# Analyzing Efficiency of Vegetable Production in Benin

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# Analyzing Efficiency of Vegetable Production in Benin

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*To*

*Christine Yasmine,*

*Lauryne Olouwatobi,*

*and Lindsey Olouwayemissi.*

## Abstract

Vegetable production in Sub-Saharan Africa plays an important role in food security and poverty reduction. Although vegetables are an important emerging cash crop for the agricultural sector in Benin, their production and marketing systems are facing many challenges. The objective of this research is to investigate the production technology and efficiency of vegetable production and marketing at the farm level in Benin. Using recent advances in cross sectional efficiency analysis, we analyze two samples of vegetable producers following different perspectives. Chapters 2 to 5 offer an in depth analysis of vegetable production performance in the lowlands and in the urban and peri urban areas. Additionally, special emphasis is given to the marketing efficiency of producers in the urban and peri-urban areas.

First, the difference in economic inefficiency among lowland producers at farming system level is examined. Second, technical and marketing inefficiency of a sample of urban vegetable producers is investigated using a non-radial Russell-type measure of inefficiency. Third, the impact of crop specialization on farm's performance is assessed using a non-neutral stochastic frontier. Finally, the efficiency of the use of pesticides and other inputs of vegetable producers is analyzed using a smooth first-stage bootstrap non-parametric approach.

The empirical results in Chapter 2 show that farms' inefficiency in lowland farming systems is the most diverse. Average scale, allocative, output and input inefficiency are significantly lower in the integrated rice-vegetable farming system than in the vegetable farming system. The results in Chapter 3 suggest that vegetable producers are more inefficient with respect to marketing than production and that marketing inefficiency is affected by the type of marketing arrangements. The analysis in Chapter 4 shows that vegetable-production technology exhibits diseconomies of scope and that the degree of specialization has a positive effect on technical efficiency. Finally, the results on pesticide use in Chapter 5 provide evidence that pesticides are overused while there is no evidence of technical interdependence between pesticides and productive inputs.

**Keywords:** Farm performance, Production function, Marketing, Efficiency, Bootstrap, DEA, Directional distance function, Russell-type measure, Input distance function, Non-neutral stochastic frontier, Specialization, Pesticides, Shadow prices, Vegetables, Lowland, Urban, Benin.

## Preface

About ten years ago, I noticed that in my daily work at the National Agricultural Research Institute of Benin (INRAB), I could not get the deepening of scientific knowledge in some microeconometric aspects I was aiming for. This motivated me to do post graduate research since 2002. Luckily, after an MSc degree in rural economics in 2007 at Université Catholique Louvain-La-Neuve in Belgium, Professor Alfons Oude Lansink accepted me as a PhD student in Business Economics Group of Social Sciences Department at Wageningen University. This thesis represents the continuation of my engagement with empirical research I performed at the Agricultural Policy Analysis Unit of the National Agricultural Research Institute of Benin (PAPA/INRAB) since 2001. In sum, this thesis is the result of the journey that brought me in September 2006 to Belgium. I am pleased to acknowledge the contributions of several people who helped in the writing of this thesis.

Foremost, I am very much indebted to my supervisor Prof. Alfons Oude Lansink to whom I express my sincere gratitude for giving me the opportunity to pursue my study at the Business Economics Group (BEC). I am deeply grateful to Alfons for allowing me to be part of the BEC. Alfons greatly contributed to this study and gave me valuable comments on earlier drafts of each chapter of this thesis. The first two years, he was my promoter and my daily supervisor and had to deal with my issues on daily basis. His stimulating comments and his realistic view on the feasibility of various ideas stimulated the progress of this thesis. His dedicated supervision shows in the co-authorship of all the chapters.

I also wish to thank Dr. (Greg) Grigorios Emvalomatis who joined the supervision team in October 2009. Greg, working with you the last three years of my PhD was a pleasure. You always offered me valuable comments and technical discussions. It was a great pleasure for me to have you as my daily supervisor.

I extend my sincere thanks to Anne Houwers, Karin Sijlmans and Ilona van den Berg for helping me with administrative matters. Working at the Business Economics Group has been a significant and unforgettable experience in my life. My warmest thanks go to all of you my colleagues and staff of BEC fellows for being there for me when I most needed your friendship and help.

In Benin, I would like to extend my gratitude to many people who help me in different ways to reach this level.

First of all, my special thanks and sympathy go to Dr. Ir. Patrice Y. Adégbola, who offered me in January 2001 the position of agricultural economics at the Agricultural Policy Analysis Unit of the National Agricultural Research Institute of Benin (PAPA/INRAB). I have learned a lot from you in many ways and I also got a lot of advice and support from you during the course of this thesis. It was a great experience for me to work closely with you for many years. I cannot forget in anyway the years I had spent in PAPA.

I take this opportunity to express my sincere gratitude to Dr. Ir. Françoise Assogba-Komlan, Head of Vegetable Production Unit at INRAB, for her fruitful collaboration work on vegetables since 2002 and for her constant support.

I wish to express my indebtedness to Dr. Ir. Guy Apollinaire Mensah, Director of Agricultural Research Centre of Agonkanmey at INRAB, for his administrative support during the course of this thesis. Your support gave me strength and confidence to continue working at INRAB.

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My gratitude to colleagues in the Agricultural Policy Analysis Unit. Each of you in one way or another supported me through encouragement, care and love. Especially remembered are: Léonard Hinnou, Mêtohoué Goudjo and Dr. Ir. Epiphane Sodjinou. I especially thank Léonard for his assistance during the last part of my field work. He helped in assisting in the data collection and data typing.

I would also like to express my appreciation to colleagues and friends in particular to Dr. Ir. Afio Zannou and Dr. Ir. Sylvain Kpènavoun-Chogou for their constant support and encouragement.

I acknowledge the special moments that I shared with my fellow students from Benin. I owe many thanks to: Euloge Togbé, Laurent Glin, Dr. Ir. Florent Okry, Guirguissou Maboudou-Alidou, Dr. Eugène Agbicodo, Augustin Kouévi, Dr. Ir. Latifou Idrissou, Clément Gbéhi, Nadia Fanou, Dr. Ir. Flora Chadaré, Dr. Ir. Honoré Biaou, Souleimane Adékambi, Djalal Arinloyé, Nathalie Kpéra, Yann Madodé, Dr. Ir. Elie Dannon, Fernande Honfo, Jonas Wanvoèkè, Romaric Vihotogbé and Simon N'Cho (my group-mate from Côte d'Ivoire). The atmosphere of supporting each other we created, like sharing diner, playing soccer and of course discussing the development patterns of Benin helped me a lot in this journey. I express many thanks to Dr. Ir. Doortje Wartena for frequently inviting students from Benin at her home for diner.

I also take this opportunity to express my gratitude to many friends in Canada for providing useful help to my family.

My most sincere appreciation to my parents, brothers, sisters, uncles and cousins whose love, care, prayer and support over the years was indispensable for this achievement.

My heartfelt acknowledgement to my mother Jeanne Ibidoun Kakpo for her love, care, wise advices and prayer.

With profound respect, I dedicate this thesis to the memory of my father, Denis Dossou Singbo, who dinned traditional value in me.

I dedicate this thesis with love and deep appreciation first to my wife, Christine Yasmine. Thanks for providing your unyielding support and encouragement throughout. I know that you suffered a lot from being away for so long time. In these four years you faced a lot of challenges for coping alone with the family responsibilities in Canada. I also dedicate the thesis to my daughters Lauryne Olouwatobi and Lindsey Olouwayemissi. Anyone can imagine the sacrifice of missing the presence and care of a darling and a dad. I love you all too much and I am so proud of you.

*Wageningen, The Netherlands* A. Singbo
*June 2012*

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# CHAPTER 1

## Introduction

### 1.1. Background and Scope

Benin's economy largely depends on agriculture, which contributes about 32.6% to GDP, compared to 1% for U.S. and 6% for Brazil. Almost, 58 percent of Benin's labor force works in agriculture and for a large proportion, it is their primary activity. In most other developed countries, this is less than 10 percent (FAO, 2011; Lewis, 2004; MAEP, 2011). The agricultural sector in Benin is characterized by more than 550,000 small-scale farms with an average size of 1.7 ha and more than 34% of farms cultivate less than 1 ha. Almost 491 million of euros of agricultural products are exported annually (80% of the total export revenue) and 791 million of euros of agricultural products are imported annually (FAO, 2011). Thus, understanding how Benin will evolve out of its predominantly agricultural setting is an important issue. It is known from the seminal book of Adam Smith (1776) that the initial move out of agriculture came from productivity improvements in this sector, freeing up labor that could produce goods and services in other sectors of the economy. Previous research has demonstrated that the increase in agricultural productivity came in steps and is strongly related to the changes in the rest of the economy (Lewis, 2004, p. 203). The power of productivity growth as a tool for overall economic development and poverty reduction has been widely documented and empirically studied over the world (for an overview, see Lewis, 2004). Furthermore, the food crises in developing countries during this last decade and the world commodity price boom that started several years ago has put agricultural productivity growth at the core of the agenda for decreasing poverty and increasing food security (Byerlee et al. 2009; Irz et al. 2001; de Janvry, 2010; Tschirley and Jayne, 2008).

This thesis focuses on the analysis of productivity in vegetable production in Benin. Vegetable producers have a strong motivation to produce vegetables for sale and household consumption is the residual of output after sales. Producers of vegetables are likely to respond to market and policy signals and can be termed as 'market-oriented subsistence farmers' as defined by Kostov and Lingard (2004). Generally, in developing countries, vegetable production stimulates the rural and urban economy, and generates employment and income (Ali and Abedullah, 2002). Producers learn to manage multiple cropping systems and to deliver quality products in a timely fashion by participating in and experiencing contractual arrangements and sophisticated marketing systems.

## 1.2. Problem Statement

Over the last decades, most of the empirical work in Benin has focused on staple crops and cash crops such as maize, cassava and cotton. However, vegetables are increasingly produced in both rural and urban zones (Moustier et al. 1998). Vegetables are cultivated in every region of Benin in the uplands, lowlands and valleys. Vegetable production in Benin is an intensive system due to the high use of external inputs (fertilizer, pesticide, improved varieties). Vegetable production is twice as labor-intensive as cereal production and yields ten times more revenues from land than cereals (World Bank, 2007). Accordingly, vegetable production is a real source of income and employment generation. However, the potential of vegetable production in rural and urban zones is limited by technical, allocative and marketing inefficiency (PADAP, 2003). Technical efficiency is defined as the ability of a producer to obtain maximal output from a given set of inputs or to use the minimum inputs required to produce a given set of outputs. Allocative efficiency is defined as the ability of a producer to use the inputs in optimal proportions, given their respective prices and the production technology (Farrell, 1957). Marketing efficiency at the farm-level is a measure of the success of a producer and is defined as the extent to which a producer succeeded in getting the maximum price for his/her output, given the resources devoted to marketing activities. Thus, marketing efficiency represents a short-run concept related to the opportunities to arbitrage price differences. A producer’s marketing performance is primarily a function of his/her choice of marketing arrangement (Wollni and Zeller, 2007). Other sources of marketing inefficiency are lack of coordination, unequal information on prices between sellers and buyers (i.e. asymmetric information), heterogeneity of product quality and gaps between demand and supply.

A major concern of vegetable productivity performance in rural areas of Benin is the effective utilization of lowlands for agricultural production (Erenstein et al. 2006). Agriculture in the lowlands takes place on small peasant farms that produce annual food crops for subsistence and markets. Rice and vegetables are the first and second most important food crops produced. Improving economic efficiency of these crop based systems will contribute to improving overall agricultural productivity. Despite the enormous potential of Benin in lowlands, only 4% of the 205,000 ha of available lowlands are cultivated (Cellule Bas-fond, 2002). Traditionally, much of the interest in lowlands has focused on the potential for technologically-intensive rice production (Abdulai and Huffman, 2002; Adesina and Djato, 1997; Audibert, 1997; Barrett et al. 2008; Sherlund et al. 2008) even though vegetable production is highly integrated into lowland cultivation practices. A major limitation of these studies is that mono-cropping rice production is considered to be independent of its lowland production system. In reality, the integrated rice-vegetable farming systems are technically integrated (Erenstein et al. 2006). Thus, ignoring the farming system level in empirical studies may likely bias estimation of efficiency of a decision making unit in the lowlands.

On the other hand, the production of vegetables in urban and peri-urban zones has increased over the past years in terms of the amount cultivated, the number of producers and the income generated. Urban and peri-urban vegetable production systems were not given much attention in past research. To date, urban and peri-urban production systems offer many opportunities for a developing-country's agriculture due to advances in production and increasing consumer demand (Keatinge et al. 2011). The growth of vegetable production in urban areas is explained in large by the good marketing opportunities (proximity to urban markets or linkage to urban markets by efficient transportation networks), increasing urbanization and changing food consumption patterns (Erenstein et al. 2006). Vegetable producers are largely market-oriented and generally grow a wide range of vegetables. Therefore, improving the marketing activities and market participation of vegetable producers may improve the overall economic performance of vegetable production. A large number of studies on agricultural marketing performance argues that marketing inefficiency may have a negative impact on allocative and technical efficiency (Sabuhoro and Larue, 1997; Seyoum et al. 1998). Thus, marketing efficiency is a particular issue to be addressed when studying the performance of vegetable production.

In Benin's vegetable sector, the majority of farms produce both traditional and non-traditional vegetables, indicating that multi-output farms are the rule rather than the exception. By producing both categories of crops instead of only one, the farm may be able to reduce risk. Another benefit associated with diversification is the complementary use of inputs on the farm (economies of scope). Diversification allows for a more efficient use of inputs that can be used in several production processes (Teece, 1980). However, specialization in crops allows operators to exploit scale economies. Moreover, specialized operators have better opportunities to fine-tune their skills (Oude Lansink and Stefanou, 2007). Therefore, the impact of crop diversification on vegetable farm's performance is an empirical issue to be investigated.

Unlike traditional food crops like cereals, cassava and rice, farmers use a large amount of pesticides on vegetables. Moreover, the use of pesticides is associated with the development of resistance (Dinham, 2003; Martin, et al. 2006). Vegetable producers in Benin used the largest volume of pesticides among West Africa countries (Williamson et al. 2008). However, vegetable producers rarely have access to training in pesticide use and have only limited, or no access, to advice on the management of pesticides. Availability and affordability of pesticides was a major concern for many vegetable producers. Therefore, it remains a challenge to gain more insight into the economic performance of pesticide use in vegetable production. The empirical literature on pesticide use in the vegetable production systems in Benin, however, has paid little attention to pesticide productivity. By investigating the efficiency of pesticide use in vegetable production, researchers may provide useful results that may serve as a reference in designing pesticide use policy in agriculture.

## 1.3. Objectives of the Thesis

The overall objective of this thesis is to analyze the production technology and the performance of vegetable producers in Benin. This was done by investigating the level of, and factors that determine marketing, allocative, technical and scale efficiency of these producers. The specific objectives are:

i) Estimate technical, allocative and scale inefficiency of lowland vegetable farming systems and analyze factors that explain inefficiencies.
ii) Measure and explain Benin vegetable producers' marketing and technical efficiency through an integrated approach.
iii) Analyze the impact of vegetable crop specialization on the production frontier and on technical efficiency.
iv) Analyze the technical efficiency and value of marginal product of pesticides in vegetable production and investigate the technical interdependence between damage abatement and productive inputs.

## 1.4. Description of the Study Area

Geographically, Benin is divided in three major agro-climatic regions: the Guinea zone, the Sudano-Guinea zone and the Sudanian zone (White 1983, p. 38; 175-178 p.). The present study was conducted in the Guinea and the Sudano-Guinea zones (Fig. 1.1). The Sudano-

Guinea is a transitional zone between the Guinea and the Sudanian zones and located in the central region of the country which extends from $7^{o}$ and $9^{o}30'$N. The mean annual rainfall varies from 1200 to 1300 mm with one rainfall season (May to November). The Guinea zone extends from the Atlantic coast and stretches between $1^{o}45'$ and $2^{o}24'$E and $6^{o}15'$and $7^{o}00'$N to the west and $6^{o}15'$ and $7^{o}30'$N to the east (Akoègninou et al. 2006, p. xiv). The climate is a subequatorial type with two rainfall seasons (April to July and October to November). The annual average temperature is around $26^{o}$C and the mean annual rainfall varies from 900 to 1400 mm. The Guinea zone is located in the southern region. In the central region, the present study was conducted in the Dassa local government of Collines Department. This region has the highest concentration of lowlands in Benin and receives a lot of support from different projects and research organizations for improving lowland farming practices.

