	
Higher Education	43	

For the 61 GCF in the sample the average ordinary DEA input orientated Eco-Efficiency score was 0.562, while the bias corrected Eco-Efficiency score was 0.449. The 95% confidence intervals of the bias-corrected Eco-Efficiency score ranged between 0.393 (Lower bound) and 0.542 (Upper Bound)

For the explanation of Eco-Efficiency a double bootstrapped truncated regression model was used. The selection of the model was based on the fact that the outcome variable is restricted to a truncated sample of a distribution. Since the dependent variable can take values between zero and one, the sample is left truncated (0≤biased corrected Eco-Efficiency). It must be noted that a censored model (e.g. Tobit) would not have been appropriate in this case since Eco-Efficiency data have the characteristics of truncated data – limited in the sample of interest. Furthermore, according to Simar and Wilson (2007) and Banker and Natarajan (2008) Tobit estimation in the second stage yields biased and inconsistent estimators. The main

[36] In order to classify farms in the FBS into different sizes the Standard Labour Requirements (SLR) for different enterprises are calculated which are then used to find the total amount of standard labour used on the farm. Once the total annual SLR has been calculated the number of hours can be converted to an equivalent number of full time workers (on the basis that a full-time worker works a 39 hour week and so 1900 hours a year). This leads to the classification of farms by number of full time equivalent (FTE) workers as follows:
Small farms: 1<FTE<2, Medium farms: 2<FTE<3, Large farms: 3<FTE<5

reason for the selection of the truncated model by Simar and Wilson (2007) is that the true efficiency estimates are unobserved and are replaced with DEA estimates of efficiency.

Table 6.6 presents a summary of the results of the truncated regression. From the initial results it can be stated that the model is a good fit with the data (Wald Chi-square=28.54, P<0.01).

The impact of farm size, agri-environmental payments, education and age are statistically significant. The assumption that higher levels of managerial skills and experience can improve input use efficiency is sustained from the results. Specifically, this is supported by the education variable which is also positive and significant at the 1% level ($\beta_5 = 0.26,\ p - value < 0.01$). Therefore, when farmers with higher education levels are compared with farmers qualified with basic education skills then the predicted Eco-Efficiency score increases by 0.26. This effect can also be related to the improved technical and also managerial skills of the farmers due to the years of experience as revealed by farmers' age variable which has also positive impact in our model ($\beta_6 = 0.01,\ p - value < 0.05$). Considering farm size, medium and small farms are indicated to be more eco-efficient than large farms, but only medium size is significant at the 1% level ($\beta_2 = 0.29,\ p - value < 0.01$). That is medium size farms perform better than large farms and their Eco-Efficiency scores is 0.29 greater on average than large farms. This is an interesting finding of our study since we would have expected that large farms in the sample would have performed better than smaller size farms in terms of managing inputs and improving efficiency. On the other hand though, production systems in large farms are more intensified and therefore, we can expect that these systems would generate higher environmental pressures and therefore would finally achieve lower Eco-Efficiency scores.

A farm being a member of the LEAF organisation was not found to be statistically significant (p-value>0.05). Environmental payments have a positive and statistically significant impact on the improvement of Eco-Efficiency ($\beta_3 = 0.0034, p - value = 0.02$), while on the other hand environmental costs have a negative impact on the improvement of Eco-Efficiency, although it is not statistically significant. The positive coefficient for Agri-Environmental payment indicates that an annual increase by £1000 would increase the Eco-Efficiency score by 0.0034.

Table 6.6: Determinants of Eco-Efficiency

	Observed Coef.	Std. Err.	t-value
(Intercept)	-0.35	0.22	-1.61
Small size (dummy)	0.18	0.12	1.46
Medium size (dummy)	0.29***	0.08	3.78
Agri-Environmental Payments ('000)	3.4e-3*	0.00	2.34
Agri-Environmental Costs ('000)	-0.01	0.00	-1.49
Education (dummy)	0.26***	0.08	3.33
Farmer Age (years)	0.01*	0.00	2.39
Leaf Membership (dummy)	-0.06	0.08	-0.68
Sigma	0.22***	0.02	8.83

Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1, ' ' 1 – No of Bootstraps 2000
Log likelihood=15.055
Wald $\chi^2(7) = 28.54$, Prob $> \chi^2 = 0.000$

6.5 Discussion

Previous research work has demonstrated that there is a strong correlation between technical inefficiency and eco-inefficiency. Further, it has been found that the lack of managerial skills is a reason for excess use of production inputs, and also that the environmental performance of a farm unit could be improved by adopting and promoting best farming techniques (Picazo-Tadeo & Reig-Martínez, 2006; 2007; Picazo-Tadeo *et al.*, 2011). In addition, Wilson (1999; 2001) emphasises on the need to improve data collection and practices in order to include managerial information that could be used to distinguish between efficient and inefficient farms. Based on this evidence similar analysis could be used for the evaluation of farms in the context of the SI of agriculture. One of the key characteristics of SI is the adoption of new innovative technologies that lead to more efficient production methods with less impact on the environment (Garnett & Godfray, 2012). Improvement in technical efficiency and Eco-Efficiency will improve the SI of agriculture. Therefore, there is a need for farm businesses to improve their managerial inputs, adopt new methods and technologies and also reduce the environmental pressure generated by the intensified production technology.

The results in Table 6.2 present strong evidence of eco-inefficiency for the GCF$_s$ in the EARBC. In order to evaluate technical efficiency of the farms a DEA input oriented model[37] has been used with variable returns of scale (VRS[38]). The results of the analysis illustrate that farmers in the sample are also relatively technical

[37] Inputs used in the model are area farmed, machinery costs, total hours spend for farming (labour and farmer hours), fertiliser costs, crop protection costs, water costs, machinery fuels and energy costs. Output used in the model is the gross margin per hectare.

[38] This is because a farmer cannot change all the inputs used for the production (limited resources land, water) as a constant returns to scale assumes (CRS). In other words, the conservative VRS approach is preferred because CRS implies linearity between inputs and outputs meaning that doubling the inputs used will double the outputs which is obviously not the case in agriculture.

inefficient with an average technical efficiency of 0.79 and 66% of the farms being below the frontier. Also, a Pearson's correlation coefficient of 0.67 reveals high correlation between technical efficiency and Eco-Efficiency. Thus, the results are consistent with the previous literature. Furthermore, the pressure specific Eco-Efficiency analysis suggests that, farmers in the research sample could introduce new strategies and technologies to reduce wastage in energy, machinery fuels and crop protection in order to improve their environmental performance. From a SI policy perspective, these results suggest the need for the introduction of incentives that reduce the excess use of crop protection expenditure and encourage farmers to install renewable energy technology.

As has been emphasised by Barnes and Thomson (2014), the choice of weights for the construction of a composite index for SI is a significant challenge. Here, by using DEA to assign the optimal weights to the environmental pressures that define the intensified production technology, the research has avoided any bias resulting from subjective judgements. Furthermore, the optimal weights assigned to the farms on the frontier can be used as indicators of performance for farms that would like to develop a strategy to reduce environmental pressures and also to improve their economic output.