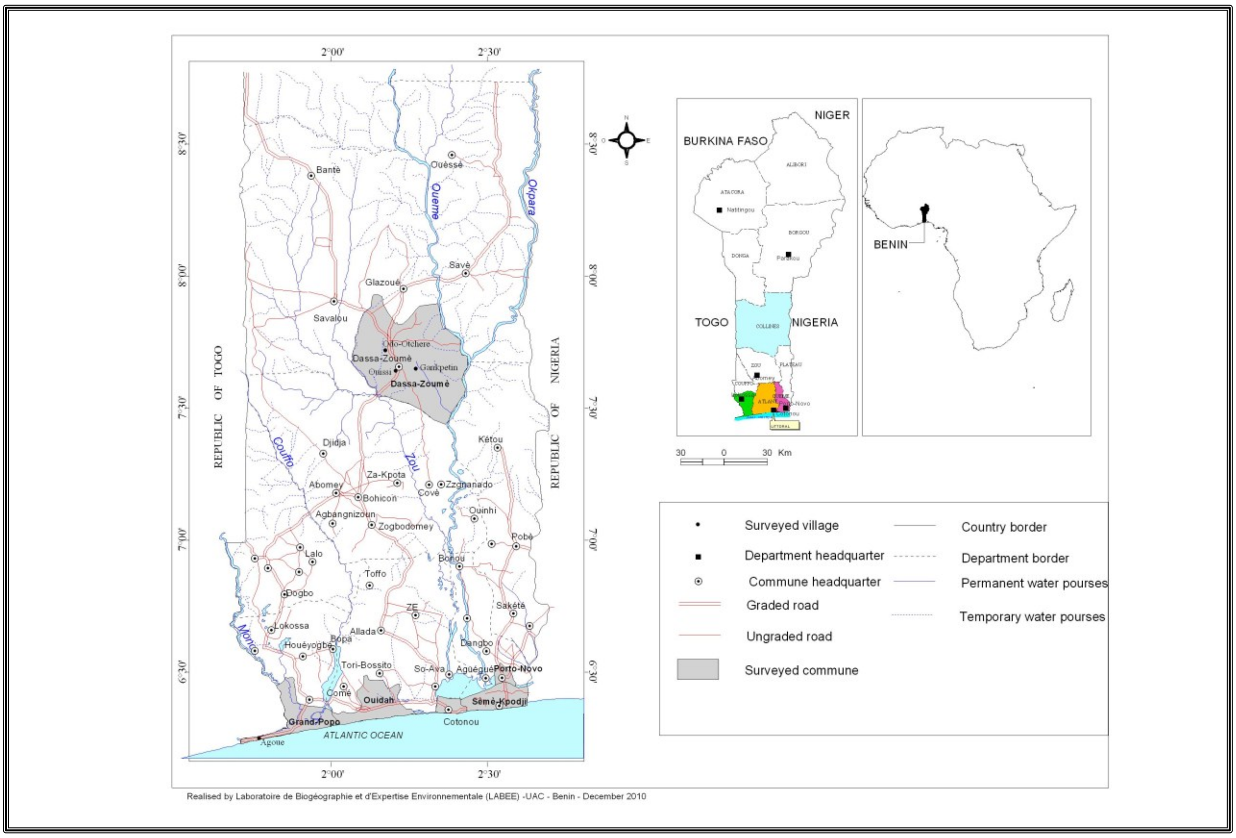


**Figure 1.1. Central and Southern Benin with the study locations**

In the southern region, the study was conducted in the area closest to the sea that is characterized by coastal vegetation on a sandy littoral zone and covered the Cotonou local government of Littoral Department, the Ouidah local government of Atlantique, the Grand-Popo local government of Mono Department, the Sèmè-Kpodji and Porto-Novo local government of Ouémé Department. All these areas are the major locations where vegetable crops are produced in urban and peri-urban areas. The subequatorial climate that characterizes the southern region facilitates vegetable production throughout the year, particularly in the low altitude floodplains, where in the dry season, farmers have good access to irrigation water. Food crops and vegetables are mainly produced in southern Benin and represent a region widely used by vegetable sellers. In total, the study was carried out in five of the 12 departments of Benin Republic according to the new territorial division and 6 out of the 77 communes of Benin.

In Benin, the annual growth rate of the population (3.25%), along with the increase of the number of people living in urban areas (an increase of 52% in the last 20 years), indicates a great opportunity for increasing food demand in urban areas. The growth in demand for food in urban areas is twice as high as the growth in food demand in rural areas (Keatinge et al. 2011). Statistics also show that the Guinea zone, covering the southern part of the country, has a population of about 4 million inhabitants (60.4% of the total Beninese population). The population density is 227 inhabitants per $km^2$ against 59 for the whole country (INSAE, 2003). This figure indicates that the increasing demand for food is attributable to southern Benin. Consequently, the higher increase in demand for vegetables in urban and peri-urban areas of southern Benin compared to the other two regions (central and north) suggests opportunities for a larger supply of vegetables.

## 1.5. Vegetable Production Systems in Benin

Vegetables in Benin are produced in many different systems and locations. More generally, two distinct production systems cohabit in Benin's vegetable sector, i.e. the rural area production system and the urban and peri-urban production system. Vegetables are cultivated in the rural area in the uplands, valleys and lowlands, depending on cultural agricultural practices. In the urban and peri-urban areas, vegetables are mainly produced on the upland and along the coast. In this thesis we focus on the vegetable production in the lowland production system in the central region and the urban and peri-urban production system in the southern region. The following sections briefly describe their particularities.

### 1.5.1. Lowland Vegetable Farming System

In Benin, due to the promotion of small-scale agricultural lowland use since 1980, intensification and diversification practices are more frequently observed in lowlands. Compared to crop production in rural areas, intensification practices are related to water control management where upstream pond and irrigation canals or canals are used to prevent flooding.

Lowland cultivation in Benin accommodates three major farming systems (Fig. 1.2). The first is the integrated Rice-Vegetable Farming System (RVFS). On the same plot, rice is produced during the rainy season, while vegetables are cultivated in the dry season. The second is the Rice Farming System (RFS) where rice is cultivated solely during the rainy season. The third is the Vegetable Farming System (VFS) in which vegetables are produced only in the dry season. Intercropping practices within the field are limited to two or three crops. The cropping pattern in vegetable cultivation is often extensive. Traditional vegetables are the most dominant type of vegetables produced in such lands. In the lowland farming system, the production of vegetables is considered as a female domain. Consequently, women play an important role in producing, marketing and trading. However, with the increasing contribution of lowland vegetable crops to cash income, norms and beliefs about men's and women's involvement in the production process may change (Weinberger et al. 2011).

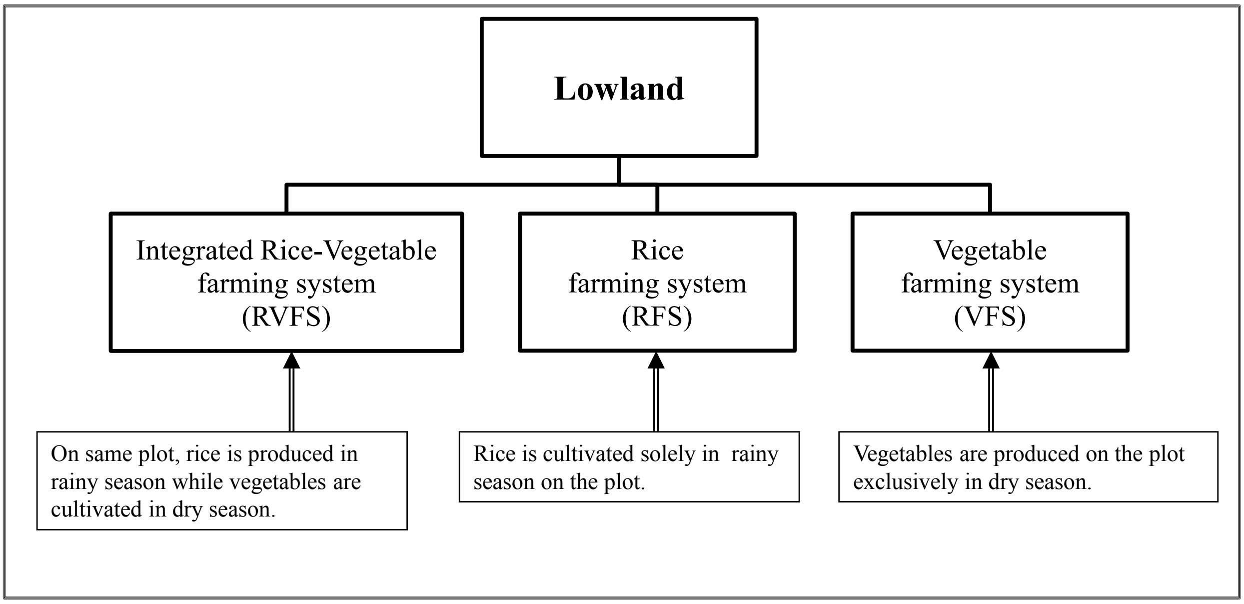


**Figure 1.2. Lowland farming system in central Benin**

### 1.5.2. Urban and Peri-urban Vegetable Production System

The origin of urban and peri-urban agriculture goes back to 1972 when a collaboration started between a Dutch NGO and the National Horticulture Center (Assogba-Komlan et al. 2002) in Cotonou. In the late 1980s, structural-adjustment programmes of the World Bank were introduced, followed by the political tolerance and administrative support for urban agriculture since 1990.

Contrary to the lowland production system, the urban and peri-urban vegetable production system is characterized by a large number of vegetable crops, both traditional and non-traditional. Generally, three farming types coexisted across and within the urban and peri-urban landscape: the intensive type characterized by vegetable mono-cropping, often on raised beds using high levels of inputs; the semi-intensive farming type of mono-crops on raised beds using fewer inputs than intensive farming type; and the extensive farming type that produces vegetables in mixed associations with staple crops with very few purchased inputs (Gockowski et al. 2003; Weinberger and Pichop, 2009).

In all three types, vegetables are produced throughout the year with big variations in the quantity supplied by producers. Intensification increases the use of labor, fertilizers, pesticides and irrigation equipment. Intercropping practices within the field production unit are the norm rather than the exception, indicating a high degree of production diversification. All types of urban and peri urban producers pursue market-oriented production. Urban and peri-urban vegetable production is mainly dominated by men contrary to the lowland production system, while women are involved in trading and marketing activities.

## 1.6. Surveys' Description: Sampling and Data

The empirical results presented in this thesis are based on data collection on two different vegetable production systems and, accordingly, concern two separate cross sectional data sets. The first cross sectional data set is used in Chapter 2 and came from a survey in the lowland production system in central Benin in 2005. This survey was funded by the World Vegetable Center (AVRDC) and the Agricultural Policy Analysis Unit (PAPA) of the National Research Institute of Benin (INRAB) during a collaboration work. Chapters 3 to 5 used a data set from a survey among urban and peri-urban vegetable farms in southern Benin in 2010. This survey was financed by a Dutch government scholarship through the Netherlands fellowship programs (NUFFIC) and the International Foundation of Science (IFS). This section briefly describes the design of each survey.

### 1.6.1. The Lowland Farming Data Set

A farm-level survey was conducted during the agricultural seasons of 2004 and 2005. The data set consisted of a stratified random sample of producers in three villages (Odo Otchere, Ouissi and Gankpetin) where the lowland farming system is used. The number of producers in this sample represents more than 60% of lowland producers registered in that region. The sampling unit was the plot and the plots were classified into the three farming systems described above. A questionnaire was used to collect data on producers' input and output use, as well as socio-economic and environmental factors. To reduce the occurrence of measurement errors in the data, the questionnaire was improved following a pre-test. Data collection took place on a monthly basis from June 2004 to June 2005.

### 1.6.2. The Urban and Peri-urban Farming Data Set

The survey was conducted from June to November 2010. Samples were collected using a multi-stage sampling procedure by selecting departments, communes, locations and smallholder producers, respectively. The quality of survey is affected by survey errors like sampling errors due to selecting a sample rather than the whole population, and non-sampling errors arising from data collection and processing. Sampling errors were minimized by using probability sampling methods to select farmers. In addition, attention was paid to non-sampling error arising from specification error, frame error, non-response, and measurement error. The sampling techniques developed by Whitley and Ball (2002) were used to determine the sample size in each location with a level of significance of 0.05 and power of 95%. First, four departments were selected from the major vegetable-producing departments, based on the intensity of vegetable production, agro-ecology, the types of crops produced and accessibility. These departments represent the major vegetable-producing areas which cover more than 80% of the smallholder urban and peri-urban vegetable producers. Second, six major locations where urban and peri-urban vegetables are mainly produced in the four departments were sampled. Third, a survey was carried out in collaboration with the local extension services to register the number of producers in each location. Fourth, a total number of 310 households producing vegetables were randomly sampled using the probability sampling method. A standardized questionnaire was used to interview producers. The survey covered information on the agricultural production year of 2009 and 2010 and data were collected on (1) socio-economic variables of the farmer and the farm household; (2) farming environment; (3) farming systems; (4) inputs, outputs, and profitability of farming enterprises; (5) marketing activities and (6) social and institutional environment.

## 1.7. Outline of the Thesis

Each chapter addresses one of the objectives of the thesis and provides an empirical application. Chapter 2 empirically investigates the importance of different types of inefficiency (technical, scale, allocative and input and output inefficiency) in three lowland farming systems in the central region of Benin. We examine the economic performance of lowland farming systems using a directional distance function.

Chapter 3 estimates technical and marketing inefficiency using a non-radial Russell-type inefficiency measure. This chapter focuses on production and marketing activities of urban and peri urban vegetable producers. Chapter 4 estimates a non-neutral stochastic frontier that captures the effects of crop specialization on the production frontier and on farm-level technical efficiency. Chapter 5 addresses the issue of pesticide productivity and estimates technical efficiency and the value of the marginal product of pesticides. Chapter 6 presents the main findings of this thesis, discusses its limitations and offers suggestions for further research.

## CHAPTER 2

# Lowland Farming System Inefficiency in Benin (West Africa): Directional Distance Function and Truncated Bootstrap approach


## Abstract

This study uses a directional distance function and a single truncated bootstrap approach to investigate inefficiency of producers in lowland farming systems in the Benin Republic. First, we employed a dual approach to estimate and decompose short-run profit inefficiency of each farming system into pure technical, allocative and scale inefficiency and also into input and output inefficiency. Second, an econometric analysis of factors affecting the inefficiency was generated using a single truncated bootstrap procedure to improve inefficiency analysis statistically and obtain consistent estimates. In the short run, scale, allocative and output inefficiency were found to be the main sources of inefficiency. Based on inefficiency results, the inefficiency of lowland farming systems is the most diverse. Compared to the vegetable farming system, technical inefficiency is significantly higher if farmers switch to the rice farming system. Scale, allocative, output, and input inefficiency are significantly lower with integrated rice-vegetable farming system and there was high prevalence of increasing returns to scale in the integrated rice-vegetable farming system. Water control and lowland farming systems are complements and play a significant role in the level of inefficiency. Input inefficiency shows the difficulty that the producers face in adjusting the quality and quantity of seeds and fertilizers. The chapter provides empirical support for efforts to promote integrated rice-vegetable farming system in West Africa lowlands to increase food security.



*Keywords*: lowlands, inefficiency, bootstrap, Benin.

*JEL classifications*: C31, C34, C61



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## 2.1. Introduction

As a result of trade liberalization, the agricultural sector of developing countries is increasingly influenced by developments in world markets. The perceived rate of food crises in those regions has increased sharply during this last decade. Moreover, recent studies found that the world commodity price boom that started several months ago has accentuated concerns about the potential severity of future crises in Southern Africa (Tschirley and Jayne, 2008). Productivity performance in the agricultural sector is thus critical to improvement in overall economic well-being and can offer good opportunities for food security and poverty reduction. One of the major concerns relates to greater and more effective utilization of lowlands for agricultural production in Sub Saharan African regions (Gockowski and Ndoumbe, 2004; Erenstein, 2006; Erenstein et al. 2006; Weinberger and Lumpkin, 2007; Barrett et al. 2008).

In Benin, due to the promotion of small scale agricultural lowland use since 1980, intensification and diversification practices are frequently observed in lowlands. Intensification is related to water control management where upstream pond and irrigation canals or canals to prevent flooding are built. Agriculture in the lowlands takes place on small peasant farms that produce annual food crops for subsistence and markets. Rice and vegetables are the first and second most important food crops produced. Improving economic efficiency of these crop based systems will contribute to improving overall agricultural productivity of this land with high agricultural potential. In addition, empirical evidence suggests that small farms are desirable not only because they reduce unemployment, but also because they provide a more equitable distribution of income as well as an effective demand structure for other sectors of the economy i.e. food security (Binam et al. 2004; Bravo-Ureta and Pinheiro, 1993, 1997). Lowland cultivation in Benin comprises three major farming systems. The first is the integrated Rice-Vegetable farming system (RVFS). On the same plot, rice is produced during the rainy season while vegetables are cultivated in the dry season. The second is the Rice farming system (RFS) where rice is cultivated solely in the rainy season (May to November). The third is the Vegetable farming system (VFS) in which vegetables are produced on the plot exclusively in the dry season (December to April). Jute leaves (*Corchorus olitorus*), okra (*Abelmoschus spp.*) and amaranth (*Amaranthus spp.*) are the main vegetables produced in the central lowlands. Despite the enormous potential of Benin, only about 4% of the 205,000 ha available lowlands are cultivated. Several authors (Agli, 2000; Adégbola and Singbo, 2003; Verlinden and Soule, 2003) found that in order to reduce the gap between domestic rice and vegetable consumption and supply for food security, the local production of rice needs to be increased by approximately 50,000 tons per year, and vegetable production by approximately 80,000 tons per year.

Traditionally, much of the interest in lowlands in West Africa has nevertheless focused on the potential for technologically-intensive rice production. Consequently, most farm level productivity growth and efficiency analysis has focused on rice production (Adesina and Djato, 1997; Audibert, 1997; Abdulai and Huffman, 2002; Sherlund et al. 2002; Barrett et al. 2008). A major limitation of these studies is that a mono-cropping rice production is considered to be independent of its production system. In reality, the integrated rice-vegetable farming systems are technically highly interdependent (Erenstein et al. 2006). Thus, ignoring the farming system level in empirical studies may bias estimates of the efficiency analysis of a decision making unit (DMU) in lowlands. Focus on farming system level is in line with the grouping method developed by Farrell and Fieldhouse (1962) which permits the creation of homogeneous output groups.

Ever since Charnes et al. (1978) first estimated a regression to explain variation in the distribution of inefficiency of a DMU, there has been a continuing search for alternative specifications and functional forms. Both parametric and non-parametric approaches to measuring inefficiency in the agricultural sector have evolved. However, parametric approaches are generally restricted by the functional specification underlying the production technology. Nonparametric approaches to measuring inefficiency are more flexible than parametric approaches, as they do not require a functional form to be specified for the production frontier. A well-known disadvantage of nonparametric approaches, however, are their deterministic nature, which implies that stochastic conditions, e.g., weather, may confound with inefficiency. Several studies that analyzed data with both non-parametric and parametric frontier estimators, however, did not show radical differences in the results with the various procedures (see Greene, 2008 for details). In sum, by comparing non-parametric and parametric approaches, some authors finally indicated that in most empirical studies the selection of the methodology used to measure inefficiency is arbitrary and mainly based on the objective of the study, the data available and the personal preference of the researcher (Resti, 2000; Wadud and White, 2000).