In addition, previous research on SI of agriculture in the UK concluded that there is evidence of intensification of agricultural production (Barnes, 2012; Firbank *et al.*, 2013; Barnes & Thomson, 2014). The slack based DEA model combined with the assessment of the environmental pressures generated at a farm level, allows policy makers and farmers to quantify the level of intensification and reduce the negative impacts emerging from the intensified production technology. Also, the consideration of the importance of slack values in the total proportional reduction of environmental pressures and the measurement of pressure specific Eco-Efficiency could aid policy makers in designing targets and legislation focused on a specific environmental pressure such as the development of policies to protect biodiversity through the controlled use of pesticides.

Results from the truncated regression show that in order to improve Eco-Efficiency in the GCF_s for the EARBC, farmers could be encouraged to develop more advanced managerial skills through training and further education and also by improving their technical efficiency. Moreover, agri-environmental payments have a positive impact and appear to be an effective policy for the reduction of environmental pressures deriving from farming.

An advantage of the methodology used here for the assessment of SI is that it is based on the use of existing data. The FBS is a valuable source of information that emphasises the production elements of farming, which is a key data set for the definition of sustainable intensification. Moreover, Barnes and Thomson (2014) also stress that such secondary data can be a rich source for creating environmental, economic and social indicators to measure sustainable intensification.

An important aspect that should also be considered in the discussion of the results is the extreme weather in the spring of 2011. Especially in East Anglia, the lack of rainfall had an adverse effect on farms. Parts of the study area have been declared as areas under high risk of future drought (Lincolnshire, Cambridgeshire, and Norwich). Therefore, the increased environmental pressure due to crop protection costs may be explained as the effort of farmers to mitigate yield losses due to drought conditions. Also, the subsequent wet harvesting conditions in 2011 for crops and the heavy machinery dependence for potatoes and sugar beet explain the excess use of machinery fuel and energy for drying crops, leading to higher than average costs in the season.

6.6 Conclusions

This chapter has presented an approach for the assessment of SI of farming systems based on the index of Eco-Efficiency. The common goals of the two concepts – improving the environmental performance of farming systems while simultaneously increasing the production efficiency- allows the consideration of the index of Eco-Efficiency for the evaluation of the performance of farms within the context of SI. The use of a well-established Eco-Efficiency index provides policy makers and farmers with valuable information for the development of targets and strategies towards the improvement of the SI of agriculture.

This research builds on the approach introduced by Picazo-Tadeo *et al.* (2011) where DEA techniques are used to assess farming Eco-Efficiency at a farm level. The consideration of slack values in the DEA model has enabled levels of pressure specific Eco-Efficiency to be defined and also allowed assessment of the intensified production technology for each farm. Following the classic definition of Eco-Efficiency, a ratio of the economic value added per farm defined as the gross margin per hectare over the environmental pressures generated was used. A set of five environmental pressures were identified for the general cropping farming system in the EARBC namely crop protection costs, fertiliser costs, water costs, machinery fuel costs and energy costs. All feasible combinations of value added and environmental pressures defined the intensified production technology for each farm. Scores of radial Eco-Efficiency and pressure specific scores of Eco-Efficiency were used to discuss the level of intensification in the farm sample and to assess directions of environmental improvements towards the SI of agriculture.

The results presented suggest that farmers in the sample are relatively eco-inefficient. Also, by considering pressure specific scores, it is concluded that crop protection, fuels and energy are the three environmental pressures with the highest importance for the farms in our sample. The greatest eco-inefficiency is observed in crop protection (slack value = 63.75). Both the optimal weights and the input slacks have shown that farms in our sample are quite efficient with respect to the management of water resources and fertilisers. Further, in terms of assessing SI, the measurement of slacks is important when explaining the aggregate potential reduction of environmental pressures since this is related to the reduction of the pressure generated by the intensified production technology.

The main advantages of this approach are:

a) the flexibility of DEA techniques and the simplicity in the calculation of the index of Eco-Efficiency that enable policy makers to assess SI at a micro-farm-level

b) the use of a representative and validated source of secondary data such as the FBS which could potentially be used to develop a persistent monitoring mechanism towards the SI of different farm systems in the UK and

c) the identification of specific areas of further reduction in the environmental pressures generated by the intensified production technology.

The latter is important because it incorporates the environmental dimensions of agricultural production into the discussion of technical and economic efficiency and hence, it could provide a further insight into the design of policy options to enable the improvement of farms in terms of both environmental and economic efficiency.

One limitation of this analysis is the lack of information on specific amounts of fertilisers and pesticides used at a farm level through the FBS. In this chapter the cost of each input is used as a proxy indicator of the pressure that is generated on the environment. Further research will consider the inclusion of this information in the DEA model. Moreover, a dynamic approach to Eco-Efficiency is required in order to evaluate the progress of farming systems towards SI. That will enable the consideration of other determinants to explain Eco-Efficiency, such us technological change over time, the influence of current policy instruments and specific management practices.

In terms of identifying the determinants of Eco-Efficiency, this research suggests that farmers with a higher level of education, who are experienced managers of medium size farms and receive agri-environmental payments are more Eco-Efficient. These determinants are also identified as important for the improvement of the performance of farmers towards SI of agriculture.

Finally, it should be noted that the design of agricultural policies in order to achieve the general objective of sustainable intensification is a difficult and complex procedure involving the encouragement of farmers to change attitudes and behaviours. Furthermore, decision making at farm level and the adoption of management practices and strategies towards SI is a complex and demanding task given that it involves the maximisation of production and profit subject to resource constraints and unpredictable external factors such as weather and changing input costs. In terms of policy goals related to SI, a holistic approach to the topic should involve an integrated analysis of the impacts on biodiversity and land use, animal welfare, human nutrients and rural economies. Future policy relevant research in this area should consider these aspects and incorporate their impacts in the assessment of SI.

Part III

Part III delivers the main conclusions and policy implications of this research study

Chapter 7

Summary, discussion and conclusions

7.1 Summary of the scope and the objectives of this research

Both the socio-economic and the biophysical environments within which agricultural systems operate are changing. The main challenges for agriculture include the development of strategies and the adaptation of management practices in order to meet the demand of a rapidly increasing population, mitigate the impacts of climate change, protect biodiversity to enhance ecosystem service provision and secure rural livelihoods. According to the Foresight Report (2011) the key priority for the future of agricultural systems is the promotion of the SI of agricultural production through simultaneously increasing yields, improving input use efficiency and reducing negative environmental outputs. For UK agriculture to meet the future challenges of increased food demand, climate change and efficient use of natural resources (land, water), SI is a practice considered to move production onto an upward trajectory and at the same time reduce the negative environmental impacts (Firbank *et al.*, 2013; Garnett *et al.*, 2013; Barnes & Thomson, 2014; Franks, 2014).

Taking into consideration the importance of the EARBC in terms of agricultural production in England and also the projected vulnerability of the area under the UKCP09 climate projections in terms of reduced rainfall and increased temperature (Jenkins *et al.*, 2009), SI would be an option to increase productivity and mitigate the impacts of climate change. The production of GCF_s is sensitive to extreme weather phenomena and according to Daccache *et al.* (2011) rain-fed production in the future will become increasingly risky and supplementary irrigation a necessity to secure agricultural production. More than half of the EARBC land surface is used for agriculture and horticulture (approximately 1.5 million hectares). Also, it is recognised as one of the most productive agricultural landscapes in England, known for its cereal crops and the production of potatoes and sugar beet. In particular, in the counties of Cambridgeshire, Lincolnshire, Norfolk and Suffolk over half of the total sugar production in England is harvested.