A two-stage approach has become a standard when Data Envelopment Analysis (DEA) is used to assess the inefficiency of decision making units (DMU) and when there are factors not under control of the DMU that influence their performance. However, a standard two-stage approach used where inefficiency is estimated in the first-stage, and then the estimated inefficiencies are regressed on a group of explanatory variables of interest, gives rise to problems. First, the two-stage estimates can suffer from the independence condition between input variables used in the first stage and the explanatory variables used in the second stage (Wilson, 2003). Second, a serious problem in this standard two-stage approach arises from the fact that DEA inefficiency estimates are serially correlated. An alternative approach that does not suffer from these drawbacks was proposed by Simar and Wilson (2007), who developed single and double bootstrap procedures. These latter approaches also allow the second-stage regression to be estimated and inferences to be made using truncated regression.

The purpose of this chapter is to estimate short run inefficiency, accounting for the farming system in lowlands based on the directional distance function and to derive implications helpful in designing appropriate policies to promote optimal use of such lands. We employed the new two-stage inefficiency procedure to examine the potential production economic effects of lowland farming systems. Our study is one of the first to use the directional distance function framework and a single truncated bootstrap approach in the context of the two-stage approach. A convenient property of the directional distance function is that, unlike the traditional radial distance function, it easily accommodates the primal (production efficiency) and dual model (allocative efficiency). This enables us to compute the overall profit inefficiency which is the most natural measure of performance that is based on a difference rather than a ratio. This profit inefficiency measure is also called the Nerlovian profit efficiency (see Färe and Grosskopf, 2004). The ratio profit level is not an adequate measure to calculate profit inefficiency not only because these ratios can result in negative profit efficiency measures (that are hard to interpret) but also because these ratios do not have a dual interpretation in terms of the required adjustments in inputs and outputs to achieve the maximum profit target (Thanassoulis et al. 2008). This is also practical, as farms may earn zero profit, which poses problems in a ratio context. We decomposed the overall inefficiency into pure technical, allocative and scale inefficiency as well as output and input inefficiency for farms at the farming system level. In the short run, lowland production technology is subject to levels of quasi-fixed inputs (land, equipments and family labor). Given that most farms can adjust variable inputs more quickly than they can adjust quasi-fixed inputs, the calculation of short run inefficiencies may be of more immediate value (Tauer, 1993). The empirical analysis of this chapter is based on a farm survey in central Benin, where monthly data were collected on rice and vegetable production in different lowland farming systems.

The remainder of the chapter unfolds as follows. Section 2.2 develops the theoretical model of inefficiency analysis based on a semi-parametric frontier approach, and especially on inefficiency measures using a short-run directional distance function and truncated bootstrapping method in the two-stage approach to analyzing inefficiency. This is followed by a description of the data and variables in Section 2.3. Section 2.4 presents the research findings and discussion. The chapter ends with a conclusion.

## 2.2. Two-stage Semi-parametric and Bootstrap Models

### 2.2.1. Semi-parametric Model for Analyzing Inefficiency

#### *2.2.1.1. Directional Technology Distance Function Theory Framework*

Since introduction of the efficiency measurement method by Farrell (1957) and Farrell and Fieldhouse (1962), there has been a growing interest in methodologies and their applications to efficiency measurement. Using dual approaches, Chambers et al. (1996 and 1998) introduced directional distance functions as additive alternatives to the distance functions concepts. The directional distance function measures the amount that one can translate an input and or output vector non-radially from itself to the technology frontier in a preassigned direction (Chambers et al. 1998; Färe and Grosskopf, 2000; Ray, 2004). Hence, the Farrell decompositions of overall cost and revenue efficiency into allocative and technical efficiency are shown to be special cases of the corresponding profit efficiency decomposition. The directional distance function provides a measure of technical inefficiency; allocative inefficiency measures the residual inefficiency due to failure to choose the profit maximizing input-output bundle given prices. The directional distance function is shown to be appropriate in measuring lowland producer inefficiency for several reasons.

In central Benin, lowland cultivation is practiced in a delimited area of land, contrary to upland systems, where households can increase their farm size. Family labor is the principal source of labor used indicating that family labor is one of the main constraints for lowland cultivation. Moreover, lowland producers face exogenously determined input and output prices and attempt to allocate inputs and outputs so as to maximize profit. Under this behavior both inputs and outputs are determined endogenously. In other words, producers have to decide not only how much of various inputs to use, but also how much rice and/or vegetables to produce. On the other hand, Kumbhakar and Lovell (2003) suggest that if one is interested in estimating profit inefficiency in a price-taking environment, then it is appropriate to conduct the analysis within a short-run framework in which some inputs are exogenously determined because inefficient producers cannot survive in a long-run. In this context, the appropriate standard against which to evaluate profit inefficiency is the variable profit frontier. Following this assumption, producers are expected to maximize short term profit from their lowland farming systems. Thus, the directional distance functions we analyze are derived from the shortage function which generalizes the profit function in the short-run (Chambers et al. 1998; Färe and Grosskopf, 2004). This approach determines the minimum combination of variable inputs such that the profit is at least as large as the profit obtained by the $k^{th}$ farm, and the quasi-fixed inputs used are no greater than the $k^{th}$ farm.

The reason for treating any inputs as quasi-fixed in the short run is to acknowledge the possibility that the first-order conditions for profit maximization are not satisfied for those inputs because of costs of adjustment. This setting is also consistent with our analysis because of the course of a single growing agricultural production year.

Assume that the directional distance function gives an appropriate representation of the production technology of a number of different lowland farming systems. Suppose that, for the $j^{th}$ farming system, there are sample data on $n_j$ farms that produce a vector of outputs $y_{(j)} \in \Re_+^M$ from a vector of inputs $x_{(j)} \in \Re_+^N$ which is decomposed as $x_{v_{(j)}} \in \Re_+^N$ variable inputs and $x_{f_{(j)}} \in \Re_+^N$ quasi-fixed inputs. This farming system technology $T_{(j)}$ is given by:

$$T_{(j)} = \left\{\left(x_{(j)}, y_{(j)}\right) \text{ such that } x_{(j)} \text{ can produce } y_{(j)}\right\} \quad (1)$$

We assume that the farming system technology is closed and convex, variables inputs $\left(x_{v_{(j)}}\right)$ and outputs are freely disposable, there is no free lunch, doing nothing is feasible (Färe, 1988; Färe and Grosskopf, 2000). The short-run directional distance function is defined as:

$$\vec{D}_{T_{(j)}}\left(x_{v_{(j)}}, y_{(j)}; g_{x_{v_{(j)}}}, g_{y_{(j)}}\right)\Big|_{x_{f_{(j)}}} = \sup_{\beta_{(j)}}\left\{\beta_{(j)} \in \Re : \left(x_{v_{(j)}} - \beta_{(j)} g_{x_{v_{(j)}}}, y_{(j)} + \beta_{(j)} g_{y_{(j)}}\right)\Big|_{x_{f_{(j)}}} \in T_{(j)}\right\}, \quad \text{if}$$

$$\left(x_{v_{(j)}} - \beta_{(j)} g_{x_{v_{(j)}}}, y_{(j)} + \beta_{(j)} g_{y_{(j)}}\right)\Big|_{x_{f_{(j)}}} \in T_{(j)} \text{ for some } \beta_{(j)} \quad (2a)$$

$$\vec{D}_{T_{(j)}}\left(x_{v_{(j)}}, y_{(j)}; g_{x_{v_{(j)}}}, g_{y_{(j)}}\right)\Big|_{x_{f_{(j)}}} = \inf\left\{\delta_{(j)} \in \Re : y_{(j)} + \delta_{(j)} g_{y_{(j)}} \in \Re_+^M\right\}, \text{ otherwise} \quad (2b)$$

where $\left(g_{x_{v_{(j)}}}, g_{y_{(j)}}\right)$ is a non zero vector in $\Re_{+}^{N} \times \Re_{+}^{M}$ and determines the direction in which $\vec{D}_{T_{(j)}}(\cdot)$ is defined. Clearly, the interpretation of the inefficiency term depends on the choice of the directional vector. This short-run directional technology distance provides the maximum amount by which output can be expanded and variable input contracted and still be feasible in the short-run (see Fig. 2.1). $\vec{D}_{T_{(j)}}(\cdot)$ provides a direct measure of how far $\left(x_{v_{(j)}}, y_{(j)}\right)$ must be projected along the $\left(g_{x_{v_{(j)}}}, g_{y_{(j)}}\right)$ direction to reach the frontier of $T_{(j)}$.

Profit inefficiency measures the normalized difference between maximum and observed profit. This allows an additive decomposition of profit inefficiency for each producer in each lowland farming system. For simplicity of presentation, after omitting the index $j$, the short-run overall profit inefficiency is defined as (Chambers et al. 1998):

$$\pi(p, w) = \sup_{x_v, y}\{py - wx_v : (x_v, y) \in T\} \tag{3}$$

where $\pi(p, w)$ is the short run maximal profit, $p \in \Re_{++}^{M}$ denote a vector of output prices and $w \in \Re_{++}^{N}$ a vector of variable inputs prices. Since $\pi(p, w)$ is by definition greater than or equal to observed profit, it follows that overall profit scores are greater than or equal to zero.

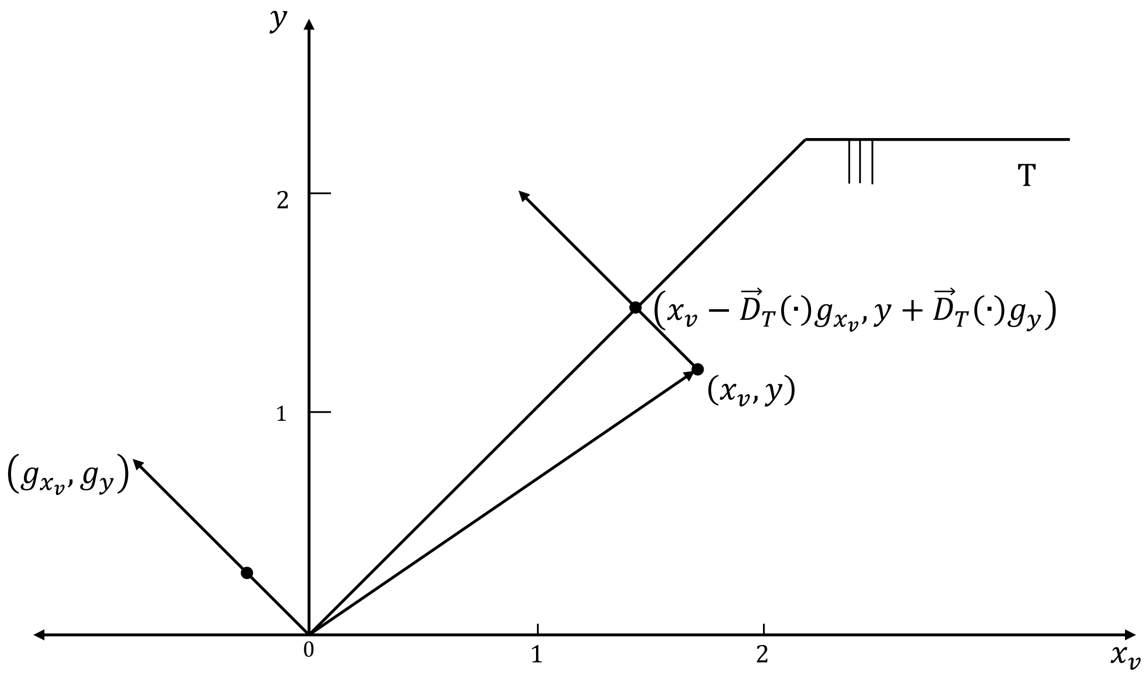


**Figure 2.1. Directional Technology Distance Function**

The profit function and the directional distance function provide the basis for defining and decomposing profit efficiency where we have a price (dual) and a quantity (primal) measure of inefficiency (Chambers et al. 1998; Färe and Grosskopf, 2000; Färe and Grosskopf, 2004; Ray, 2004).

The overall profit inefficiency (OIE) is defined as the difference between the maximum profit and observed profit, normalized by the value of the reference variable inputs and output combination $(pg_y + wg_{x_v})$ which implies that zero profit poses no computational problems (Eq. 4). This inefficiency measurement also has the desirable property of being homogenous of degree zero in prices in the sense that it is independent of the measurement units.

$$\mathrm{OIE}\left(p, w, y, x_v; g_{x_v}, g_y\right)\Big|_{x_f} = \frac{\pi(p,w)-(py-wx_v)}{pg_y+wg_{x_v}} \tag{4}$$

In each lowland farming system, farm $k$ is overall efficient if $\mathrm{OIE}\left(p, w, y, x_v; g_{x_v}, g_y\right)\Big|_{x_f} = 0$ indicating that this specific farm achieves maximum profit.

*2.2.1.2. Directional Distance Function Computational Procedure*

The measure of short run technical inefficiency relative to a constant returns to scale $(C, S)$ technology for each producer by farming system is obtained by solving several linear mathematical programming problems. Suppose a case of data for one farming system. Consider that, for each farming system, there are $k = 1, \ldots, K$ observations of inputs (variable and quasi-fixed) and outputs $(x^k, y^k)$. First, the short-run directional distance function used to describe the technical inefficiency in a particular farming system for observation $k'$ is defined by:

$$\vec{D}_{TE}\left(x_v^{k'}, y^{k'}; -x_v, y | C, S\right) = \max_{\beta, z} \beta$$

s.t.

$$\sum_{k=1}^{K} z_k y_{km} \geq y_{k'm} + \beta y_m,\ m = 1, \ldots, M, \tag{5}$$

$$\sum_{k=1}^{K} z_k x_{kv} \leq x_{k'v} - \beta x_v,\ v = 1,$$

$$\sum_{k=1}^{K} z_k x_{kf} \leq x_{k'f},\ f = 1,2,3,$$

$$z_k \geq 0,$$

where the $z_k$ are the intensity variables, $v$ denotes the variable input factors (operating costs. i.e. seeds and fertilizers) and where $f = 1{,}2{,}3$ are the fixed factors (labor, capital cost, and plot size)[1]. The technology sets (5) also allows for variable returns to scale $(V, S)$ due to the convexity constraints in order to compute pure technical inefficiency (PTIE); then $\vec{D}_{TE}(x_v^{k'}, y^{k'}; -x_v, y|V, S)$ is computed as in (5) by adding the $\sum_{k=1}^{K} z_k = 1$. That is, variable returns to scale allows the lowland farming technology to exhibit increasing, constant or decreasing returns to scale. The convexity restriction $\sum_{k=1}^{K} z_k \leq 1$ in $\vec{D}_{TE}(x_v^{k'}, y^{k'}; -x_v, y|NI, S)$ and $\sum_{k=1}^{K} z_k \geq 1$ in $\vec{D}_{TE}(x_v^{k'}, y^{k'}; -x_v, y|ND, S)$ display nonincreasing and nondecreasing returns, respectively. Consequently, this convexity constraint allows for the possibility of negative, positive or zero profit (Fukuyama, 2003).

Second, to compute the profit decomposition, we compute maximal profit for each producer relative to the technology $T$ by solving the following linear programming problem for observation $k'$ for each farm in each farming system:

$$
\begin{aligned}
&\max_{y, x_v, \lambda} (py - wx_v) \\
&\text{s.t.} \\
&\sum_{k=1}^{K} \lambda_k y_{km} \geq y_{k'm}, m = 1, \dots, M, \\
&\sum_{k=1}^{K} \lambda_k x_{kv} \leq x_{k'v}, v = 1, \qquad (6) \\
&\sum_{k=1}^{K} \lambda_k x_{kf} \leq x_{k'f}, f = 1{,}2{,}3, \\
&\lambda_k \geq 0, \\
&\sum_{k=1}^{K} \lambda_k = 1,
\end{aligned}
$$

where the $\lambda_k$ are the intensity variables, and all the other variables are the same as defined in (5). The short run maximum profit model (6) assumes variable returns to scale (VRS) as, for a technology exhibiting globally constant returns to scale (CRS), either the maximum profit level is zero or the solution of the maximum profit model is undefined (Thanassoulis et al. 2008). Profit maximization in relation to a VRS technology implies that perfectly competitive markets are not assumed, since under this assumption all farms have zero profits in the long run.

[1] The directional distance function contracts variable inputs and expands output, at given levels of the three quasi-fixed inputs as demonstrated in Eq. 5. However, in order to make a correct representation of the production technology all inputs (variable and fixed) must be included in the model, where the fixed inputs are not corrected (see equation 5). If not, the estimates will suffer from omitted variable bias. The estimated profit function maximises the difference between revenues and variable costs at given levels of the three quasi-fixed inputs.

As mentioned above, maximal profit $\pi(p,w)$ minus observed profit $(py - wx_v)$, normalized by $(pg_y - wg_{x_v}) = (py + wx_v)$, yields overall profit inefficiency (OIE). Since overall profit inefficiency (OIE) consists also of pure technical inefficiency (PTIE), allocative inefficiency (AIE) and scale inefficiency (SIE) such that OIE = PTIE + AIE + SIE, the next step is to compute short-run allocative inefficiency for each observation in each farming system by subtracting its short-run overall inefficiency from its short-run pure technical and scale inefficiency. In our DEA modeling approach, the allocative inefficiency also incorporates inefficiency due to slacks.

Since overall profit inefficiency (OIE) also consists of input inefficiency (INIE) and output inefficiency (REVI) such that OIE = REVI + INIE, the third step is to compute short-run input and output inefficiency.

### 2.2.2. Second-stage Analysis: Truncated Bootstrap Model

The conventional two-stage approach used censored regression and has been widely applied to determine whether or not certain factors influence the decision making unit's (DMUs) inefficiency scores (see Fried et al. 2002; Gattoufi et al. 2004 for a comprehensive bibliography). This traditional censored regression procedure, however, is invalid because of the presence of the inherent dependence among the DEA efficiency scores which are a relative efficiency index instead of an absolute efficiency index. This suggests the violation of one of the basic model assumptions required by regression analysis. Authors found that a more serious problem in these methods arises from the fact that non parametric efficiency estimates are serially correlated in a complex way. Simar and Wilson (2007) found that it is difficult to give a statistical interpretation to the second stage estimator and also not provided a coherent description of a Data Generating Process (DGP). To overcome the problem of complex serial correlation in analysis of the DEA efficiency scores, Xue and Harker (1999) used a naïve bootstrap approach to address different problems in regression analysis (e.g. the non-normality of the distribution).