When discussing sustainability, and especially the intensification of the production process, the high risk of drought in the EARBC as well as the increased demand for direct abstraction of water is an important environmental pressure generated from the GCF system. More specifically, reduced summer rainfall could lead to irrigation water shortages and associated conflicts over water use, insufficient water flow to dilute pollution, inability of soil to absorb rainfall, reduced crop yield and increased fire risk (Charlton *et al.*, 2010).

Hence, when defining SI, three targets must be met; increase productivity, improve input use efficiency and reduce any environmental damaging production outputs (Baulcombe *et al.*, 2009; Foresight Report, 2011; Garnett & Godfray, 2012; Firbank *et al.*, 2013). The main scope of this research is to provide a holistic approach over the discussion and evaluation of SI for the GCF_s in the EARBC. By employing DEA models this research estimates changes in agricultural productivity, WUE and a composite indicator of Eco-Efficiency at farm level. In addition, in the context of SI the additive (slack based) DEA model is used to estimate specific input reductions and hence suggests reductions in the intensified production technology of farming systems. Data for the empirical application of the models is obtained from the FBS which is a comprehensive and detailed database that provides information on the physical and economic performance of farm business in England.

The empirical analysis answers three main questions (as outlined in section 1.3) which are in line with the objectives of this research.

Research question 1: How is FBS data used to develop an index of TFP in order to assess the impact of extreme weather phenomena in agriculture? – Sub-question: How are existing DEA techniques used to build on improving benchmarking methods by considering non-discretionary variables in the production function?

The main objective associated with this question is to estimate indices of TFP, technical efficiency, pure efficiency and scale efficiency change at a farm level for a period of five years in order to explore the impact of the recent extreme weather phenomena (floods of 2007, drought conditions of 2010-2011) in agricultural productivity in the EARBC. In addition, the analysis underlines the importance of accounting for non-discretionary inputs (rainfall) when benchmarking methods such as DEA are used to compare the performance between farming systems. Not accounting for variations in non-discretionary inputs characterising the physical environment of farms might lead to biased estimates of efficiency (Dyson *et al.*, 2001).

7.2 Assessing productivity of farming systems over time

In Chapter 3 two DEA models, a conventional and a sub-vector (non-discretionary) model, were used to report farm level technical efficiency estimates for the GCF_s in the EARBC for a five year period. The sub-vector model included annual rainfall measurements for each farm in the sample in order to reduce any bias in benchmarking farms with different rainfall levels and also to capture the impact of variations in annual rainfall on the technical efficiency of the farms.

According to the results obtained from the conventional DEA model, when rainfall variations are ignored, the average technical efficiency is lower (0.85) and more farms are reported as inefficient when compared with the outcomes of the sub-vector model (overall mean technical efficiency, 0.87). In particular, the distribution of the farms in the sub vector model became increasingly skewed towards the higher efficiency rankings when compared with the ranking of the conventional model. With regards to the potential proportional input saving, it was 13% for the sub vector model and 15% for the conventional model. However, the Spearman's rank correlation test (*rho*>0.9 for each year and p-value<0.01) showed that there is no difference in the ranking of farms between the conventional and sub-vector DEA models. In addition, the drought period of 2010-2012 (Kendon *et al.*, 2013) in East Anglia, had a negative impact on technical efficiency. Technical efficiency in 2011 was reduced by 3.4% for the sub-vector model and by 2.3% for the conventional model in relation to 2010 levels. Analysis of the results on returns to scale and scale efficiency over the five year period indicates that appropriate scale adjustments are required in order to achieve the maximisation of both efficiency and productivity. The mean value of OTE (0.81) suggests a reduction of 19% in the management of inputs in the long run is needed in order to improve control over the production process.

The decomposition of TFP into the efficiency and technical index components and the observation of the trends in consecutive years, contribute to the design of targeted policies aimed to improve agricultural productivity and sustainable development. According to the results during the two periods of extreme weather phenomena, 2007/2008 floods and the 2010/2011 drought, productivity significantly deteriorated, especially during the first period. Furthermore, the average MI for the five year period for the large, medium and small farms is 0.99, 0.97 and 0.96 respectively indicating a slight deterioration of productivity over the period. The most important improvement in MI during the five year period is between 2008 and 2009 where 73% of the farms had a significant improvement in TFP. Over the study period, 15% of the farms have been constantly reported with a MI of TFP above unity (i.e. improvement in TFP between the subsequent periods). The remainder 85% of the sample has fluctuated around unity indicating either an improvement or deterioration in TFP between subsequent periods. In addition, farms on the efficient frontier are becoming more efficient due to improvements in pure efficiency index rather than technical change while the performance gap between the different sizes of farms is widening and is depicted by the technical scale efficiency index.

Research question 2: How can FBS data be used to improve benchmarking techniques and to identify farm management practices to reduce water consumption at a farm level?

According to Daccache *et al.* (2011) rain-fed UK agricultural production in the future will become increasingly risky and the importance of supplementary irrigation in securing agricultural production especially in the eastern parts of England will raise. The main objective behind asking this question was to provide an estimate of excess in water use for the GCF_s in the EARBC. In the context of SI, farms in East Anglia, where the risk of drought is higher compared to other parts of the UK and the use of irrigation is required to secure yield and income, managing water resources efficiently is a priority for the future sustainability of farming systems in the area. Hence, the research aimed to identify practices and specific farm management practices that improve WUE at a farm level.

7.3 Summary of results on WUE in the EARBC

Within the context of SI, the efficient management of limited natural resources, such as water for the GCF_s in the EARBC becomes a priority due to the high risk of drought, water shortages and over abstraction of water resources. In Chapter 4 a sub-vector and a conventional DEA model are used as a benchmarking tool to assess WUE, suggest pathways to improve farm level productivity and to identify best practices for reducing or preventing water pollution. Data is obtained from the 2009/2010 FBS database which provides additional information on water usage and management practices at a farm level. The sample was grouped into irrigating and non-irrigating farms in order to satisfy the homogeneity assumption of the DEA theory. The estimated mean technical efficiency for the irrigating and the non-irrigating farms was 0.97 (STD=0.02) and 0.94 (STD=0.02) respectively implying a 3% and a 6% equiproportional reduction in inputs without any size adjustments (PTE is considered – short run). In relation to the average technical efficiency under the CRS assumption (OTE is considered), the equiproportional reduction in inputs is 5% and 11% for the irrigating and non-irrigating farm respectively. Furthermore, the average estimate of sub-vector WUE is 0.87 and 0.81 for the irrigating and non-irrigating farms respectively suggesting that improvements can be made towards the management of water resources for the GCF_s in the EARBC.

In addition, analysis on returns to scale indicates that 27% of the irrigating and 31% of the non-irrigating GCF_s operate on the downward sloping part of the long run average cost curve implying the potential to increase production and hence profitability. This information, in addition to the results derived from the PTE analysis; indicate also a need for change in the management of inputs in the short run in order to improve control over the production process.