The bootstrap is a method for estimating the distribution of an estimator or test statistic by resampling the data or a model estimated from the data (bootstrap sampling). Therefore, the bootstrap is a practical procedure for reducing errors in inference (Horowitz, 2001). The main idea of the naïve bootstrap approach is to substitute the incorrect conventional estimators for the standard errors of the regression coefficient estimates with bootstrap estimators for the standard errors of these estimates. A naïve bootstrap method requires only the randomness of the observed sample. In Xue and Harker (1999), this requires the independence among the DMUs in terms of their inputs, outputs and the explanatory variables but not the independence of their DEA efficiency scores. Recently, Simar and Wilson (2007) demonstrated that this naïve bootstrap approach is inconsistent in the context of non-parametric efficiency estimation and it is unclear what is being estimated. To rationalize the two-stage analysis, they proposed single and double bootstrap procedures which allow not only for heterogeneity in the distribution of inefficiency, but also incorporate assumptions on separability between the production set and the covariates. Given the small size of the sample and the number of variables considered in this study, a single truncated bootstrap is used. This single truncated bootstrap is an application of the Simar and Wilson (2007) method for radial distance functions to the case of the directional distance function[2].

## 2.3. Data and Variables

This study was conducted in the Dassa local government area of Collines Department, Benin. The town of Dassa (2°02 N, 2°20 W) is located in central Benin, 250 km north of the economic capital Cotonou and close to the nationally and regionally important agricultural market Glazoue. The road from Dassa to Cotonou is paved and many heavy trucks transport agricultural goods from Collines Department to Cotonou. The region has the highest concentration of lowlands in Benin and receives a lot of support from different projects and research organizations. For instance, since 2000 the Africa Rice Centre (WARDA) increased lowland activities in this region through their national lowlands consortium. This suggests that the area has good market access and high agricultural potential. A farm-level survey was conducted during the agricultural seasons of 2004 and 2005 to provide demographic data. The data set consisted of a stratified random sample survey of 72 producers in three villages (Odo Otchere, Ouissi and Gankpetin) where lowlands are cultivated and the study followed their activities on 93 plots. It is worth noting that the number of producers in this sample represents more than 60% of lowland producers registered in that region. To avoid heterogeneity problems at farm level analysis in cross-selection data, lowland farming system is used as stratification criterion for sampling farms. The sampling unit was the plot. Some producers had more than one plot. The 93 plots were classified into 30 plots for the integrated rice-vegetable farming system (RVFS), 28 plots for the rice farming system (RFS) and 35 plots for vegetable farming system (VFS).

[2] The application to the directional distance function follows the same reasoning as Simar and Wilson (2007). Details on the algorithm are available upon request from the authors.

Questionnaires were used to collect data on producers' input and output use as well as socio-economics and environmental factors. To reduce the occurrence of measurement errors in the cross-section data, the questionnaire was improved following a pre-test. Data collection took place on a monthly basis from June 2004 to June 2005. Collecting data on a monthly basis enabled this study to capture the detailed cost and the revenue of production (measuring the quantities of inputs used, the prices at farm gate, labor used, measuring the output quantities obtained). Questionnaire design and data collection work were carried out under the supervision of the first author.

### 2.3.1. First Stage Data

The first stage data consisted of two outputs and three types of inputs. Outputs are rice and/or vegetables. The most important inputs in lowland cultivation are operating costs, labor and small materials (hoes, axes, machetes, watering cans, baskets, basins, etc.). Cultivation practices include land clearing, soil tillage, construction of beds, fertilization, planting, irrigation, weeding, and harvesting. Variables collected from the farmer survey were revenues from lowland crops (rice, and vegetables), expenses (seeds, labor, fertilizers, equipment, etc.). As rice is produced from May to November, inputs used to produce rice in this period were aggregated. Vegetables are cultivated in lowland from December to April. Inputs and outputs of vegetable were also aggregated for this period. Output consisted of rice or vegetables produced in each farming period.

The inputs and the outputs we specify are based upon the production process of lowland farms. We had to address the trade off between using technical details by applying more inputs and adding the risk of multicollinearity on the one hand, and aggregating the inputs and sacrificing potentially useful information on the other hand. To avoid the risk of multicollinearity and the 'zero-observation' problem for input variables in the first stage, the inputs were aggregated into three categories (labor costs, operating costs, and capital), and the outputs were aggregated into a single index of lowland farm output. The linear aggregator was used to aggregate inputs and outputs. The input and output prices obtained did not vary across farms, implying that differences in the composition of a netput on the quality were reflected in the quantity (Cox and Wohlgenant, 1986). Thus, to implement the overall profit inefficiency given by (6) we assumed that all farms face the same output-input prices vector (i.e. unity).

Labor input consisted of family labor and paid labor, measured at their effective costs. A problem was that reported hours of work may have had errors. The opportunity cost of family labor is determined within the household rather than by market forces and consists of expenditures for food to sustain family labor of the farm operator capturing cross-sectional price variation. In Benin rural area, the labor market is constrained; especially women have a limited set of alternatives to remunerate their labor. In addition, neither hired and family labor nor the labor inputs of different family members are perfectly substitutable in agricultural production (Jacoby, 1993). As family and hired labor are not perfect substitutes, the labor supply model could be used to estimate the household's unobserved shadow wage (Barrett 1997; Barrett et al. 2008). However, the objective of this chapter was not to estimate structural labor supply in order to determine the shadow wages allocative inefficiency; the direct realized labor prices were used rather than the subjective, *ex ante* expected prices as proposed by Barrett (1997). It is also important to remember that our inefficiency method is homogeneous of degree zero in prices. Since labor input was treated as quasi-fixed in our model, the choice was consistent so that allocative and scale inefficiency were related to operating inputs. Labor was assumed to be a quasi fixed input because a large share of total labor consisted of family labor. The family labor represented about 80% to 90% of the total labor used in the Beninese lowlands (measured in man-days). The capital cost was computed as the sum of the real annual costs of materials involved in the production system[3]. The operating costs were computed as the sum of seed and mineral costs. The output value denotes the value of output involved in the given farming system evaluated at their farm-gate prices. In the directional distance function, we need to choose a directional vector, $\left(g_{x_v}, g_y\right)$, common to all farms in each farming system to aggregate the measures' technical inefficiency. Following Färe and Grosskopf (2004), in a given lowland farming system, if each farm's technology is such that the maximal profit function yields optimal outputs and optimal inputs which are the same for all farms, then a natural direction yielding for $k = 1, \dots, K$ farms is $(x_v^*, y^*)$. Unfortunately, in each farming system the optimal outputs and optimal inputs varied for each farm. Therefore, we measured technical inefficiency in the direction of the realized variable inputs-output vector $(x_v, y)$ (Chambers et al. 1998): in this case $\left(pg_y + wg_{x_v}\right) = (py + wx_v)$. This directional vector implies that the directional technology distance function gives an estimate of the maximum feasible expansion in outputs and the contraction in variable inputs. Thus, it is possible to make a radial interpretation of our inefficiency measures.

[3] The partial annual cost of each material was calculated as follow: the number of a given material really used in the plot multiplied by its purchase price at farm gate divided by the probable length of time that it will be used for (in one year). The real annual cost is then calculated by multiplying this partial annual cost by the proportion of time the involved material was used in a given production system or to produce a given crop.

Descriptive statistics of variables for different lowland farming systems is presented in Table 2.1. These statistics indicate that there were considerable differences within and among the three farming systems in terms of the means and standard deviations of the outputs and inputs.

### 2.3.2. Second Stage Data

The second stage involves an explanatory analysis of the inefficiency scores using environmental and farmers' characteristic variables to account for exogenous factors that affect the inefficiency performance of producers. This explanatory analysis assumes that the environmental and farmers' socio-economic variables only affect the inefficiency and not the

**Table 2.1. Summary statistics for data on lowland farms in the central Benin ($1US=527.35 FCFA in 2005)**

| Lowland farming System | | Variables | Mean | St. Deviation | Minimum | Maximum |
|---|---|---|---|---|---|---|
| **C1 : Rice and vegetable farming system (RVFS), $n_1$=30** | | | | | | |
| Output (F CFA) | | $Y_1$ | 45,494.07 | 25,316.23 | 13,093.75 | 106,000 |
| Variable input: Operating costs (F CFA) | | $x_{1v}$ | 5,714.37 | 3,081.70 | 1,559 | 18,150 |
| Fixed inputs: | Labor (F CFA) | $x_{1f_1}$ | 5,555.25 | 3,041.84 | 2,412.5 | 17,750 |
| | Annual Capital cost (FCFA) | $x_{1f_2}$ | 3,191.88 | 1,750.45 | 891.67 | 7,189.2 |
| | Land area ($m^2$) | $x_{1f_3}$ | 506.33 | 392.46 | 120 | 2,100 |
| Variable profit of C1 (FCFA) | | $\pi_{C1}$ | 39,779.69 | 23,641.85 | 9,786.25 | 100,823.5 |
| **C2 : Rice farming system (RFS), $n_2$=28** | | | | | | |
| Output (F CFA) | | $Y_2$ | 16,770.54 | 10,454.09 | 6,750 | 54,450 |
| Variable input: Operating costs (F CFA) | | $x_{2v}$ | 340.625 | 178.69 | 50 | 700 |
| Fixed inputs: | Labor (F CFA) | $x_{2f_1}$ | 2,420.98 | 1,306.19 | 675 | 4,887.5 |
| | Annual Capital cost (FCFA) | $x_{2f_2}$ | 1,763.32 | 925.94 | 465 | 4,170 |
| | Land area ($m^2$) | $x_{2f_3}$ | 250,36 | 151.91 | 100 | 800 |
| Variable profit of C2 (FCFA) | | $\pi_{C2}$ | 16,429.91 | 10,332.7 | 6,575 | 53,750 |
| **C3 : Vegetable farming system (VFS), $n_3$=35** | | | | | | |
| Output (F CFA) | | $Y_3$ | 13,411.15 | 10,144.95 | 2,082.25 | 61,500 |
| Variable input: Operating costs (F CFA) | | $x_{3v}$ | 3,910.7 | 3,478.51 | 600 | 19,633.33 |
| Fixed inputs: | Labor (F CFA) | $x_{3f_1}$ | 2,650.53 | 2,289.88 | 375 | 13,525 |
| | Annual Capital cost (FCFA) | $x_{3f_2}$ | 1,186.08 | 855.28 | 132.8 | 3,342.01 |
| | Land area ($m^2$) | $x_{3f_3}$ | 312.86 | 282.89 | 40 | 1,600 |
| Variable profit of C3 (FCFA) | | $\pi_{C3}$ | 9,500.45 | 7,126.09 | 837.5 | 41,866.67 |

*Note:* Outputs and inputs were computed in monetary value because of aggregation so that outputs and inputs prices were set to one in the profit maximizing programme.

transformation process of inputs into outputs. Possible factors influencing lowland inefficiency include environmental factors (water control), farming system (integrated rice and vegetables), as well as producers' characteristics. Variables collected from the farmer survey were farm characteristics (upland farm size, number of family members, marital status, level of education, age, years of management experience in the lowland, etc.) and environmental factors (type of lowlands). The following variables were assumed to explain the variation of pure technical, allocative and scale inefficiency scores:

- *Number of family members available for lowland farm work in adult workforce (NHADULT)*. Lowland cultivation is often considered more onerous and labor demanding than upland cultivation (Spencer and Byerlee, 1976; Richards, 1986). In addition, rice production coincides with the rainy season. Therefore, farmers with limited family labor are less likely to produce rice, as they would have to hire labor for rice production, reducing expected profits. Also, the production of vegetables has higher labor requirements than the production of staple crops or grains. Weinberger and Lumpkin (2007) found that vegetable production required twice as much, sometimes up to four times as much labor as the production of cereal crops. Therefore, a negative relationship was expected between technical or scale inefficiency scores and availability of family labor. On the other hand, family labor in rural areas is assumed to be less productive because this type of labor has low opportunity costs (Gockowski and Ndoumbe, 2004). Thus, this variable was expected to increase allocative inefficiency.
- *Formal Education of the farmer (EDUC)*. Various types of training help the farm operator to enhance profitability. Farmers who received a formal education are more likely to have been exposed to information on lowland cultivation technologies. Furthermore, educated farmers are expected to have better capabilities in processing information and searching for appropriate technologies to reduce use of inputs. Education of the farmer is expected to reduce technical inefficiency or what Welch has called 'worker effect' (Welch, 1970; Sidhu and Baanante, 1979). However, Huffman (1974) reported that the contribution of education is only an 'allocative effect'. Stefanou and Saxena (1988) found that education may enhance the farmer's ability to allocate inputs efficiently across competing uses, and contribute to good farm planning. Therefore, it was assumed in this study that the variable EDUC had a negative effect on technical, allocative and scale inefficiency.
- *Age of* farmers *(AGE)*. The age of producers captures differences in the quality of management. Age provides a major source of possible variation of inefficiency across producers since older farmers may lack up to date technology, machinery, equipment or

structures. Richards (1986) argued that participating in brushing and ploughing in lowland made clear that the most strenuous tasks are placed on young people. Old farmers are less likely to conduct lowland activities. In contrast, young women tend to work very hard in the lowlands. Therefore, the age of farmers was assumed to have a positive effect on inefficiency scores. Hence, the variable AGE was assumed to increase technical inefficiency in lowland farming systems; the effect was less clear for allocative and scale inefficiency.

- *Marital status (MARRIED).* The effect of marital status on the level of inefficiency is difficult to predict. The lowland producers in the sample mainly consisted of women (85%). Married women are known to be responsible for many activities (cooking, fetching and carrying water, etc.) which decrease their performance in the agricultural sector (Gockowski and Ndoumbe, 2004). In contrast, older married women tend to have more family labor at their disposal, which is expected to decrease technical inefficiency of lowland cultivation (Richards, 1986). Thus, this variable could have either a positive or a negative effect on farmers' inefficiency.
- *Irrigated lowland (TYBAS).* Water control in lowlands has a particular importance in increasing agricultural production and productivity and facilitates intensification. It enhances weed control, improves N-fertilizer use efficiency in rice and makes cultivation less risky (Becker and Johnson, 1999 and 2001). Lack of water control can be an important constraint to lowland intensification (Erenstein, 2006). This variable also measures the physical environment of the farm. It is therefore expected that irrigation may decrease technical, allocative and scale inefficiency scores. To be consistent with the separable condition between environmental factors and inefficiency estimates, water control was coded as a dummy variable.
- *Years of management experience in lowland (YEAR).* This variable is related to the lowland management quality and can also be seen as an informal training 'learning by doing'. As the results of experimenting with alternative production techniques, the management experience can lead to gains in efficiency through better organization and knowledge (Stefanou and Saxena, 1988). Therefore, it was assumed that a decrease in lowland farming systems inefficiencies may result from more management experience.
- *Upland farm size (UPLAND).* At farm system level, lowland and upland cultivation are complementary, but during the rainy season, lowland cultivation often comes second to upland cultivation due to the generally stricter timeliness, larger crop areas, increases diversity through preference heterogeneity and lower labor intensity of upland cultivation

(Lavigne-Delville and Boucher, 1998; Richards, 1986). Consequently, there may be limited interest in lowland intensification for farmers who hold large upland areas. Therefore, this variable was expected to increase technical inefficiency scores and scale inefficiency as well. But, a farmer who owns a large area of upland was expected to decrease allocative inefficiency because of the higher opportunity cost of the inputs used.

- To test whether the inefficiency of the three farming systems differs, we created two indicator (dummy) variables: *RVFS* (integrated rice-vegetable farming system) and *RFS* (rice farming system). We compared these variables to the reference system (VFS). Compared to vegetable farming systems, integrated rice-vegetable farming systems and rice farming systems were expected to be more technical, allocative and scale efficient.

The dataset shows that 21 producers engaged simultaneously in two farming systems (RFS and VFS). However, the correlation matrix of the explanatory variables showed that none of the Pearson partial correlation coefficients was high, indicating that there were no multicollinearity problems (see Annex).

Also, we assumed that the effects of the variable *TYBAS* and the farming systems were dependent and strictly multiplicative, so that the joint effect was the product of the marginal effects. This implies that we allowed for interaction effects in evaluating these qualitative factors. Then, we created two variables: *TYBAS**RVFS* and *TYBAS**RFS*.

## 2.4. Results and Discussion

### 2.4.1. Inefficiency Results

A profit function and directional distance function was estimated using GAMS (General Algebraic Modeling System). The measures of short-run overall profit inefficiency, pure technical, allocative, and scale inefficiency as well as input and output inefficiencies for individual decision making unit in each lowland farming system were calculated and summarized in Table 2.2. The last column shows the directional technology scale inefficiency status identified with the use of the Fukuyama (2003) description. Recall that values of the overall, pure technical and allocative inefficiency scores equal to zero signify efficiency and values of the scores greater than zero signify inefficiency. Integrated rice-vegetables farming system (RVFS) had one third farmers (11 out of the 30 RFVS) who operated at the frontier of overall efficient (OIE=0) and rice farming system (RFS) had 13 out of the 28 farmers fully efficient; vegetable farming system (VFS) had only 3 out of the 35 farmers who were efficient. Although for a few lowland farmers in each farming system, pure technical inefficiency was an important source of inefficiency, for most lowland producers allocative inefficiency and scale inefficiency were the major components for overall inefficiency. The results indicate that variable resource (seeds and minerals) allocation decisions particularly lacked profit maximizing behavior. Only 4 out of the 30 producers of RVFS, 7 out of the 28 of RFS, and only 2 out of the 35 of VFS were fully allocatively efficient in the short run (AIE=0). This implies that 87% of producers in RVFS, 75% in RFS, and 94% in VFS were allocatively inefficient.

The arithmetic mean value of pure technical inefficiency (PTIE) measure in the short run at the farming system level ranged from 0.169 for VFS to 0.349 for RFS, indicating that gains from improving pure technical inefficiency existed. For example, average farms in Rice farming system (RFS) could expand rice output by 34.9% and contract seed and fertilizers use by 34.9% while farms in Vegetable farming system (VFS) could expand vegetable output by 16.9% and contract seeds and fertilizers by 16.98%. Eleven producers in RVFS, two in RFS and nine in VFS produced the maximum output possible, indicating that the majority of producers encountered problems which could include technical production constraints and socioeconomic and/or environmental factors. The results of this chapter imply that many of the lowland farms operate at technical inefficiency levels well below the efficient frontier. The inefficiency levels observed suggest a substantial amount of variable input savings and output expansions. If the average farmer in each group of the sample could eliminate pure technically inefficiency then he could realize a gain of 20% of the sum of revenue and variable cost in RVFS, 35% in RFS, and 17% in VFS. This result suggests that the majority of lowlands producers may have a substantial gain from improving efficiency of variable resource use.

**Table 2.2. First stage Inefficiency Results (Standard deviation in parenthesis)**

| Farming System | Mean of Inefficiency | | | | | | RS |
|---|---|---|---|---|---|---|---|
| | Profit (OIE) | Pure technical (PTIE) | Allocative (AIE) | Scale (SIE) | Output (REVI) | Input (INIE) | |
| C1: Rice and vegetable farming system(RVFS), $n_1$=30 | 0.401 (0.091) | 0.200 (0.035) | 0.030 (0.079) | 0.171 (0.039) | 0.470 (0.113) | - 0.035 (0.053) | IRS |
| C2: Rice farming system (RFS), $n_2$=28 | 0.085 (0.025) | 0.349 (0.038) | 0.006 (0.017) | - 0.224 (0.019) | 0.082 (0.025) | - 0.069 (0.151) | DRS |
| C3: Vegetable farming system (VFS), $n_3$=35 | 0.280 (0.043) | 0.169 (0.026) | 0.117 (0.036) | - 0.006 (0.030) | 0.335 (0.065) | 0.006 (0.094) | DRS |

*Legend.* RS – returns to scale, IRS – increasing returns to scale, DRS – decreasing returns to scale.
*Notes.* (1) estimated values were obtained in the direction vector $(g_{x_v}, g_y) = (x_v, y)$. (2) The scale nature is determined by the sign of SIE.

The overall profit inefficiency equals the normalized difference between maximal and actual profits. The mean of overall profit inefficiency (OIE) ranged from 0.085 for RFS to 0.401 for RVFS indicating greater profit inefficiency in lowland farming systems. The residual difference between overall inefficiency and technical inefficiency is allocative inefficiency. In the short run, farmers in VFS appeared to be more allocatively inefficient: mean allocative inefficient measures were 0.006 in RFS, 0.030 in RVFS, and 0.117 in VFS. This result is in line with the finding of Erenstein (2006) that lowlands are not always as valuable as they may seem, and there may be limited incentives to intensify.

On average, farmers of integrated rice-vegetable farming system (RVFS) were found to be more scale inefficient than they were allocatively inefficient. This implies that there was a scale effect on the overall inefficiency of RVFS. By contrast, farmers in RFS and VFS appeared to be less scale inefficient than they were allocatively inefficient. Mean scale inefficiency ranged from 0.171 in RVFS to – 0.224 in RFS. Within the sample, only 13.33% farms in RVFS, 17.14% farms in VFS and 3.57% farms in RFS were scale efficient (i.e. operating at constant returns to scale: SIE = 0). Thus, most of the farms in the sample were scale inefficient and this type of inefficiency appears to be as serious a problem as overall inefficiency. Scale inefficiency indicates that lowland farms do not have the optimal size. The study further reveals scale inefficiency among farming systems and shows that the range of optimal scale is extremely wide, with both the maximal and minimal outputs as the optimal scale. Increasing returns to scale was the predominant form of scale inefficiency observed in RVFS while decreasing returns to scale was the predominant form in RFS. Furthermore, both increasing returns and decreasing returns to scale were the prevalent scale inefficiency in VFS. Approximately four-fifth of the farms in RVFS (83.33%) against one-half of the farms in VFS (48.57%) and no farm in RFS were found to operate at increasing returns to scale. By contrast, 3.33% of the farms in RVFS, against approximately one-third of the farms in VFS (34.29%) and 96.43% of the farms in RFS were operating at decreasing returns to scale. The farms with increasing returns to scale should consider increasing their size and those with decreasing returns to scale should consider reducing their size. On average, farmers in RVFS had a positive directional technology scale elasticity value of 0.171 and hence displayed increasing returns to scale. The high prevalence of increasing returns to scale in RVFS implies that farms which adopted the integrated system should increase their size indicating expansion of rice and vegetable outputs and simultaneously contraction of variable inputs to increase unit profit. However, the high presence of decreasing returns to scale in RFS indicates farmers who cultivated only rice should reduce their size. In RVFS, farms that were scale efficient had a variable farm profit that was 52 percent larger than that of the scale inefficient farms. Similarly, farms that were scale efficient in VFS had a variable farm profit that was 48 percent larger than that of the scale inefficient farms. In contrast, the unique farm that was scale efficient in RFS had a variable profit that was 41 percent smaller than that of the scale inefficient farms. The results confirmed that decreasing returns to scale is the predominant form of scale inefficiency observed in RFS.

Finally, in the short run, farmers appeared to be more output inefficient (REVI) than they were input inefficient (INIE). Output inefficiency was mainly due to low yields, implying that a major effort has to be undertaken to increase yield levels and/or postharvest facilities that help to conserve yield (Weinberger and Lumpkin, 2007). The input inefficiency demonstrated that the observed variable inputs (seed and fertilizers) were not used at the optimal level showing that access to good quality seeds and fertilizers was a severe constraint for most farms (Cox and Wohlgenant, 1986). This finding also implies that farmers face high (shadow) prices for cash inputs because of liquidity constraints. First, farmers were mostly using the same traditional seeds, or if they had ever used improved hybrid seeds, they propagated it themselves, and the productivity of the seed would have deteriorated over time as a result. Second, the NPK fertilizers available in Benin are recommended and commercialized especially for cotton. Input inefficiency was also caused by the difficulty that producers face in adjusting the quality and quantity of inputs. This is in line with the findings of Crawford et al. (2003) who found that the increase in fertilizer in Benin is largely attributable to the expansion of fertilizer use by the cotton sector. The authors categorized the causes of low input use (fertilizer and seed) in food crops as a function of weak incentives and capacity to purchase inputs. Following Crawford et al. (2003), Jayne et al. (2003) and Kelly (2005), successful increase in the use of fertilizer and seeds requires policies and programs that ensure economically sound and technically efficient use. The results suggest that lowland producers face managerial or organizational problems that inhibit them from adjusting the use of operating inputs. To address the question why inefficiency is so pervasive in lowland farming in Benin, factors contributing to these inefficiency scores were further investigated.

### 2.4.2. Truncated Bootstrap Analysis of Sources of Inefficiency

A single truncated bootstrap procedure explaining inefficiency as defined in section 2.2.2 were estimated using Stata software version 9.0. $B = 2{,}000$ bootstrap replications were used as suggested by Simar and Wilson (2007) by pooling data across all three farming systems.

Table 2.3 shows the second stage coefficients and Bootstrap Confidence Intervals for pure technical, allocative and scale inefficiency estimates. Positive coefficients indicate that the associated variable increases inefficiency while negative coefficients decreases inefficiency. A parameter estimate is significant when the value of zero is not within the confidence interval.

Technical inefficiency was significantly and negatively affected by *TybasRVFS* (joint effect of water control and integrated rice-vegetable farming system), *TybasRFS* (joint effect of water control and rice farming system), *Married* (married household), *Educ* (producers who have a formal education), *Nhadult* (number of family members available for lowland farm work), and *Year* (number of years of management experience in the lowland). On the other hand, technical inefficiency was significantly and positively affected by *RFS* (rice farming system), *RVFS* (integrated rice-vegetable farming system), *Tybas* (water control), and *Age* (farmer's age). The significance of the effects of the two farming systems (*RVFS* and *RFS*) suggests in the short run, that the three lowland farming systems are different in terms of technical inefficiency. Their positive effects imply that the rice (RFS) and the integrated rice-vegetable farming systems (*RVFS), ceteris paribus,* have a higher technical inefficiency than the vegetable farming system (*VFS*). This suggests that the degree of technical inefficiency of vegetable's producers is less than that of rice farmers. The result indicates that despite the fact that much of the interest in lowlands in West Africa has focused on the potential for technologically-intensive rice production (Erenstein et al. 2006), rice production technology is still a severe constraint for farmers. The effect of water control (*Tybas)* was shown to have significant and positive effects on technical inefficiency, indicating that technical efficiency is not enhanced by only water control. The joint effect of water control and rice farming system (*TybasRFS)* and the joint effect of water control and integrated rice-vegetable farming system (*TybasRVFS)* were shown to have significant and negative effects on technical inefficiency, suggesting that water control and farming systems have a decreased interaction effect on technical inefficiency. Thus, the level of irrigation and lowland farming systems are complements and play a significant role in the level of inefficiency. Furthermore, the results indicate that formal education and additional years of management experience resulted in lower technical inefficiency. This implies that increasing investment in formal and informal education might lead to better performance in the agricultural sector (Dhungana et al. 2004) and that education and experience are substitutes and play a significant role in the level of technical inefficiency. The positive effect of producer age on technical inefficiency suggests that younger farmers are more likely to be technical efficient than their older counterparts.

This is consistent with the findings of Dhungana et al. (2004) who showed that, in Nepalese rice farms, younger farmers may be more willing to adopt new technologies and/or to have a stronger educational background. The households that had a higher number of family members performed better in terms of technical efficiency. The hypothesis that a higher upland farm size significantly raises technical inefficiency in the lowlands was not confirmed. A plausible explanation is that higher upland farm size is interpreted by households as a strategy for risk diversification.

**Table 2.3. Second stage coefficients and Bootstrap confidence intervals at 5% (L=2000)**

| **Pure Technical inefficiency (PTIE)** | **Coefficients** | **Std. Err.** | **Intervals, 5%** |
|---|---|---|---|
| Constant | 0.154* | 0.005 | [0.144;0.1633] |
| System 1 (RVFS) | 0.328* | 0.0039 | [0.3202;0.3354] |
| System 2 (RFS) | 0.4105* | 0.004 | [0.4027;0.4183] |
| Age of producer | 0.001* | 0.00007 | [0.0011;0.0014] |
| Married | - 0.0495* | 0.0022 | [-0.0537;-0.0451] |
| Educ (formal education) | - 0.0488* | 0.0013 | [-0.0514;-0.0463] |
| Tybas (water control) | 0.1442* | 0.0037 | [0.1369; 0.1515] |
| Nhadult (family member) | - 0.0173* | 0.0004 | [-0.01803;-0.01666] |
| Year (experience) | - 0.0029* | 0.0001 | [-0.0031;-0.0027] |
| Upland (upland size) | 0.0008 | 0.0006 | [-0.0003;0.0019] |
| Tybas*RVFS (interaction) | - 0.2450* | 0.0042 | [-0.2532;-0.2369] |
| Tybas*RFS (interaction) | - 0.2820* | 0.0041 | [-0.2901;-0.2739] |
| **Allocative inefficiency (AIE)** | **Coefficients** | | **Intervals, 5%** |
| Constant | 0.3750* | 0.1845 | [-0.7368;-0.0133] |
| System 1 (RVFS) | 0.0879 | 0.1169 | [-0.1414;0.3171] |
| System 2 (RFS) | - 6.2461* | 0.1672 | [-6.5741;-5.9182] |
| Age of producer | 0.0027 | 0.0027 | [-0.0025;0.0079] |
| Married | - 0.6658* | 0.0959 | [-0.8539;-0.4776] |
| Educ (formal education) | 0.0906* | 0.0461 | [0.0003;0.1809] |
| Tybas (water control) | - 1.0274* | 0.1044 | [-1.2321;-0.8227] |
| Nhadult (family member) | 0.1225* | 0.01207 | [0.0988;0.1462] |
| Year (experience) | 0.0568* | 0.0032 | [0.0505;0.0631] |
| Upland (upland size) | - 0.2687* | 0.0211 | [-0.3101;-0.2272] |
| Tybas*RVFS (interaction) | 0.4288* | 0.1296 | [0.1747;0.6829] |
| Tybas*RFS (interaction) | - 0.6691* | 0.1685 | [-0.9997;-0.3386] |
| **Scale inefficiency (SIE)** | **Coefficients** | | **Intervals, 5%** |
| Constant | 1.135* | 0.0371 | [1.0619;1.2073] |
| System 1 (RVFS) | - 0.0347 | 0.0253 | [-0.0843;0.0149] |
| System 2 (RFS) | 0.0617* | 0.0256 | [0.0115;0.1120] |
| Age of producer | 0.0130* | 0.0006 | [0.0117; 0.0142] |
| Married | - 0.7010* | 0.0201 | [-0.7405;-0.6615] |
| Educ (formal education) | - 0.6728* | 0.0141 | [-0.7005;-0.6451] |
| Tybas (water control) | - 1.4172* | 0.0268 | [-1.4698;-1.3646] |
| Nhadult (family member) | - 0.2061* | 0.0043 | [-0.2145;-0.1977] |
| Year (experience) | - 0.0140* | 0.0008 | [-0.0156;-0.0124] |
| Upland (upland size) | 0.0311* | 0.0052 | [0.0208;0.0414] |
| Tybas*RVFS (interaction) | 1.4232* | 0.0315 | [1.3614;1.4850] |
| Tybas*RFS (interaction) | - 0.0894* | 0.0289 | [-0.1461;-0.0327] |

*Legend.* RVFS-Integrated rice-vegetable farming system; RFS- Rice farming system
* significance at 5% level

Results showed that allocative inefficiency was affected significantly and negatively by *RFS* (rice farming system), *Tybas* (water control), *TybasRFS* (joint effect of water control and rice farming system), *Married*, and *Upland* (upland farm size) and positively by the joint effect of water control and integrated rice-vegetable farming system (*TybasRVFS)*, number of adult members available for lowland farm work (*Nhadult*), *Educ* (formal education) and *Year* (number of years of management experience in lowlands). Further, the results indicated that water control and farming system have a joint negative effect on allocative inefficiency. Producers dealing with the rice farming system on irrigated plots were more successful in choosing a mix of variable inputs that maximizes profit at given input prices than those who grow only vegetables on the same type of plot. However, the results also suggest that producers who farm in water control lowland succeed better in making profit efficient choices of variable inputs. Thus, the best irrigation scheme has a negative effect on allocative inefficiency. The hypothesis that educated farmers and lowland management experience have a negative effect on allocative inefficiency is rejected. This is not consistent with the finding of Stefanou and Saxena (1988) who found that operators of dairy farms in Pennsylvania with post-secondary education demonstrated a greater degree of flexibility in the allocation of variable inputs. The significant effect of the joint interaction of water control and lowland farming systems (*TybasRFS and TybasRVFS)* on allocative inefficiency indicates that the level of irrigation and lowland farming systems are complements and also play a significant role in allocative efficiency. This result corroborates the finding of Erenstein et al. (2006) that temporal integration of rice and vegetables is constrained by the limited degree of water control in West African lowlands.

Scale inefficiency was affected negatively and significantly by *Tybas*, *Married*, *Educ*, *Nhadult*, *TybasRFS*, and *Year* and positively by *TybasRVFS*, *RFS*, *Upland*, and *Age*. The insignificant coefficient of the *RVFS* indicates that the scale inefficiency effect of the integrated rice-vegetable farming system is similar to that of vegetable farming system. The results also suggest that water control and lowland farming systems are complements and play a significant role in scale inefficiency. Our results show that irrigated lowland and rice farming system have a negative joint interaction on scale inefficiency indicating that producers who cultivated only rice on irrigated plots operate on a more optimal (higher) scale than those who produced only vegetables on irrigated plots. This result demonstrates that the contribution of the policy of technologically-intensive rice production is a scale effect. The results also suggest that educated farmers and more years of management experience in lowland cultivation decrease scale inefficiency. The implication is that education and experience are substitutes and also play a significant role in the level of scale efficiency. The producer age and additional upland size increase scale inefficiency. It appears that farmers with relatively higher upland size are less scale efficient than the others. Also, young farmers tend to be more scale efficient than old farmers. Large number of family members available for lowland farming decreased scale inefficiency, implying that households with much family labor tend to operate at the optimal size.

The joint test of water control and farming systems interaction coefficients rejects the null hypothesis of independence of water control and farming systems. Because the interaction terms are jointly significant, it would be a misspecification to fit the regression based on independent and strictly additivity of the two factors.

The results in this chapter are in line with previous findings (Erenstein, 2006; and Erenstein et al. 2006) indicating that the degree of economic motivation and success in the allocation of resources in Benin's lowlands differ significantly among farming systems. In the short run, producers were not able to allocate their resources optimally in the profit maximizing sense. Furthermore, technical, allocative, and scale inefficiencies differed significantly among farming systems. Researchers who have examined lowlands practices in West Africa believed that inefficiency could be improved through better management practices (Erenstein et al. 2006). Management practices do play an important role in production as shown by the parameter estimates for family labor, water control and upland farm size. In addition, a better policy should be implemented for seeds and fertilizers to increase outputs and reduce inputs used. The results of the three farming systems indicated that the profit loss due to technical inefficiency is quite similar across them. This implies that all producers have difficulty obtaining optimum input-output mixes, although vegetables producers were somewhat more technically efficient than the farmers of the other systems. A more likely explanation, as shown by the second stage result, may be the educational need to teach farmers the value and use of lowland technology (irrigation, inputs used in lowland, etc.). In the short run, basic farm management training could possibly address this problem. Allocative inefficiency increased with the variability of prices faced by producers in local markets implying that alternative strategies for reducing producers' price volatility might be implemented. Finally, the results of this study are in line with the policy implication of the OECD (Organization for Economic Co-operation and Development) that agricultural production in developing countries can be enhanced through appropriate technology and management techniques applied to farms, resources and land. These will not harm the environment and will enable developing countries to reach the goal of food security. To reach this goal, lowland production processes could be reorganized and resources managed more effectively. Producers' levels of education and farming skills should be upgraded and policy makers must search for incentives conducive to farmers' adoption of appropriate technology (OECD, 2008).

## 2.5. Conclusions

This chapter aimed at examining the differences in economic inefficiency among lowland producers at farming system level to assess a farm's competitive position. It estimated several performance measures such as overall, technical, allocative, scale, input, and output inefficiency; moreover sources of inefficiency are analyzed. We employed a new robust two stage semi-parametric directional technology distance function approach and a single truncated bootstrap procedure to analyze the inefficiency performance of lowland farming systems.