A set of management practices for improving agricultural WUE is identified for both irrigating and non-irrigating groups in the sample. In particular, the set of management practices identified through this analysis involves;

a) the management of irrigation systems to ensure the right water pressure, water use and irrigation uniformity (i.e. all areas within an irrigated field receive the same amount of water);

b) in-field soil moisture measurement (including assessing the soil and crop inspection);

c) water balance calculations and;

d) the use of a decision support tool for short and long term irrigation planning and monitoring.

Further management practices to reduce or prevent water pollution include tramlines, buffer strips, ponds and wetlands to reduce run-off and store water. The potential benefits of the application of these management practices from the perspective of the farmer include best value from fertilisers and manures used, reduced input costs and also enhanced crop yield and quality. In addition, in the context of improving SI there are reduced environmental risks due to leakages and excess of nutrients which could damage biodiversity and water quality. Finally, an important finding deriving from the benchmarking analysis of the irrigating farms is that the reason for adopting irrigation management practices is to improve WUE and to protect the environment while for the non-irrigating farms it is to comply with legislation.

Research question 3: Is it possible to build on existing methodological research to derive an FBS data based composite indicator to explore the different levels of intensification between farming systems in the context of SI?

According to Garnett and Godfray (2012) any efforts made to intensify agricultural production are required to be balanced by management options that employ new emerging, efficient and innovative production technologies as a response to the future challenges for agriculture. It is therefore required to identify the appropriate methods and metrics for the evaluation of SI of farming systems to guide the decision making at a farm level and strategy design for policy interventions. The main objective in line with this research question is to fill the gap in the literature of evaluating and measuring SI (Firbank *et al.*, 2013; Barnes & Thomson, 2014; Franks, 2014). DEA methods and data obtained from the FBS are used to provide an estimation of a composite indicator of Eco-Efficiency. Further, a slack based DEA model is used to identify specific input reductions and hence, slack values serve as an indication of the level of intensification of the agricultural production in an effort to secure yields and increase profit.

7.4 Evaluating SI of farming systems

A composite indicator of Eco-Efficiency, accounting for the environmental pressures generated and the economic value added at a farm level, is estimated to evaluate SI for the GCF_s in the EARBC. DEA techniques are used to estimate technical efficiency and also to identify specific input use improvements in order to reduce the environmental pressure generated by the intensified production technology at a farm level. Results showed that 18% of the farms are on the frontier with the remaining 82% of the farms being characterised as Eco-Inefficient. This means that there is a potential for a proportional reduction of environmental pressures in the EARBC area and therefore improvement of the Eco-Efficiency of the GCF. In particular, the mean Eco-Efficiency of 0.56 means that environmental pressures can be reduced equiproportionally by 44%.

Considering specific input reduction of the intensified production technology, costs related to crop protection, machinery fuel and energy are the three environmental pressures that require the highest extra proportional reduction per farm. That is the reduction in excess of specific inputs whilst keeping efficiency at its maximum level. In particular, pressure specific Eco-Efficiency can be further reduced by 8.1% in the case of energy costs, 5.1% in the case of machinery fuel and by 4.8% in crop protection costs.

For the econometric estimation of the drivers of Eco-Efficiency a double bootstrapped truncated regression model was used. The significant positive ($\beta_5 = 0.26,\ p - value < 0.01$) education variable supports the assumption that higher levels of managerial skills and experience can improve input use efficiency. In addition, a significant positive impact was noted for the years of experience of the farmer in the model($\beta_6 = 0.01,\ p - value < 0.05$). Considering farm size, medium size farms perform better than large farms and their Eco-Efficiency scores were 0.29 greater on average than large farms. A possible explanation of this could be that although large farms have developed economies of scale that improve productivity and efficiency, their large scale of operation requires more intensified use of damaging environmental inputs and hence generate further pressures to the environment. Membership of the LEAF organisation was not found to be statistically significant (p-value>0.05). Furthermore, the positive coefficient for Agri-Environmental payments indicates that an annual increase in payments of £1000 would increase the Eco-Efficiency score by 0.0034.

7.5 Discussion and conclusions

Since the introduction of the sub-vector DEA models by Kopp (1981) and Färe *et al.* (1983) only few studies have used these models in agriculture in order to account for non-discretionary inputs in the production technology (Piot-Lepetit *et al.*, 1997; Henderson & Kingwell, 2005). The majority of the studies employed the sub-vector DEA model to generate technical efficiency measures for a subset of inputs and to measure specific input technical efficiency respectively or to account for negative environmental outputs (Lansink *et al.*, 2002; Lansink & Silva, 2003; Asmild & Hougaard, 2006; Lilienfeld & Asmild, 2007; Speelman *et al.*, 2008). In this research, both the conventional and sub-vector DEA models were employed to compare differences in the technical efficiency ranking of farms when rainfall is considered in the production technology as a non-discretionary input. Spearman's correlation test showed no difference between the two models. However, this research demonstrates that the inclusion of exogenous parameters influencing farms' production performance ensures the homogeneity of the sample and provides better benchmarking estimates. This was also the conclusion of Henderson and Kingwell (2005).

According to Piesse *et al.* (1996) the technical efficiency change index component of the MI of TFP allows for the estimation of the impacts of exogenous parameters and shocks in the socio-economic and biophysical environment that farming systems operate. Thus, an analysis of TFP was performed using a MI estimated by DEA techniques in order to evaluate the impact of the two recent extreme weather phenomena on agricultural productivity for the GCF_s in the EARBC. Results showed that the index of technical efficiency change and also the MI have deteriorated during the period of floods in 2007 and the drought period between 2010 and 2011. However, the pure efficiency change index has been positive through the five year study period indicating that farms are improving their management skills and are adopting input saving technologies. On the other hand, pure technical efficiency deteriorates and is the main reason for reducing productivity of the GCF_s in the EARBC. In addition, the research emphasises that with the exception of the years with extreme weather phenomena, the technical change index shows substantial progress compared with the farm level efficiencies that remained at a constant level or deteriorated (2009/2010 period). Piesse and Thirtle (2010a) have also estimated a difference between technical efficiency progress and farm level efficiency. An advantage of the bootstrapped MI of TFP estimated in this research is that it provides a correction for the inherent bias in nonparametric distance functions and allows statistical inference for the results. Hence, it is possible not only to indicate changes in the MI of TFP but also to indicate if these changes are statistically significant. Analysis of the returns to scale suggests that the majority of the farms need to shift down their long-run average cost curve and adjust their size in order to achieve cost savings (operating under IRS). Furthermore, the estimates of PTE and OTE also indicate the need for input adjustment in the short run and in the long run respectively in order to improve control over the production process.

The EARBC has been characterised as one of the areas with the highest risk of drought in the UK (Environment Agency, 2011). Water resources for agriculture may become scarcer and more variable due to the increased abstraction rates in the EARBC and the increased occurrence of drought phenomena during the crop development period. In addition, the need to secure agricultural production in order to meet increasing food demand is likely to require supplementary irrigation of crops which generates further pressures on water resources in the catchment. Hence, in the context of SI, GCF_s in the EARBC need to both maximise productivity and efficiency while directing their strategies towards minimising excess of water use for irrigation and other agricultural purposes (washing, spraying).