The first stage results indicated that there is evidence of significant technical, allocative and scale inefficiencies among producers of which scale inefficiency, allocative inefficiency and output inefficiency were the main sources of inefficiency. It is possible for the producers to increase profit gain of rice and vegetable production by removing these inefficiencies. Increasing returns to scale prevailed in the integrated rice-vegetable farming system. Input inefficiency indicated that variable inputs (seed and fertilizers) were not used at the optimal level, reflecting limited access to quality and quantity of seeds and fertilizers for most farms.

To address the issue of why inefficiency is so pervasive, the second stage results examined the influence of environmental and socio-economic factors on the inefficiency performance of the lowlands producers. There were substantial differences between the three lowland farming systems. Compared to the vegetable farming system, technical inefficiency increased significantly when farmers produced only rice in the rainy season. Allocative and scale inefficiency decreased more significantly with rice farming system or an integrated rice-vegetable farming system. Water control, size of family workforce, years of management experience in lowland cultivation and the upland farm size held by the households were other factors influencing inefficiency of farmers in lowlands. Formal education and experience were substitutes whereas water control and lowland farming systems were complements, each having a significant effect on the level of inefficiency. Finally, there is economic and food security gain in promoting lowland development strategies with integrated rice-vegetable farming systems.

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**Annex. Correlation matrix between explanatory variables**

| Variables | syst1 | syst2 | age | simat | inst | tybas | nhadult | year | upland |
|---|---|---|---|---|---|---|---|---|---|
| syst1 | 1.0000 | | | | | | | | |
| syst2 | -0.4529 | 1.0000 | | | | | | | |
| age | -0.1915 | 0.1644 | 1.0000 | | | | | | |
| simat | -0.0997 | -0.0185 | -0.1815 | 1.0000 | | | | | |
| inst | 0.1067 | -0.1000 | -0.1378 | -0.0840 | 1.0000 | | | | |
| tybas | -0.2113 | -0.0208 | 0.0544 | -0.1462 | -0.1572 | 1.0000 | | | |
| nhadult | 0.0994 | -0.1286 | 0.0608 | 0.1619 | 0.1135 | 0.0191 | 1.0000 | | |
| year | -0.0412 | 0.0539 | 0.6729 | 0.0112 | -0.1897 | 0.1656 | -0.0802 | 1.0000 | |
| upland | 0.0352 | -0.0306 | 0.1307 | 0.1483 | -0.0204 | 0.1165 | 0.4826 | 0.0606 | 1.0000 |

# CHAPTER 3

## Estimating farmers' productive and marketing inefficiency: An application to vegetable producers in Benin


### Abstract

This study estimates the technical and marketing inefficiency of a sample of urban vegetable producers in Benin. The study proposes a Russell-type measure of inefficiency using a directional distance function that accounts simultaneously for the expansion of outputs and prices and the reduction of variable inputs. A truncated bootstrap regression is used in the second stage to consistently analyze factors that underlie differences in inefficiencies. The first-stage results suggest that vegetable producers are more inefficient with respect to marketing than production. The second-stage results indicate that technical inefficiency is affected by the production environment and private extension services. Marketing inefficiency is affected by the type of marketing arrangements and specialization in production.



*Keywords:* Vegetables, technical inefficiency, marketing inefficiency, Russell-type measure, bootstrap, Benin.

*JEL classifications*: C34, C61, C67, D24, D49

## 3.1. Introduction

Improving the performance of the agricultural sector remains an important issue in many developing countries. This topic has been addressed by a considerable volume of work that assesses technical efficiency relative to a production frontier representing the benchmark. However, producers are different not only with respect to efficiency in the production process, but also with respect to efficiency in marketing outputs. In farm management theory, farms are involved in three basic activities: production, marketing and investment activities. In developing countries, investment activities are a major constraint and are problematic due to a lack of bank institutions in the agricultural sector. Farm profitability, therefore, is related not only to production efficiency but also to the farmers' marketing strategies. Charnes et al. (1985) were the first to apply data envelopment analysis (DEA) to measure the efficiency of marketing efforts. Yet, thus far, no studies have integrated the measurement of technical and marketing efficiency (Rust et al. 2004). Doing so, however, could provide insights on the efficient utilization of resources that are used in the production process and in marketing outputs, such as labor and fuels. Such insights would help farmers better target improvement in their overall efficiency. Moreover, insight into the factors that underlie the differences in technical and marketing inefficiency are required, as such information would allow governments and extension services to assist farmers in improving their performance.

In West Africa, the rapid population growth, infrastructure development and urbanization require the intensification of agricultural systems in urban regions. The production of vegetables in urban zones has increased over the past several years in terms of the amount of area cultivated, the number of producers and the income generated. Urban vegetable producers are largely market oriented and generally grow a wide range of vegetables. Although there have been quite a large number of studies on technical and allocative efficiency in sub-Saharan Africa (rice, cereals and coffee are the most commonly analyzed products), there are only a few studies related to vegetable production and marketing in West Africa (Haji, 2006; Haji and Anderson, 2006).

The purpose of this chapter is twofold. First, this chapter develops an integrated approach to assessing technical and marketing inefficiency. Marketing inefficiency, in this study, reflects the failure of farmers in achieving a high price for their outputs. Our study is the first to measure marketing inefficiency simultaneously with output- and input-oriented technical inefficiency using a Russell-type measure of inefficiency. As the resources used for production and marketing activities are not separable at the farm level (i.e., the problem of production is not separable from the marketing decisions), a Russell-type measure is straightforward for measuring technical and marketing inefficiency. In this chapter, marketing activities refer to choices regarding product quality and distribution channels. The inefficiency measure reflects the maximum feasible equiproportionate reduction of inputs and expansion of outputs and output prices. The conceptual model of the integrated measurement of marketing and technical inefficiency is applied to a sample of urban vegetable producers in Benin. Second, this chapter analyzes the determinants of urban vegetable producers' marketing and technical inefficiencies. In recent years, the bootstrap technique has become a valid approach in the semi-parametric DEA method to correct for small sample bias. Therefore, in this chapter, we apply the single truncated bootstrap procedure that enables statistical inference in the second-stage regression.

The remainder of the chapter is organized as follows. Section 3.2 describes the vegetable marketing channels of urban vegetable producers in Benin. Section 3.3 describes the conceptual framework of our approach. Section 3.4 presents the data, the grouping method and the construction of the variables and identifies the factors that explain technical and marketing inefficiency. Section 3.5 presents and discusses the results, and section 3.6 provides conclusions and policy implications.

## 3.2. Background Description of Vegetable Marketing Channels in Benin

Urban vegetable production is one of the high-value agriculture food activities in Benin. As the major portion of vegetables is sold in rural and urban markets through many marketing arrangements, there is no doubt that marketing plays a role in the economic development of the country. Pepper, tomato, amaranth, carrot, cabbage, cucumber, solanum plants (black morelle), lettuce, onion, corchorus, okra and bitterleaf are the major vegetable crops cultivated year round on mostly small, scattered pieces of land ranging from 0.005 ha to 12 ha.

Similar to the cereal market, the distribution of vegetables is regulated by a private market system. Vegetables are available in the market every month of the year with significant variations in the quantity supplied. While most transactions between producers and buyers occur at the farm gate, the vegetables are transferred from producers to the final consumers through conventional marketing channels, where fresh products are traded between actors who are involved in recurrent trade relationships. In contrast to the cereal market (Kuiper et al. 2003), vegetable retailers prefer to obtain their products either from the wholesaler or directly at the farm gate, as production occurs closer to the consumer. Vegetable producers market much of their produce in bulk at harvest time because of the highly perishable nature of their products. In general, producers conduct all of their sales immediately after harvest.

The long marketing channel of vegetables in urban areas involves two types of intermediaries, the wholesalers and the retailers. These two groups serve as the link between producers and consumers and other buyers of vegetables, though producers may also sell a portion of their products directly to consumers. As a result, farmers primarily use three channels to market their products, that is, the wholesalers, retailers and consumers.

During the last 25 years, vegetable crop production and marketing in Benin has experienced two significant changes. First, the sector has become increasingly concentrated. Second, for the procurement of market vegetables, the buyers (wholesalers and retailers) increasingly rely on alternative marketing arrangements (AMAs), such as contracts, thus decreasing their dependency on the spot market (Akplogan et al. 2007).

## 3.3. Theoretical Framework and Empirical Specification

We assume that producers decide not only how many resources to devote to production, but also how many resources to devote to their marketing strategy. The marketing process in a farm involves choices regarding product quality and distribution channels, each of which affects output. As previously indicated, from the producers' perspective, selling their products at the highest possible price constitutes efficient marketing (Abbott and Markeham, 1981). Hence, we assume that producers seek the optimal output prices in their marketing arrangements. The pricing decision is at the core of every business plan, as it directly impacts the critical components of a farm's marketing strategy. Furthermore, the marketing process is likely to affect production-related decisions, such as the area allocated to each crop and whether to purchase modern inputs.

Let $y \in \Re_{+}^{r}$ denote the output vector, $x \in \Re_{+}^{m}$ the input vector and $p \in \Re_{++}^{\mathrm{r}}$ the output price vector. The reference production technology $T$ is fully characterized by the input-output-price requirement set:

$$T(x, y, p) = \{(x, y, p): x \text{ can produce } y, p\} \tag{1}$$

The technology set is nonempty, compact and convex. We assume that the technology set allows for variable returns to scale and strong disposability of outputs and inputs. Output prices are assumed to be weakly disposable, as prices cannot be expanded freely due to certain market regulations (for instance, producers and buyers agreed on the maximum output price levels in the previous year or period). Relative to this technology, we can define a measure of inefficiency in which the output quantity and prices are expanded, while, simultaneously, inputs are contracted. A non-radial representation of the technology is as follows:

$$T(x,y,p) = \{(x,y,p;-g_x,g_y,g_p): Y'\lambda \geq y_i + g_y, X'\lambda \leq x_i - g_x, P'\lambda = p_i + g_p, \lambda \geq 0\} \quad (2)$$

where $\lambda$ is a vector of intensity variables (producer weights), which identifies the producers who determine the production frontier. The vectors $g_x \in \Re_+^m$, $g_y \in \Re_+^r$ and $g_p \in \Re_{++}^r$ are the directional vectors. The directional distance vector $(g_x, g_y, g_p)$ assumes a direction in which efficiency is gauged. It expands outputs and prices in the directions $g_y$ and $g_p$, respectively, and contracts inputs in the direction $g_x$. In this chapter, a measure of technical and marketing inefficiency is computed using Russell-type measures of inefficiency (Färe et al. 1994, p. 81 & 115; Oude Lansink and Ondersteijn, 2006). The Russell measure of technical and marketing inefficiency is based on maximum required outputs, optimal obtained prices and minimum required inputs in the $(g_x, g_y, g_p)$ direction (see Fig. 3.1). The equality $P'\lambda = p_i + g_p$ in (2) implies weak disposability of output prices. Specifically, the Russell measure of the directional technology distance function can be defined as follows:

$$\vec{D}(x_i^v, y_i, p_i; g_x, g_y, g_p) = max\{(\theta_{TE} + \theta_{ME}): (y_i + \theta_{TE} g_y, x_i^v - \theta_{TE} g_x, p_i + \theta_{ME} g_p) \in T\} \quad (3)$$

where $\theta_{TE}$ is the technical inefficiency ($\theta_{TE} \geq 0$) for the $i^{th}$ producer and $\theta_{ME}$ is the marketing inefficiency ($\theta_{ME} \geq 0$). All other variables are as defined in (1) and (2). Following Färe and Grosskopf (2005, p. 8-10), our directional technology function measure satisfies the translation property and is homogeneous of degree – 1 in the directional vector $(g_x, g_y, g_p)$. In other words, there is no free lunch. The directional distance function measures the distance to the boundary of $T$ in a preassigned direction. It is important to note that our directional distance function is a complete characterization of the technology $T$, that is,

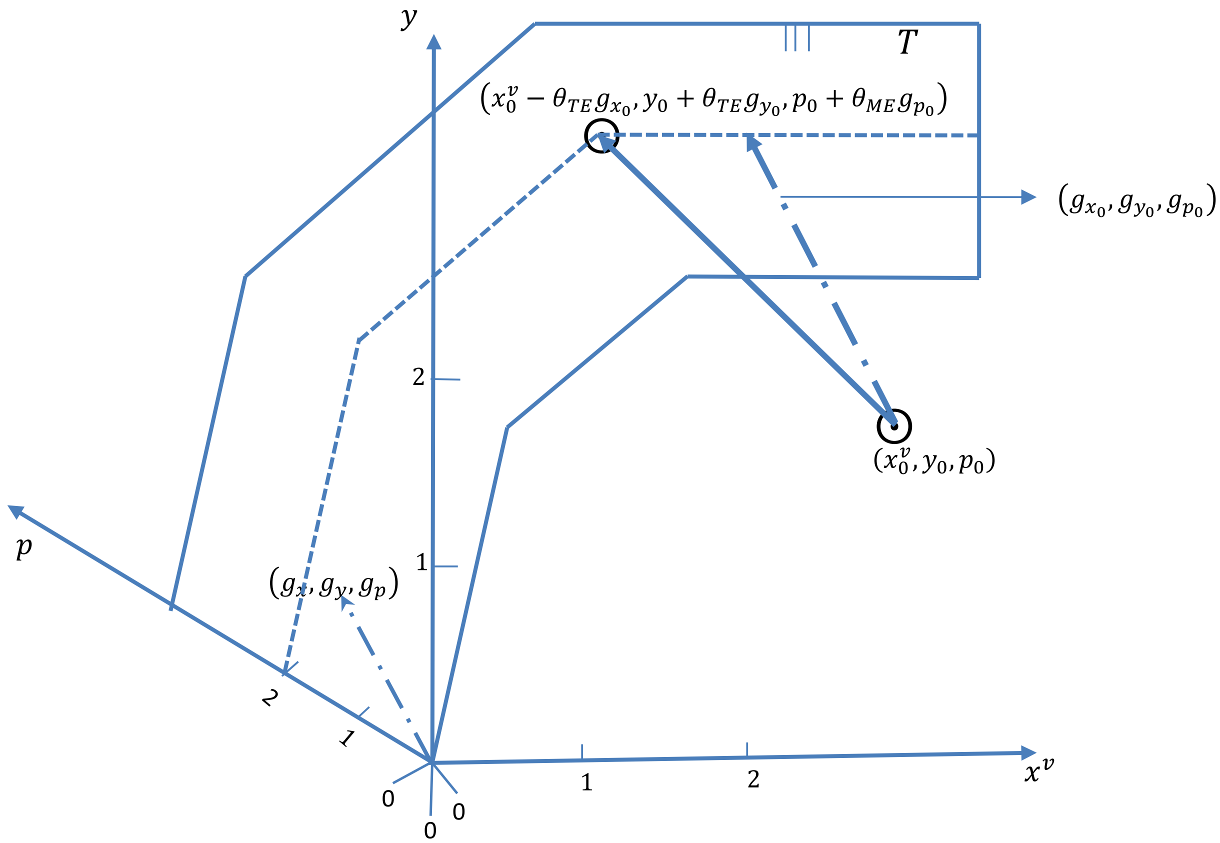


**Figure 3.1. Russell-type measure of technical and marketing inefficiency**

$\vec{D}(x_i^v, y_i, p_i; g_x, g_y, g_p) \geq 0 \Leftrightarrow (x, y, p) \in T$ (Chambers et al. 1998). As the technology $T$ is convex, $\vec{D}(x_i^v, y_i, p_i; g_x, g_y, g_p)$ is concave in $(x^v, y, p)$ (see Chambers et al. 1996 for proofs). A producer is fully efficient in the $(g_x, g_y, g_p)$ direction if $\vec{D}(x_i^v, y_i, p_i; g_x, g_y, g_p) = 0$, that is, if $\theta_{TE} = 0$ and $\theta_{ME} = 0$. This implies that a producer is fully efficient in the $(g_x, g_y, g_p)$ direction if he/she is simultaneously technical and marketing efficient.

The Russell-type measure in the case of a directional distance function (DDF) model measuring inefficiency (technical and marketing) of DMU $i$, under the assumption of variable returns-to-scale, can be computed as the solution to the linear programming problem:

$$\vec{D}(x_i^v, y_i, p_i; g_x, g_y, g_p) = \max_{\theta_{TE}, \theta_{ME}, \lambda} (\theta_{TE} + \theta_{ME})$$

$$\begin{aligned} &\text{s.t.} \\ &Y\lambda \geq y_i + \theta_{TE} g_y \\ &X^v \lambda \leq x_i^v - \theta_{TE} g_x \\ &P\lambda = p_i + \theta_{ME} g_p \\ &X^f \lambda \leq x_i^f \\ &N1'\lambda = 1 \\ &\lambda \geq 0 \end{aligned} \tag{4}$$

where $x^v \in \Re_+^{m_1}$ is a vector of variable inputs and $x^f \in \Re_+^{m_2}$ is a vector of fixed inputs with $m = m_1 + m_2$. All other variables are as defined in (1), (2) and (3). The directional vectors $(g_x, g_y, g_p)$ used in this study are the observed variable input, output and output prices, respectively, implying that the directional vector is specific to DMU (Chambers et al. 1998; Färe and Grosskopf, 2005, p. 141). With this choice of directional vector, the inefficiency measures have a radial interpretation. In this specification, technical efficiency refers to the achievement of the maximum potential output and the minimum potential use of variable inputs, taking into consideration physical production relationships. Marketing efficiency represents the optimal prices a producer could obtain through his marketing arrangements, subject to a given production technology. The model consists of a convex combination of inputs, outputs and output prices of the most efficient farms.