Excess water use was estimated for a set of GCF_s in the EARBC with the employment of a sub-vector DEA model. The advantages of the method are the identification of specific input reductions (water use) at a farm level, and the potential development of an online water use benchmarking tool. This online tool could also be available to farmers through the FBS farm business online benchmarking tool in order to enable them to improve WUE and compare their performance with other farms in the same sector and area. Furthermore, the estimation of technical efficiency enables the analysis of returns to scale providing pathways for long term improvements and planning which could be used to strategically position a farm in relation to the long term average cost curve and hence improve economic efficiency and productivity of the GCF_s.

Taking into consideration the common goals of SI and Eco-Efficiency - improving the environmental performance of farming systems while simultaneously increasing the production efficiency – enabled the development of an adjusted index of Eco-Efficiency for the evaluation of the performance of agricultural systems towards SI. The use of the slack based DEA model has enabled the estimation of pressure specific levels of Eco-Efficiency and also allowed the assessment of the intensified production technology for each farm. The estimation of specific input reductions and the pressure specific Eco-Efficiency provides valuable information for the development of targets and strategies towards the improvement of the SI of agriculture. Furthermore, accounting for slacks in the additive DEA model is important since the aggregate potential reduction of environmental pressures is linked to the reduction of the pressure generated by the intensified production technology.

Both the optimal weights and the input slacks in the DEA model have shown that farms in the research sample are quite efficient with respect to the management of water resources and fertilisers. This can be further explained from the outputs of the WUE analysis. In particular, the majority of the farms and especially the farms on the sub-vector WUE frontier (peer farms) follow a prescriptive system for the management of nutrient input; test soil nutrients; calibrate fertiliser spreaders; use a decision support tool for short and long term irrigation planning and monitoring; take measurements of in-field soil moisture; and finally use the method of water balance calculations.

As outlined in Chapter 6 the main advantages of this approach are:

a) the flexibility of DEA techniques and the simplicity in the calculation of the index of Eco-Efficiency that enable policy makers to assess SI at a micro-farm-level

b) the use of a representative and validated source of secondary data such as the FBS which could potentially be used to develop a persistent monitoring mechanism towards the SI of different farm systems in the UK and

c) the identification of specific areas for further reduction in the environmental pressures that are generated by more intensified production technology.

The latter is important since it incorporates the environmental dimensions of agricultural production into the discussion of technical and economic efficiency and hence, it could provide a further insight into the design of policy options to enable the improvement of farms in terms of both environmental and economic efficiency.

7.6 Policy implications

Agricultural productivity is important not only in terms of food security, and input use efficiency (fertilisers, machinery, energy and irrigation) but also in affecting the growth and competitiveness of the sector, generating income to farm businesses and their supporting industries, achieving efficient distribution of scarce resources (land and water) and generating employment. Results of previous research (Thirtle *et al.*, 2004; Piesse & Thirtle, 2010a; 2010b) have shown that there is a stasis in agricultural productivity in the UK. This research has focused in a specific region (EARBC) and type of farm (GCF_s) in order to evaluate the impact of extreme weather phenomena on TFP. Results have shown that the technical efficiency index is sensitive to exogenous shocks with a significant impact on productivity. Moreover, this research suggests that the efficiency change index remained almost unchanged (except the 2009/2010 period) indicating a need for a change in the management of inputs and management practices. Results relating to returns to scale suggest that WUE and SI improvements are required in the direction of adjusting scale size for the majority of the GCF_s in the EARBC and also to improve the management of crop protection, energy and machinery fuels inputs.

From a policy perspective, the current water abstraction regulation in the UK is under reform. The main pillars of the reform are based on the need to face challenges of water availability due to changing weather conditions, the increased demand for water from a growing population and the need to enable trading of water rights (Defra, 2013a). This research suggests that the new legislation should incentivise farmers to improve management practices for efficient water use not only for irrigation but also for other agricultural purposes and to improve water storage at farm level through rain harvesting and on farm reservoirs. Furthermore, it is essential that any reform accounts for the importance of supplementary irrigation for cash crops (potatoes, sugar beet) and the need to secure yield. Any restriction on water abstraction during the growth period due to water shortages or drought conditions would result in failure to meet quality standards and consequently income loss to farmers. Therefore, it is important that the new regime considers the economic significance of irrigated agriculture not only for farming systems but also for the local jobs and local economies.

The design of agricultural policies in order to achieve the general objective of sustainable intensification is a difficult and complex procedure involving the encouragement of farmers to change attitudes and behaviours. Results of this research recommend improvements in the design of strategies and policies to improve input use efficiency and also to develop further farmers skills. Farms in the sample according to the WUE analysis and the slack based DEA model are performing well on the management of water resources and fertilisers although there is still potential for improvement. Further attention is required to improve the management of crop protection, energy and machinery fuels inputs. Policies in the future need to consider the promotion of incentives to farmers for adopting and establishing sources of renewable energy. Furthermore, the regulation of the use of pesticides, fungicides, insecticides and other crop protection chemicals is required in order to improve the performance of farms in relation to SI and safeguard the provision of ecosystem services.

Decision making at farm level and the adoption of management practices and strategies towards SI is a complex and demanding task given that it involves the maximisation of production and profit subject to resource constraints and unpredictable external factors such as weather and changing input costs. In terms of policy goals related to SI, a holistic approach to the topic should involve an integrated analysis of the impacts on biodiversity and land use, animal welfare, human nutrients and rural economies. Future policy relevant research in this area should consider these aspects and incorporate their impacts in the assessment of SI.

7.7 Implications for the FBS and further research directions

The FBS is widely recognised as the most authoritative source of information on the financial, physical and environmental performance of farm businesses in England. The farms in the sample are classified by size and type while annual information is available at regional and country level. The main purpose of the FBS is to serve the needs of farmers, farming and land management interest groups, policy designers, and researchers. Annual reports summarising key results are produced and published by the Department for Environment, Food and Rural Affairs (Defra), whilst others are produced and published by Rural Business Research (RBR) teams.

This research has extensively used all the available FBS information in order to estimate changes in TFP, WUE and to evaluate the SI of GCF_s in the EARBC. The detailed, representative and comprehensive structure of the FBS enables the reproduction of this research and the generalisation of the methods to other farm types beyond the GCF_s.

- **Assess the impact of policy interventions in the agricultural sector**

A different future research approach in the case of the bootstrapped MI of TFP could involve the use of an unbalanced farm data sample and hence, to estimate changes in TFP for longer periods in order to evaluate the impact of specific policy interventions at a farm level. Moreover, as was discussed in Chapter 3, the MI of TFP can also be used to explore differences in productivity among different regions in a country and also by linking the FBS with its equivalent FADN data to compare the performance of England with other countries of interest in the EU. As was mentioned in Chapter 4 the annual report on agricultural productivity published by Defra uses an ideal Fisher index, while other research studies in the past have used the Tornqvist-Theil TFP index. The use of the MI of TFP estimated by DEA methods has the advantage that multi-input and multi-output technologies can be estimated even in the absence of price data. A comparison study among the three (Fisher index, Tornqvist-Theil and Malmquist TFP index) would be useful for policy makers in order to explore the full potential for each of the methods, understand their limitations and their potential in utilising FBS to enable the design of policies and strategies in the agricultural sector.