To determine why inefficiencies are present, we add a two-stage approach to our model to account for the nondiscretionary factors that influence the inefficiency scores. We add to our first-stage model a truncated bootstrap regression of the estimated inefficiencies on the environmental factors for purposes of statistical inference. A major problem in a standard two-stage approach relates to the dependence of the inefficiency scores, which violates the dependency assumption within the sample required by regression analysis. To resolve this problem, Simar and Wilson (2007) developed two complementary consistent procedures in the two-stage DEA approach: the double bootstrap and the single truncated bootstrap. The double bootstrap procedure facilitates statistical inference in the first and second stages. However, this technique is too complex and it is not yet developed for the DEA estimators of the directional distance function approach. Therefore, in this chapter, we adapt the single bootstrap technique, thus enabling statistical inference in the second-stage regression. The description of the algorithm of this chapter is similar to that by Singbo and Oude Lansink (2010). The truncated bootstrap regression is defined as:

$$\begin{aligned} \hat{\theta}_{TE_i} &= z_i \beta + \xi_{TE_i} \geq 0, \\ \hat{\theta}_{ME_i} &= A_i \delta + \xi_{ME_i} \geq 0, \end{aligned} \tag{5}$$

where $\hat{\theta}_{TE_i}$ and $\hat{\theta}_{ME_i}$ are, respectively, the technical inefficiency and marketing inefficiency for the $i^{th}$ producer obtained in (4); $z$ and $A$ are exogenous variables ($z \neq A$); $\beta$ and $\delta$ are parameters to be estimated; and $\xi$ are the error terms. The error components in this second-stage truncated bootstrap regression are probably not identically and independently distributed, since the technical and marketing inefficiency scores are derived simultaneously from the first stage non-radial Russell-type model. Thus, it might be preferable to stack the two regressions and estimate via seemingly unrelated regression (SUR), allowing for the two error terms to be correlated. This would be feasible within a conventional error structure. However, the truncated-bootstrap framework accounting for possible correlation of the error terms is complex and extremely demanding from a computational perspective (Hajivassiliou, 1993). As the truncated bootstrap regression consistently corrects for the correlation between the error terms and the explanatory variables in (5), we estimate each model separately to control for the within correlation in each model.

## 3.4. Data Description and Variables

Data for this chapter were obtained from a survey conducted among 186 producers in six cities and towns in Benin. The data were collected during the agricultural production year of 2009/2010 using a two-stage stratified random sampling procedure. A structured questionnaire was used and was designed in such a way that the data for specific crops and activities that had been introduced could be collected. To avoid or minimize measurement errors and non-response bias, specific aspects of the questionnaire were addressed two or three times in each household. With respect to farm size, our sample consists of small, medium and large farms, with medium and large farms being the majority. Questionnaire design and data collection were conducted under the supervision of the first author.

Data were obtained on more than 30 vegetable crops. Vegetables are aggregated into two groups, that is, the traditional vegetables and the non-traditional vegetables. This grouping strategy is based on the classification by Achigan-Dako et al. (2009), who asserted that traditional vegetables refer to all plant species that have been used by communities for several generations and are integrated as part of the cultural habits. Our grouping method identifies 23 non-traditional vegetables and 10 traditional vegetables, implying that vegetable farms are well diversified[1]. Our grouping method is also consistent with the categorization according to the managerial practices used by Haji and Andersson (2006).

Two outputs (traditional vegetables and non-traditional vegetables), five inputs (operating costs, land, labor, capital and water), and two Laspeyeres weighted-average output price indices are distinguished. Output in each category consists of the average price of crops

[1] The term non-traditional vegetables refers to species such as lettuce, cabbage, courgette, cucumber, beet, carrot, radish, turnip, french bean, melon, squash, watermelon, celery, chicory, chives, coriander, dill, fennel, garden mint, leek, overripe, parsley, rocket and thyme. Species such as tomato, solanum plants, okra, pepper, amaranth, corchorus, bitterleaf, African basil, cockscomb and onion are considered as traditional vegetables.

times the quantity produced. Variable input represents the operating costs that include fertilizers (mineral and organic), pesticides, seeds, and other miscellaneous expenses. Fixed inputs are land, labor, capital and water. Land is measured in hectares, while labor consists of family labor and hired labor and is measured in hours. Labor is assumed to be a fixed input, as a large share of total labor consists of family labor and permanent contract labor. Capital consists of machinery and equipment and is assessed in terms of the replacement cost. As water is one of the major constraints in vegetable production in urban areas, the quantity of water used for irrigation is included as an input.

The model for computing marketing inefficiency requires output price indices that reflect the farmer's success in marketing outputs. The farm-specific price index we constructed reflects price differences that result from differences in the quality of output and differences due to the choice of the marketing channel. For each output category, we constructed a Laspeyeres price index $P_{ik}$ for producer $i$ and aggregate output $k$ (=1 for traditional vegetables, and 2 for non-traditional vegetables); furthermore, $j$ reflects a crop in category $j = 1, \dots, N$. The Laspeyeres weighted average price index of each category of producer $i$ ($P_{ik}$) is computed as follows:

$$P_{ik} = \frac{\sum_{j \in k}^{n} P_{ij} q_{ij}}{\sum_{j \in k}^{n} \bar{P}_j q_{ij}} \tag{6}$$

where $q_{ij}$ is the output quantity in kg of crop $j$ for producer $i$ and $\bar{P}_j$ is the average output price of crop $j$.

The second stage of our procedure involves explanatory variables that influence our inefficiency estimates. This property implies that changes in the exogenous variables do not affect the shape of the distribution of inefficiency scores but that they affect the level of inefficiency. Several variables have been evaluated in previous studies as possible determinants of technical and marketing inefficiencies. Among the variables used in this analysis are the following: (a) market competition, where distance to the central market is used as a proxy, (b) alternative marketing arrangements, (c) output specialization index, (d) extension services such as public and private extension visits, (e) soil fertility index, and (f) farm characteristics. The distance between the production site and the main market place is assumed to reflect the impact of more distant production areas on efficiency. To determine whether heterogeneity in selling outlets affects marketing inefficiency, the main target of the exogenous variables is the effect of alternative marketing arrangements on inefficiency. As a proxy for this variable, we use the proportion of vegetable outputs sold to wholesalers, retailers and consumers. As the proportions add up to one, two variables are included in the regression, that is, the proportion sold to the wholesaler and to the consumer. Hence, the proportion sold to the retailer serves as the reference level. The interpretation of the parameters is made relative to the reference.

The specialization variable used in our inefficiency effects model is specified as a normalized Hirschman index of the concentration of output shares for each vegetable crop. This index discriminates between producers who are relatively more specialized. It is a widely used measure of concentration and was used, for example, by Al-Marhubi (2000) to specify the concentration of output shares in his analysis of export diversification and growth. Following Al-Marhubi (2000, p. 561), the normalized Hirschmann index is defined as follows:

$$H_i = \frac{\sqrt{\sum_j^{33}\left(\frac{q_j}{\sum_j^{33} q_j}\right)^2} - \sqrt{1/33}}{1-\sqrt{1/33}} \qquad (7)$$

where $i$ is the producer index, $q_j$ represents the producer output quantity of vegetable crop $j$, and 33 is the number of vegetables produced in the data set. The Hirschmann index is normalized to assume values ranging from 0 to 1. Note that a normalized Hirschmann index of 1 indicates perfect specialization. Likewise, a value closer to 0 signifies a more diversified vegetable crop production.

Agricultural extension services are considered as a single mechanism by which information on new technologies, more effective management options, and better practices can be transmitted to farmers (Owens et al. 2003). In Benin, there are two types of extension services: the national public extension services and the private extension services provided by NGOs. In general, both services work separately, though in some cases, they collaborate to extend programs. Public and private extension services are found by many authors to have complementary effects on inefficiency (Dinar et al. 2007). We include the number of extension visits in the specification without any prior hypothesis.

Summary statistics of the data used in this chapter are presented in Table 3.1. This table shows the inputs, outputs and the Laspeyeres weighted average price index for each output category, as well as the summary statistics for the exogenous variables that affect the magnitude of technical and marketing inefficiencies. A simple comparison indicates considerable variations among the variables.

**Table 3.1. Descriptive Statistics**

| **Variable (n=186)** | | Unit | Mean | St. Deviation |
|---|---|---|---|---|
| Aggregate output for traditional vegetables | | $10^3$ FCFA | 2,546 | 6,659 |
| Aggregate output for nontraditional vegetables | | $10^3$ FCFA | 1,674 | 3,531 |
| Laspeyeres weigthed average price index for traditional vegetables | | Index | 1.1086 | 0.4204 |
| Laspeyeres weigthed average price index for nontraditional vegetables | | Index | 0.9145 | 0.3225 |
| Variable input: Operating costs | | $10^3$ FCFA | 435.583 | 694.455 |
| Fixed inputs: | Labor | Man-hour | 313.573 | 129.271 |
| | Capital | $10^3$ FCFA | 509.470 | 829.234 |
| | Land area | ha | 0.539 | 1.347 |
| | Water | $10^3$ Liter | 4,137 | 1.06E+04 |
| Exogenous variables | | Unit | Mean | St. Deviation |
| Gender of household head (1=male, 0=female) | | Dummy | 0.892 | 0.311 |
| Years of management experience in vegetable production[2] | | Year | 15.102 | 9.459 |
| Number of years spent in formal education by the producer | | Years of schooling | 7.344 | 5.335 |
| Concentration of output shares | | Hirschmann normalized index | 0.530 | 0.137 |
| Number of public extension service visits to the producer during the campaign 2009-2010 | | Number | 6.41 | 13.184 |
| Number of private extension service visits to the producer during the campaign 2009-2010 | | Number | 0.866 | 3.547 |
| Best soil fertility index (1=best, 0=others) | | Dummy | 0.151 | 0.359 |
| Medium soil fertility index (1=medium, 0=others) | | Dummy | 0.667 | 0.473 |
| Amount of credit received by the producer during the campaign 2009-2010 | | $10^4$ FCFA | 24.559 | 68.399 |
| Distance of the farm to the central market | | km | 15.738 | 17.561 |
| Fraction of vegetables output sold to Wholesaler | | Number | 0.307 | 0.416 |
| Fraction of vegetables output sold to Retailer | | Number | 0.687 | 0.413 |
| Fraction of vegetables output sold to Consumer | | Number | 0.006 | 0.042 |

*Note:* \$1US = 494.030 FCFA in 2010 or 1 Eur = 655.957 FCFA.

[2] As the correlation of the explanatory variables showed that the Pearson partial correlation coefficients between the variable age of the household head and the number of years for management experience of the household head is high, we remove the variable age of the household head from both models.

## 3.5. Empirical Results and Discussion

### 3.5.1. Inefficiency Results

Table 3.2 provides the technical and marketing inefficiency scores. The directional vector we have chosen for $g_x$, $g_y$, and $g_p$ is the observed values for $x^v$, $y$, and $p$, respectively, as suggested by Chambers et al. (1998). A particular advantage of our global measures of inefficiency is that they do not impose a single orientation (e.g., output-oriented or input-oriented). The outcome gives an estimate of the maximum feasible expansion in outputs and price indices and the contraction in variable inputs, implying a radial interpretation of our inefficiency measures. In general, the first-stage estimates indicate that vegetable producers appear to be less technically inefficient than they appear to be marketing inefficient.

The results suggest that the directional distance function model yielded average inefficiency scores of 0.137 and 0.25 for technical and marketing inefficiency, respectively. Approximately 54% (101 out of 186) of the farmers are technically efficient, and 45% (84 out of 186) attain full marketing efficiency. Only 40% (77 out of 186) of the vegetable producers are located in the economically efficient frontier, meaning that they are simultaneously technically and marketing efficient[3].

The average technical inefficiency score of 0.137 means that, on average, vegetable producers can simultaneously reduce their variable input use by 14% and increase their output level by 14% if they were to become production efficient. One can briefly compare this set of results to those reported by Singbo and Oude Lansink (2010) in their study on lowland farming system inefficiency in Benin. The same results are noted by Haji (2006) when addressing the technical efficiency of vegetable farming systems in eastern Ethiopia. This result is also consistent with the findings of Iráizoz et al. (2003) in their study on horticultural production in Spain. The conclusion is that most of the producers who cultivate vegetables demonstrate high managerial skills on the production side, though to some extent, they over-utilize fertilizers, pesticides and other variable inputs.

The average marketing inefficiency score of 0.25 means that, on average, vegetable producers can increase their output price levels by 25% if they were to become marketing efficient at the optimal price level. In addition, the distribution of the marketing inefficiency scores suggests that approximately a fourth (48 out of 186) of the vegetable producers

[3] To check whether the most technically efficient producers are also the most efficient with respect to marketing, we use the Pearson rank correlation statistic. The result gives a coefficient value of 0.21 with a p-value of 0.035, indicating the correlation between technical inefficiency scores and marketing inefficiency scores. This result implies, to some extent, that technically efficient farms have a good marketing strategy.

relinquish at least half of the optimal price. First, the result suggests that, given the level of the resources they use, vegetable producers in the urban areas of Benin are facing marketing problems. Second, the result captures the major differences in the quality of vegetables available in the markets, meaning that the best-quality vegetables bring higher prices. The high-level marketing inefficiency suggests the need for producers to incorporate a profitable pricing strategy into their overall marketing strategy. Vegetable producers must be well prepared to develop profitable pricing strategies, that is, to develop a proactive pricing approach. The above findings confirm, to a large extent, the normative recommendations that have been proffered within the existing marketing literature (e.g., Monroe, 2003; Nagle and Holden, 1995).

Our findings suggest that vegetable producers must pursue not only a high productive performance but also a profitable marketing strategy. Producers need to shift from pricetaking behavior and engage in profitable pricesetting behavior by paying more attention to the market conditions. This implies that producers have to search for other marketing outlets or conduct better negotiations, as indicated by Jaleta and Gardebroek (2007) in their study on the tomato market in Ethiopia where farmers succumb three times more often in reducing prices from their initial price quotes. Producer organizations must assume a major role by becoming proactive actors in assisting their members to improve their marketing strategies. As producers sell the vast majority of their products at the farm gate, this result possibly suggests that middlemen (wholesalers and retailers) create barriers to entry in the spot markets for producers to maintain low prices at the farm gate. Consequently, policy makers must exert parallel efforts to promote effective vegetable producer organizations that can influence market regulations.

**Table 3.2. Inefficiency scores (n=186).**

| **Parameters** | **Ineff. Scores $(\hat{\theta})$** | **Minimum** | **Maximum** |
|---|---|---|---|
| Technical inefficiency (TE) | 0.137<br>(0.191) | 0.000 | 0.695 |
| Marketing inefficiency (ME) | 0.250<br>(0.309) | 0.000 | 0.971 |

Note. *As the DEA estimators are generally known to be sensitive to extreme observations, we also implemented the method for detecting outliers developed by Tran et al. (2010). After dropping from the sample 26 observations that have a high level of the defined weights (efficient farms), the technical inefficiency scores still range from 0 to 0.695 and the marketing inefficiency scores from 0 to 0.971, showing that the datasets do not suffer from extreme observations that could drive the frontier far from the inefficient farms.*

As urban vegetable production is input intensive (e.g., the use of high pesticides and mineral fertilizers), the quality of vegetables produced raises questions regarding asymmetric information for plant health in the market (Oude Lansink, 2011). On average, producers use 33 kg/ha (std. 70) of pesticides. Whereas vegetable producers know the phytosanitary history of their products at the moment of delivery, the phytosanitary history of the product is not directly observable for the buyers in the market. The outcome of this asymmetry is that, while many policy makers seek policies related to the use of chemical inputs in Southern Africa, attention must be paid to the appropriate use of pesticides and mineral fertilizers (Nakano et al. 2011).

### 3.5.2. Determinants of Inefficiency

The second stage of the model uses the inefficiency scores and regresses them on non-discretionary variables. The truncated bootstrap regression model results are presented in Table 3.3. The two models are strongly significant with a Wald $\chi^2$ value of 745.46 and 40.88 for the marketing inefficiency and technical inefficiency models, respectively.

Technical inefficiency in urban vegetable production is strongly related to four variables: soil fertility (best and medium soil fertility types), amount of credit received by producers, private extension service visits, and years of formal education. The estimated coefficients of the soil fertility index are statistically significant and negatively related to the technical inefficiency measure. The best fertility type reduces technical inefficiency, implying that farmers producing vegetable crops in sandy soil use more operating inputs (especially fertilizers) and achieve lower output levels than farmers producing crops in loamy soil.

The results in Table 3.3 also show that private extension services contribute positively to technical inefficiency. This finding could be attributed to private extension service agents who mainly focus on the worst performing producers and provide less attention to well-performing farmers. In practical terms, this suggests that vegetable producers who are not performing well are those searching for solutions to specific management problems, such as disease controls or yields management, and that they need advice. The insignificant effect of public extension services is surprising but could be interpreted as an indirect effect of farmers' behavior against public extension services[4] or the selection bias in targeting farmers. In addition, this result may suggest that public extension services do not provide useful technology messages due to a shortage of qualified staff. In addition, the positive effect of the

[4] We also experimented with the joint effect of public and private extension services to search for the complementary effect on technical inefficiency, but the results are not statistically significant.

amount of credit the producer receives implies that access to credit increases technical inefficiency. This result suggests that the amount of credit received by vegetable producers is not sufficient to allow farmers to purchase a better quality of inputs and services or to close the technology gap. Furthermore, the result may indicate that producers who have access to credit overinvest in inputs and technology[5]. As the average amount of credit received in the agricultural year 2009-2010 by producers was 245 $10^3$ FCFA and ranged from 0 to 5 $10^6$ FCFA, the latter implication is plausible, meaning that the loan must be adapted and be compatible with vegetable production constraints. This result is in line with a criticism of the role of microfinance in agricultural production, that is, credit does not really improve agricultural production (Cole, 2009). Specialization has an insignificant effect on technical inefficiency, although a positive effect was expected, a priori (see also Coelli and Fleming (2004) for Papua New Guinea).

Marketing inefficiency is strongly related to six variables: marketing arrangements (fraction of output sold to wholesaler and fraction of output sold to consumer), specialization index, years of management experience, distance to market, gender of producer, and number of years spent in formal education. The negative and significant coefficients of the specialization index on marketing inefficiency indicate that, other things being given, greater crop diversification and lower vegetable crop specialization are associated with marketing inefficiency. The positive effect of selling to wholesalers implies that farms selling output to wholesalers, *ceteris paribus*, have a higher marketing inefficiency than those selling to retailers. As retailers are in direct contact with consumers (and they know the preferences of final consumers), this result implies that better quality products go to retailers, and the long-term relationship results in higher prices to producers. This is because the retailers have long-term contact with all categories of producers (small and large) unlike the wholesalers, who buy mainly from large producers. Compared to retailers, the negative effect of selling to consumers indicates that selling directly to consumers increases the marketing efficiency of the vegetable producers. This implies that vegetable producers should diversify their marketing outlets to increase their marketing efficiency. As indicated by many authors, producers who rely completely on wholesalers may have weak bargaining power (Haji and Andersson, 2006; Jaleta and Gardebroek, 2007). As producers are often concerned about maintaining a good relationship with their customers to secure their selling opportunities in the long term, the customers may take a lower price for granted (Lancioni, 2010). The

[5] There may also be an endogeneity issue where the worst managers receive more credit.

positive effect of the distance to the central market variable indicates that longer distances to the central market are likely to increase marketing inefficiency. The result implies that vegetable producers far from the central market have a weakened bargaining position due, in part, to the short-term life of the products. This result is in line with the findings of Jabbar and Akter (2006, 2008) in Vietnam.