- **Measure input use efficiency at a farm level to improve management practices**

The use of the sub-vector model to estimate WUE has the potential to explore also other specific input use efficiencies in the agricultural sector in England. Examples in this case could be the estimation of nitrogen use efficiency, energy efficiency, crop protection efficiency and labour efficiency. As outlined in Chapter 5 the best performing farms in the sample could also define the set of management practices (depending on the availability of FBS data) for efficient use of agro-chemicals, energy, fertilisers and thus, reduce input costs and improve the environmental performance of the farms. In the case of WUE, it is of significant importance that the FBS collects information on the annual use of water for agriculture at a farm level. That will enable the development of a dynamic benchmarking tool of WUE and will also provide better management recommendations since the impact of management practices will be evaluated over time. The data requirements for this would include information on the primary sources of water for agriculture, the volume of water abstracted from bore holes, rivers and reservoirs, the volume of water from mains water and the volume of water used at a farm level for irrigation, spraying, vegetable washing, wash down and drinking water for livestock and also for other agricultural uses.

- **Develop a dynamic approach to evaluate the SI of farming systems**

In relation to use of the FBS to evaluate the SI of farming systems, a limitation of the data is the lack of information on specific amounts of fertilisers and pesticides used at a farm level through the FBS. In this research the cost of each input is used as a proxy indicator of the pressure that is generated on the environment. However, since the 2012/2013 accounting year the FBS is also collecting information on the fertiliser quantities at a farm level. In addition to that, there is information available on management practices such as precision farming, soil nutrient software packages to help determine fertiliser applications and use of green manures in arable rotation. Further research will consider the inclusion of this information in the DEA model to estimate the index of Eco-Efficiency and also at the second stage of the determinants of Eco-Efficiency.

Moreover, a future possible direction for research is the dynamic approach of Eco-Efficiency as a requirement in order to evaluate the progress of farming systems towards SI. The Kuosmanen and Kortelainen (2005) approach adapted in this research for the estimation of the Eco-Efficiency index is further extended by Kortelainen (2008) which enables the assessment of a dynamic ecological – economic performance and its two determinants respectively the ecological-economic efficiency change and technical change at a specific environmental pressure level. This can be either evaluated through the estimation of a MI based on DEA methods as described in Chapter 2 and also suggested by Kortelainen (2008) or by DEA estimated Luenberger indices as suggested by Picazo-Tadeo *et al.* (2013). That will enable the consideration of other determinants to explain Eco-Efficiency, such us technological change over time, the influence of current policy instruments and specific management practices. In this context, the new annual core FBS data on fertiliser quantities and farm management practices will be of significant importance.

- **Improve benchmarking methods in agricultural sector**

As part of the empirical analysis of this research the sub-vector DEA model was used to demonstrate the importance of considering exogenous parameters with an impact on the productivity of the farms within the DEA model specifications. Results showed that the inclusion of non-discretionary inputs ensures the homogeneity of the sample and therefore provides better benchmarking results. However, when the conventional DEA model was compared with the sub-vector DEA model in terms of farm ranking no significant difference was observed. Future research should expand this analysis over a larger geographic area in England and also include other exogenous parameters such as temperature, altitude and soil characteristics. In addition, instead of using average annual rainfall or temperature values, it is suggested that future work should include information on climate variables during the stage of development and yield of the crop. Furthermore, in terms of the development of the DEA theory on estimating the MI of TFP future work is required in order to account for non-discretionary factors in the estimation of productivity over time. The latter will enable the direct assessment of technical and economic efficiency change when exogenous parameters such as rainfall and other non-discretionary variables are included in the analysis.

- **Merge the available FBS data with other datasets related to agriculture**

Finally, it is suggested that the FBS database improves the linkages with other available datasets in England. This research attempted to merge the available information on water abstraction licences and volumes of water abstracted per farm available from the National Abstraction Licensing Database (NALD) of the Environment Agency (EA) with farm data obtained from the FBS. However, due to lack of additional information on the Grid reference of the FBS farms the final merger of the two datasets was not successful. Future research design and storing of the data should consider the possibility of building an identification variable that will enable researchers to successfully merge the geographic location of the individual farm with available datasets such as the soil types, water abstraction licences and climatic conditions.

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Appendices

Appendix A Decomposition of the Malmquist Index of Total Factor Productivity

Efficiency change component of the MI of TFP

$$\Delta Eff = \frac{D_I^{t+1}(x^{t+1}, y^{t+1})}{D_I^t(x^t, y^t)}$$

Table A.1: Efficiency change index

Farm ID	2007-2008	2008-2009	2009-2010	2010-2011
1	1.000	1.036	1.203*	1.101
2	0.835**	1.437***	0.903	0.945
3	0.920	0.843*	1.303	0.807***
4	1.072	1.043	0.910	0.929
5	1.236**	1.252**	1.383	0.787***
6	1.620***	0.798***	1.351**	0.691***
7	1.000**	1.013	0.987	1.000**
8	1.013	0.617***	1.180	0.847
9	1.000**	1.000**	1.000**	1.000**
10	1.000**	1.529	0.654	1.000**
11	1.199**	0.729***	0.830*	1.297***
12	0.892**	1.055	1.523***	0.938
13	1.000	1.000**	1.000**	1.000**
14	0.918	1.089	0.929	1.682***
15	0.919	1.367***	0.829***	0.970
16	1.009	1.328*	0.666***	0.935
17	1.000**	1.000**	1.000	1.000
18	0.963	1.148	0.869***	1.076
19	1.000**	1.000**	1.000**	1.000**
20	1.000**	1.000**	1.000**	1.000**
21	1.000**	1.000**	1.000**	1.000**
22	0.915	0.917	1.307	0.722***
23	1.000**	1.225	0.829**	1.076
24	1.053	1.153	1.111	0.955
25	0.760***	1.320***	1.031	0.881
26	1.080*	1.031	1.124	0.988
27	1.071	0.934	1.007	0.993
28	1.229**	0.930	1.155	1.275**
29	1.202**	0.877	1.331**	1.027
30	1.133*	1.042	0.858**	1.179*
31	1.187*	0.868	1.074	1.100**
32	1.172	1.008	0.847**	1.000**
33	0.874	0.999	1.000**	1.000**
34	0.721***	1.280***	0.910	0.881
35	0.951	1.065	1.013	0.900
36	1.039	1.012	1.304**	1.184
37	1.228***	0.772**	1.455	1.062
38	0.988	1.297*	0.906	1.449***
39	0.841**	1.120	0.894	1.216
40	1.000**	1.007	1.084	0.916
41	0.977	1.156	0.960	1.025

* Significantly different from unity at 0.1 level,
**Significantly different from unity at 0.05 level,
***Significantly different from unity at 0.01 level

Technical change component of the MI of TFP

$$\Delta Tech = \left[\frac{D_I^t(x^{t+1},y^{t+1})}{D_I^{t+1}(x^{t+1},y^{t+1})}\frac{D_I^t(x^t,y^t)}{D_I^{t+1}(x^t,y^t)}\right]^{1/2}$$

Table A.2: Technical change index

Farm ID	2007-2008	2008-2009	2009-2010	2010-2011
1	0.796***	1.145	1.038	0.815*
2	0.832**	1.077	0.975	1.132
3	0.738***	1.007	1.322	0.952
4	0.809***	1.156	0.982	1.069
5	0.675***	1.285**	1.117	0.761***
6	0.656***	1.257**	1.043	0.931
7	0.801***	1.082	0.995	0.984
8	0.689***	0.881**	1.338	0.902
9	0.665***	1.185	1.071	1.096
10	0.819*	1.466	0.760*	0.819*
11	0.701***	1.283***	1.117	0.777***
12	0.750***	1.272**	1.001	0.916
13	0.791**	1.235	0.915	0.696**
14	0.825***	1.173*	0.851**	0.981
15	0.798***	1.036	1.114	1.089
16	0.789***	1.026	0.946	1.236
17	0.785***	0.560***	1.630*	1.174
18	0.905	1.107	1.089*	0.809***
19	0.856	0.664***	1.547*	0.669**
20	0.743***	0.285***	5.227**	0.934
21	0.631***	1.091	1.121	1.035
22	0.756***	1.143	0.855	1.496***
23	0.871	0.974	1.260**	1.032
24	0.683***	1.259**	1.039	0.745***
25	0.813***	1.095	1.030	1.088
26	0.730***	1.124	1.046	0.977
27	0.775***	1.047	1.122	0.968
28	0.764***	1.180**	0.930	0.767***
29	0.786***	1.179*	0.851*	0.986
30	0.770***	1.070	1.118*	0.953
31	0.774***	1.082	1.063	0.916*
32	0.793***	1.081	1.149	0.935
33	0.788***	0.982	1.226*	0.858***
34	0.776***	1.033	1.073	1.121
35	0.765***	1.038	1.102	1.094
36	0.779***	1.264**	0.847*	0.874*
37	0.770***	1.192*	1.051	1.089
38	0.770***	1.113	1.051	0.829**
39	0.770***	1.022	1.057	1.085
40	0.782***	1.030	1.118	0.851****
41	0.783***	1.100	0.975	1.046

* Significantly different from unity at 0.1 level,
** Significantly different from unity at 0.05 level
*** Significantly different from unity at 0.01 level

Appendix B Decomposition of the efficiency change component of the MI of TFP into pure and scale efficiency

Pure efficiency change index

$$\Delta PureEff = \frac{D_I^{Vt+1}(x^{t+1}, y^{t+1})}{D_I^{Vt}(x^t, y^t)}$$

Table B.1: Pure efficiency change

Farm ID	2007-2008	2008-2009	2009-2010	2010-2011
1	1.000**	1.000**	1.000**	1.000**
2	0.855*	1.409**	0.851**	0.952
3	1.000**	1.000**	1.000**	1.000**
4	1.081	1.032	0.927	0.931
5	1.227	1.244**	0.889***	1.072
6	1.651***	0.781***	0.933	1.017
7	1.000**	1.000**	1.000	1.000**
8	1.014	0.711*	1.167	0.857
9	1.000**	1.000**	1.000**	1.000**
10	1.000**	1.000**	1.000**	1.000**
11	1.190***	0.915	0.660***	1.084
12	1.000**	1.027	1.052	0.982
13	1.000**	1.000**	1.000	1.000**
14	0.923	1.061	0.737***	1.692***
15	0.951	1.217	0.980	0.838
16	0.988	1.327**	0.652***	1.000**
17	1.000**	1.000**	1.000**	1.000**
18	1.000**	1.249	0.955*	1.127
19	1.000**	1.000**	1.000**	1.000**
20	1.000**	1.000**	1.000**	1.000**
21	1.000**	1.000**	1.000**	1.000**
22	0.660***	0.737	2.242	0.579***
23	1.000**	1.062	0.941	1.000
24	1.259***	1.145	0.737***	1.150**
25	1.097	1.060	0.928	1.059
26	0.981	1.091	0.947	1.011
27	1.000**	1.000**	1.000**	1.000**
28	1.148	0.966	1.104	1.158*
29	1.198	0.855**	0.965	1.163**
30	1.035	1.145	0.912	1.041
31	1.163	0.870	1.071	1.085
32	1.160	0.958	0.900	1.000**
33	0.882	1.000**	1.000**	1.000**
34	0.725***	1.266	0.908	0.870**
35	0.968	1.058	0.999	0.924
36	0.957	1.093	1.180	1.168
37	0.870	0.813	1.978	1.062
38	1.000**	1.260*	0.825*	1.332**
39	0.844**	1.104	0.779*	1.336
40	1.000**	1.000**	1.036	0.965
41	0.958	0.995	0.907	1.114*

* Significantly different from unity at 0.1 level,
** Significantly different from unity at 0.05 level
*** Significantly different from unity at 0.01 level

Scale efficiency change index

$$\Delta ScaleEff = \frac{D_I^{t+1}(x^{t+1},y^{t+1}) / D_I^{Vt+1}(x^{t+1},y^{t+1})}{D_I^{t}(x^{t},y^{t}) / D_I^{Vt}(x^{t},y^{t})}$$

Table B.2: Scale efficiency change

Farm ID	2007-2008	2008-2009	2009-2010	2010-2011
1	1.000**	1.036	1.203*	1.101
2	0.976	1.020	1.061*	0.992
3	0.920	0.843***	1.303***	0.807***
4	0.992	1.010	0.981	0.999
5	1.007	1.006	1.555***	0.734***
6	0.981	1.022	1.448***	0.680***
7	1.000**	1.013	0.987	1.000
8	0.999	0.868***	1.012	0.989
9	1.000*	1.000**	1.000***	1.000***
10	1.000***	1.529	0.654*	1.000***
11	1.008	0.796***	1.259***	1.196***
12	0.892**	1.028	1.448***	0.955
13	1.000**	1.000**	1.000***	1.000***
14	0.994	1.027	1.260***	0.994
15	0.965	1.123	0.846**	1.157
16	1.021	1.001	1.021	0.935***
17	1.000**	1.000*	1.000**	1.000**
18	0.963	0.919	0.909	0.955
19	1.000	1.000***	1.000**	1.000***
20	1.000**	1.000***	1.000**	1.000**
21	1.000**	1.000**	1.000**	1.000**
22	1.385*	1.244	0.583***	1.247
23	1.000	1.153	0.880*	1.076
24	0.837	1.007	1.507***	0.830***
25	0.693	1.245***	1.110	0.832***
26	1.102**	0.945	1.187***	0.978
27	1.071	0.934	1.007	0.993
28	1.071	0.963	1.046***	1.101***
29	1.003	1.026	1.380***	0.883*
30	1.095	0.910	0.941*	1.133***
31	1.021	0.997	1.003	1.014
32	1.011	1.052	0.941*	1.000**
33	0.990	0.999	1.000**	1.000**
34	0.994	1.011	1.002	1.013
35	0.983	1.007	1.014	0.974
36	1.085	0.926	1.105***	1.014
37	1.410**	0.949	0.736*	1.000**
38	0.988	1.029	1.098***	1.088
39	0.996	1.014	1.148	0.910
40	1.000**	1.007	1.046	0.949
41	1.020	1.161***	1.059	0.920

* Significantly different from unity at 0.1 level,
** Significantly different from unity at 0.05 level
*** Significantly different from unity at 0.01 level

Appendix C Decomposition of the technical change component of the MI of TFP into pure and scale technical efficiency

Pure technical efficiency change index

$$\Delta PureTech = \left[\frac{D_I^{Vt+1}(x^t,y^t)}{D_I^{Vt+1}(x^{t+1},y^{t+1})}\,\frac{D_I^{Vt}(x^t,y^t)}{D_I^{Vt}(x^{t+1},y^{t+1})}\right]^{1/2}$$

Table C.1: Pure technical efficiency change

Farm ID	2007-2008	2008-2009	2009-2010	2010-2011
1	0.905	1.127	1.055	0.975
2	inf	1.144	1.055	1.028
3	0.832*	0.989	1.432***	0.972
4	inf	1.161	0.964	inf
5	0.679***	1.306***	1.245***	0.852***
6	0.695***	1.235**	1.087	0.964
7	inf	1.131	0.980	0.901
8	0.481***	0.819***	2.050***	0.704***
9	inf	inf	inf	inf
10	inf	inf	inf	inf
11	0.812***	1.160	1.306***	0.869***
12	0.763*	1.271***	1.184**	0.925*
13	inf	1.205	0.926	0.471***
14	inf	1.140	1.082	0.853***
15	inf	1.185	1.030	1.365
16	inf	0.936	1.047	1.042
17	0.808***	0.549***	1.715	0.877
18	inf	inf	1.072	inf
19	0.802**	0.607***	1.596*	0.556***
20	inf	inf	inf	0.762**
21	inf	2.312*	0.972*	inf
22	inf	1.124	inf	2.187***
23	inf	1.803*	1.199	0.651***
24	0.756***	1.239***	1.270***	0.797***
25	0.889**	1.073	1.136*	1.000
26	inf	1.049	1.105*	0.971
27	inf	1.030	1.122	0.844
28	inf	1.155	0.997	0.820***
29	0.788***	1.204***	1.082	0.815***
30	0.822*	1.029	1.089	0.988
31	0.656***	1.088	1.094	0.938
32	inf	1.101	0.911	inf
33	inf	0.773**	inf	inf
34	inf	1.080	1.090	1.159
35	inf	1.030	1.174	1.066
36	inf	1.184	0.962	0.878**
37	inf	1.318	1.086	1.060
38	inf	1.080	1.129	0.874**
39	inf	1.018	0.920	1.212
40	0.669***	0.985	1.133*	0.718***
41	inf	1.059	1.076	0.931

* Significantly different from unity at 0.1 level,
** Significantly different from unity at 0.05 level
*** Significantly different from unity at 0.01 level
inf – Infeasible to compute

Scale technical efficiency change index

$$\Delta ScaleTech = \left[\frac{D_I^{t+1}(x^t,y^t) / D_I^{Vt+1}(x^t,y^t)}{D_I^{t+1}(x^{t+1},y^{t+1}) / D_I^{Vt+1}(x^{t+1},y^{t+1})} \frac{D_I^{t}(x^t,y^t) / D_I^{Vt}(x^t,y^t)}{D_I^{t}(x^{t+1},y^{t+1}) / D_I^{Vt}(x^{t+1},y^{t+1})} \right]^{1/2}$$

Table C.2: Scale technical efficiency change

Farm ID	2007-2008	2008-2009	2009-2010	2010-2011
1	0.880	1.016	0.984	0.836***
2	inf	0.941	0.925**	1.101**
3	0.888	1.018	0.924	0.980
4	inf	0.995	1.018	inf
5	0.994	0.983	0.897***	0.893**
6	0.944	1.018	0.959	0.966
7	inf	0.957	1.015	1.092
8	1.433**	1.075**	0.653***	1.282**
9	inf	inf	inf	inf
10	inf	inf	inf	inf
11	0.863***	1.106**	0.855***	0.895*
12	0.982	1.001	0.846***	0.990
13	inf	1.025	0.987	1.477
14	inf	1.029	0.787***	1.151**
15	inf	0.874	1.081	0.798**
16	inf	1.096**	0.904***	1.187**
17	0.972	1.019	0.950*	1.338
18	inf	inf	1.016*	inf
19	1.068	1.094***	0.970	1.203**
20	inf	inf	inf	1.226
21	inf	0.472***	1.153	inf
22	inf	1.017	inf	0.684**
23	inf	0.540***	1.051	1.586*
24	0.903**	1.017	0.818***	0.935
25	0.915	1.021	0.907	1.087
26	inf	1.072**	0.946*	1.006
27	inf	1.017	1.000	1.146
28	inf	1.021	0.932***	0.936**
29	0.998	0.979	0.787***	1.209**
30	0.936	1.041	1.027	0.965
31	1.181	0.994	0.972	0.976
32	inf	0.981	1.261	inf
33	inf	1.270*	inf	inf
34	inf	0.956	0.985	0.967
35	inf	1.008	0.939	1.027
36	inf	1.068	0.880***	0.996
37	inf	0.904	0.968	1.028**
38	inf	1.031	0.931***	0.949
39	inf	1.004	1.149	0.896
40	1.169	1.046	0.987	1.185
41	inf	1.038	0.906	1.123

* Significantly different from unity at 0.1 level,
** Significantly different from unity at 0.05 level
*** Significantly different from unity at 0.01 level
inf – Infeasible to compute

Appendix D Product of scale efficiency and scale technical efficiency change

Table D.1: Scale efficiency change

Farm ID	2007-2008	2008-2009	2009-2010	2010-2011
1	0.880***	1.052	1.183***	0.921
2	inf	0.960***	0.981***	1.092***
3	0.817***	0.858***	1.204**	0.791***
4	inf	1.005	0.999	inf
5	1.001	0.989	1.396***	0.656***
6	0.926***	1.040	1.389***	0.657***
7	inf	0.969*	1.003	1.092*
8	1.432	0.933*	0.660***	1.267
9	inf	inf	inf	inf
10	inf	inf	inf	inf
11	0.870***	0.881***	1.077***	1.071***
12	0.876***	1.029	1.225***	0.946
13	inf	1.025*	0.987**	1.477
14	inf	1.056	0.991**	1.144***
15	inf	0.982	0.914***	0.923***
16	inf	1.096*	0.923***	1.109
17	0.972***	1.019	0.950***	1.338
18	inf	inf	0.924**	inf
19	1.068	1.094***	0.970***	1.203
20	inf	inf	inf	1.226
21	inf	0.472***	1.153*	inf
22	inf	1.265*	inf	0.853***
23	inf	0.623***	0.925***	1.707*
24	0.756***	1.024	1.233***	0.776***
25	0.634***	1.271***	1.007	0.905***
26	inf	1.012	1.123***	0.984
27	inf	0.950*	1.008	1.138
28	inf	0.983	0.975	1.030**
29	1.002	1.004	1.085***	1.068***
30	1.026	0.947***	0.966***	1.093***
31	1.205	0.992	0.975	0.989
32	inf	1.032	1.187	inf
33	inf	1.269	inf	inf
34	inf	0.966**	0.986**	0.980***
35	inf	1.015	0.952***	1.000
36	inf	0.989	0.973**	1.010
37	inf	0.858	0.712***	1.028
38	inf	1.061***	1.023	1.032*
39	inf	1.018	1.319***	0.816***
40	1.169*	1.054**	1.032	1.125
41	inf	1.205***	0.960***	1.034***

* Significantly different from unity at 0.1 level,
** Significantly different from unity at 0.05 level
*** Significantly different from unity at 0.01 level
inf – Infeasible to compute