In addition, we found that years of management experience of household head and the number of years spent in formal education negatively affect marketing inefficiency, thus implying that more experienced producers have increased bargaining power and generate a higher price for their products. The negative impact of the amount of credit received suggests that microfinance in agriculture helps farmers improve their market participation. The positive effect of the gender of the producer implies that women producers have more power in output price negotiations.

**Table 3.3. Second-stage coefficients and confidence intervals at 5% (n=186, B=2,000)**

| **Technical inefficiency ($\hat{\theta}_{TE}$)** | **Coefficients** | **Std. Err.** | **Intervals, 5%** |
|---|---|---|---|
| Constant | $0.5159^{***}$ | 0.0768 | [0.4109;0.7142] |
| Gender of the household head | - 0.0634 | 0.0435 | [-0.1015;0.0699] |
| Years of management experience of the household head | - 0.0024 | 0.0015 | [-0.0039;0.0018] |
| Number of years spent in formal education by the producer | $0.0009^{*}$ | 0.0026 | [-0.0094;0.0005] |
| Concentration of output shares | - 0.0842 | 0.0997 | [-0.3348;0.0563] |
| Number of public extension visits per year | - 0.0006 | 0.0010 | [-0.0019;0.0023] |
| Number of private extension visits per year | $0.0114^{**}$ | 0.0037 | [0.0017;0.0160] |
| Best soil fertility | $- 0.1518^{***}$ | 0.0469 | [-0.3432;-0.1479] |
| Medium soil fertility | $- 0.1571^{***}$ | 0.0346 | [-0.2485;-0.1062] |
| Amount of credit received | $0.00022^{***}$ | 0.00019 | [0.0001;0.0009] |
| Distance of the farm to the central market | 0.0022 | 0.0008 | [-0.0004;0.0027] |
| Statistics: Wald $\chi^2$ (10) = $40.88^{***}$ | | | |
| **Marketing inefficiency ($\hat{\theta}_{ME}$)** | **Coefficients** | **Std. Err.** | **Intervals, 5%** |
| Constant | $0.4454^{***}$ | 0.0389 | [0.2543;0.4154] |
| Gender of the household head | $0.01005^{**}$ | 0.0237 | [0.0004;0.1003] |
| Years of management experience of the household head | $- 0.0073^{***}$ | 0.00085 | [-0.0079;-0.0044] |
| Number of years spent in formal education by the producer | $0.0038^{**}$ | 0.0014 | [0.00096;0.0065] |
| Concentration of output shares | $- 0.3189^{***}$ | 0.0536 | [-0.3097;-0.0935] |
| Amount of credit received | $- 0.00024^{*}$ | 0.0001 | [-0.0004;0.00002] |
| Distance of the farm to the central market | $0.0021^{***}$ | 0.0005 | [0.0018;0.0037] |
| Fraction of vegetables sold to the wholesaler | $0.3533^{***}$ | 0.0224 | [0.2856;0.3744] |
| Fraction of vegetables sold to the consumer | $- 0.2080^{**}$ | 0.2151 | [-1.4193;-0.685] |
| Statistics: Wald $\chi^2$ (8) = $745.46^{***}$ | | | |

*Legend.* *** Significance at 1% level, ** Significance at 5% level, * Significance at 10% level.

As the parameter estimates for the inefficiency model presented in Table 3.3 only indicate the direction of the effects these variables have upon inefficiency levels, we estimate the contributions of these variables to the levels of inefficiency. The contributions are determined by the marginal effects, and we use the partial differentiation of the inefficiency predictors with respect to each of the inefficiency variables (Wilson et al. 2001; Zhu and Oude Lansink, 2010). Following Cameron and Trivedi (2009, p. 527), the marginal effect of a variable that is left-truncated at 0 is defined as follows:

$$\frac{\partial E(\hat{\theta}_{TE}|z,\hat{\theta}_{TE}>0)}{\partial z} = \left\{1 - \frac{z'\hat{\beta}^*_{TE}}{\hat{\sigma}^*_{TE}} * \frac{\phi(z'\hat{\beta}^*_{TE}/\hat{\sigma}^*_{TE})}{\Phi(z'\hat{\beta}^*_{TE}/\hat{\sigma}^*_{TE})} - \left[\frac{\phi(z'\hat{\beta}^*_{TE}/\hat{\sigma}^*_{TE})}{\Phi(z'\hat{\beta}^*_{TE}/\hat{\sigma}^*_{TE})}\right]^2\right\}\hat{\beta}^*_{TE} \tag{8}$$

where $\hat{\boldsymbol{\theta}}_{TE}$ is the technical inefficiency estimate, $z$ is an explanatory variable, $\hat{\beta}^*_{TE}$ are the consistent coefficients of the explanatory variables obtained from the truncated bootstrap regression, $\hat{\sigma}^*_{TE}$ is the standard deviation of the error term, $\phi(\cdot)$ is the standard normal distribution, and $\Phi(\cdot)$ represents the standard normal cumulative distribution function. We also compute the marginal effects for the case of marketing inefficiency. In Table 3.4, we only report the contributions of the variables that are significant.

**Table 3.4. Marginal effects of inefficiency effects model variables**

| **Technical inefficiency $(\hat{\boldsymbol{\theta}}_{TE})$** | **Coefficients** | **Std. Err.** | $\boldsymbol{P > \lvert z \rvert}$ |
|---|---|---|---|
| Best soil fertility | - 0.2334 | 0.0236 | 0.000 |
| Medium soil fertility | - 0.16099 | 0.0314 | 0.000 |
| Number of private extension visits per year | 0.0069 | 0.0032 | 0.030 |
| Amount of credit received | 0.00076 | 0.00017 | 0.000 |
| Number of years spent in formal education by the producer | - 0.0069 | 0.0023 | 0.003 |
| **Marketing inefficiency $(\hat{\boldsymbol{\theta}}_{ME})$** | **Coefficients** | **Std. Err** | $\boldsymbol{P > \lvert z \rvert}$ |
| Concentration of output shares | - 0.2595 | 0.0504 | 0.000 |
| Fraction of vegetables sold to the wholesaler | 0.3665 | 0.0215 | 0.000 |
| Fraction of vegetables sold to the consumer | - 0.0723 | 0.1703 | 0.671 |
| Distance of the farm to the central market | 0.0022 | 0.00046 | 0.000 |
| Years of management experience of the household head | - 0.0052 | 0.00078 | 0.000 |
| Number of years spent in formal education by the producer | 0.0027 | 0.0013 | 0.036 |
| Amount of credit received | - 0.000195 | 0.0001 | 0.058 |
| Gender of household head | 0.0875 | 0.0231 | 0.000 |

*Note. The marginal effect of each variable is evaluated at their mean value and discrete change of the dummy variable from 0 to 1.*

First, the marginal effect of the soil fertility index on technical inefficiency scores is -0.23 and -0.16 for best and medium soil fertility, respectively, suggesting that producers who farm poor land using organic fertilizer have an expected increase of approximately 23% in their technical inefficiency, most likely because they use more mineral and organic fertilizers to facilitate intensive cultivation. Second, for each additional private extension visit, the expected technical inefficiency of a producer decreases by 0.7%. As previously indicated, this suggests that private extension addresses practical problems associated with the use of inputs, indicating that extension visits help the worst performing producers focus on their management strategy. Our finding is consistent with the finding of Dinar et al. (2007). The policy implication of the results on extension services is that private extension improves the management skills of the worst performing producers. Third, farm debt is found to increase technical inefficiency, indicating that producers who have access to credit have an expected increase of 0.08% in technical inefficiency.

The parameter associated with the concentration of output share suggests that a vegetable producer who increases his/her specialization index by one unit reduces his/her marketing inefficiency by 26%. The results show that specialization increases the marketing performance of vegetable farmers and provides additional information to the common view that diversification is a strategy used by smallholders to manage risk. This finding is consistent with the findings of other authors (Allen and Lueck, 1998) that producers who focus on a small number of crops may be more efficient than those who are more diversified because of the relatively high skill level associated with individual crops. The contribution of the variable fraction of vegetables sold to wholesalers is 0.37, implying that producers who sell their products to retailers are expected to decrease their marketing inefficiency by 37%. Because the vegetable market is characterized by a large number of retailers, the result from selling to retailers implies that the long-term relationship of producers with retailers helps producers to obtain higher prices. Compared to retailers, selling directly to consumers would reduce the marketing inefficiency scores of producers by 7%. The results of this chapter stress the evidence that marketing activities are also important for vegetable producers in their production management strategy.

## 3.6. Conclusions

This study estimates technical and marketing inefficiency of a sample of urban vegetable producers in Benin. The study proposes a Russell-type measure of inefficiency using a directional distance function that accounts simultaneously for the expansion of outputs and prices and the reduction of variable inputs. The results indicate that producers are more inefficient in marketing (25%) than in production (14%). Additionally, results suggest that farmers vary widely in their technical and marketing inefficiency.

The truncated bootstrap regression of the determinants of the two inefficiency terms shows that more specialized producers have lower marketing inefficiency, and the soil fertility index negatively affects technical inefficiency. Another important finding that emerges from our analysis is that producers using retailer marketing arrangements are more marketing efficient than those selling to wholesalers. The result also suggests that private extension service agents mainly focus on the worst-performing producers.

The results further imply that agricultural policies should improve the capacity of producers to apply the available technology more efficiently. In addition, public and private extension services must focus on the managerial skills and sales management to help producers implement a profitable pricing strategy, rather than focusing solely on the production process. In conclusion, even though it is important to reduce the technology gap and improve the managerial skills of producers, agricultural policy must be accompanied by increasing market participation of farmers and market access to increase the economic impact of agriculture.

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# CHAPTER 4

## Assessing the impact of crop specialization on farms' performance in vegetables farming in Benin: a non-neutral stochastic frontier approach

**Abstract**

A non-neutral stochastic distance function model is used to examine whether output specialization has an impact on the economic performance of vegetable producers in Benin. Specialization is assumed to have an effect on the production frontier and on the distance to the production frontier (technical inefficiency). The technology is found to exhibit diseconomies of scope, indicating that vegetable producers have an incentive for specialization. At the same time, the degree of specialization has a positive effect on technical efficiency. From a policy perspective, the findings imply that current government policies to encourage diversification may lead to a lower performance.

*Keywords:* Farm performance, Specialization, Impact, Input distance function, Non-neutral stochastic frontier, Benin.

*JEL classifications*: C34, C52, Q12, Q16

## 4.1. Introduction

Over the last four decades, agricultural productivity has been growing at fairly high rates in most regions of the world, reflecting the important role played by innovations in agriculture. However, Sub-Saharan African countries are still far behind (Chavas, 2011; Fuglie, 2008). The main cause of the low levels of agricultural productivity in Sub-Saharan Africa is the ineffective establishment of agricultural R&D institutions to sustain productivity growth. This suggests the need for a more selective strategy that can help to increase the competitiveness of agriculture and the viability of small-scale farms in Sub-Saharan Africa. It is worth noting that Sub-Saharan African countries are categorized as agriculture-based countries in which agriculture contributes to approximately one third of overall GDP (Byerlee et al. 2009). Additionally, to reduce poverty and secure food needs in Sub-Saharan Africa, there is a growing interest in green revolution through diversifying production toward higher-value outputs. Vegetables in West Africa are an important crop and its importance is increasing over time. As fresh vegetables are characterized by high elasticity of demand, there is overwhelming evidence that vegetable production can contribute importantly to economic growth and food security. In Benin's vegetable sector, a large majority of farms produce both traditional and non-traditional vegetables, indicating that multi-output farms are the rule rather than the exception. By producing both categories of crops instead of only one, the farm may be able to reduce risk. For example, in some periods of the year, low revenues from traditional vegetables may be counterbalanced by relatively high revenues from non-traditional vegetables.

Another benefit associated with diversification is the complementary use of inputs on the farm (economies of scope). Diversification allows for more efficient use of inputs that can be used in different production processes (Teece, 1980). However, other studies have shown that specialization in crops allows operators to exploit scale economies. Moreover, specialized operators have better opportunities to fine-tune their skills (Oude Lansink and Stefanou, 2007). To the best of our knowledge no studies in West Africa explore the direct impact of horizontal crop choice strategies on producers' multi-output performance.

Most studies on the impact of specialization on technical efficiency regress the technical efficiency scores obtained from a stochastic frontier model on a specialization index using one- or two-stage procedures (Coelli and Fleming, 2004; Rahman and Rahman, 2008). This technique of measuring the effect of specialization on technical efficiency assumes a neutral effect of specialization, i.e. the composition of outputs is independent of the production process. The neutral specification ignores the adjustment of inputs with different output choices. In a multiple-output production technology the effects of specialization on technical efficiency may be related to input use, indicating that the effect of crop composition on technical efficiency is non-neutral. The non-neutral frontier model assumes that the method of application of inputs as well as the level of inputs (i.e. scale of operation) determine the potential output composition (Dinar et al. 2007; Huang and Liu, 1994; Karagiannis and Tzouvelekas, 2009).

The objective of this chapter is twofold. The first is to evaluate the causal effect of specialization on technical efficiency. The second objective is to investigate the presence or absence of economies of scope in vegetables farming. The non-neutral stochastic frontier approach is adopted to estimate the effect of specialization on production technology and technical efficiency. This flexibility of the model allows direct computation of a measure of economies of scope by exploiting the duality theory between the cost function and the input distance function.

The rest of this chapter is organized as follows. Section 4.2 discusses the conceptual framework and our modelling approach. The data and the empirical specification are described in Section 4.3. The empirical results are discussed in Section 4.4 and the chapter concludes in section 4.5.

## 4.2. Conceptual Framework and Modeling Approach

### 4.2.1. Distance Function

To explore the impact of crop diversification vs. specialization on the production process (i.e. on the shape of the production frontier) and on technical efficiency, we require a multi-output, multi-input specification of the technology. Distance functions developed by Shephard (1953, 1970) are shown to be a convenient way to represent a multiple-input multiple-output production technology (Coelli and Perelman, 1996; Färe and Primont, 1995; Morrison-Paul and Nehring, 2005). Such a specification may be characterized from the output or input perspective. Vegetable producers are likely to have more control over inputs rather than outputs, so input orientation is used here.

The input requirement set $L(y)$ represents the set of all input vectors, $x \in \Re_{+}^{K}$, which can produce the output vector $y \in \Re_{+}^{M}$:

$$L(y) = \{x \in \Re_+^K \ : x \ can \ produce \ y\} \tag{1}$$

This relationship can be used to develop an estimable form of an input distance function. The input distance function $D^I(x,y)$ identifies the quantity of $X$ necessary to produce $Y$, conditional on $L(y)$. More formally, as developed by Färe and Primont (1995):

$$D^I(x,y) = max\left\{\rho : \left(\frac{x}{\rho}\right) \in L(y)\right\} \tag{2}$$

where $\rho$ is a positive scalar "distance" by which the input vector can be deflated.

$D^I(x,y)$ can be interpreted as a multi-output input-requirement function allowing for deviations (distance) from the frontier. It gives the maximum amount by which an input vector can be radially contracted while still being able to produce the same output. The input distance function is greater than or equal to one if the input vector is an element of the feasible set, $L(y)$. The distance function is equal to unity if $x$ is located on the boundary of the input set. $D^I(x,y)$ is assumed to be non-decreasing, positively linearly homogenous and concave in inputs and non-increasing in outputs (Kumbhakar et al. 2008). Thus, all the deviations from the frontier are interpreted in terms of technical efficiency, $TE$. The input-contracting view of technical efficiency leads to the following definition:

$$TE^I(x,y) = [D^I(x,y)]^{-1} \tag{3}$$

This measure assumes values in the interval $(0, 1]$ and the points for which $D^I(x,y) = 1$ define the boundary of the input requirement set and can be interpreted as the proportion of the observed inputs that could be used to produce the same amount of output (Kumbhakar and Lovell, 2003, p. 50). To empirically estimate this function, linear homogeneity with respect to inputs must be imposed. This can be accomplished by normalizing by one input, i.e. $D^I(wx,y) = wD^I(x,y)$ for any $w > 0$, so if $w$ is set at $1/x_1$, $D^I(x,y)/x_1 = D^I(x/x_1, y) = D^I(x^*,y)$, where $x^* = x/x_1$.

Suppose that we have data on inputs and outputs for a sample of farms. Then, for producer $i$ we get:

$$TE_i^I = [D^I(x_i,y_i)]^{-1}e^{-v_i} \Leftrightarrow lnD^I(x_i,y_i) = -lnTE_i^I - v_i \tag{4}$$

where $v_i$ is a white-noise error term. From the above homogeneity property, we have:

$$lnD^I(x_i, y_i) = lnD^I(x_i^*, y_i) + lnx_1 \Leftrightarrow -lnx_1 = lnD^I(x_i^*, y_i) - lnD^I(x_i, y_i) \quad (5)$$

with $x_i^* = \frac{x_i}{x_1}$ and $x_1$ being the normalizing input. Substituting (4) in (5) we get an estimable form of the input distance function:

$$-lnx_1 = lnD^I(x_i^*, y_i) + lnTE_i^I + v_i = lnD^I(x_i^*, y_i) - u_i^I + v_i \quad (6)$$

where $u_i^I = -lnTE_i^I$ is treated as an one-sided error term. The equation can be estimated econometrically using maximum likelihood techniques, assuming that $v_i$ is independently and identically distributed random variable, $N(0, \sigma_v^2)$. However, as output crop composition influences both the production frontier and the efficiency with which producers utilize the resources, a modified non-neutral approach developed by Huang and Liu (1994) has to be employed. In reality, technical efficiency is dependent on the input choices and the method of application of inputs. Some vegetables may need more inputs and require more management skills than other vegetables . Following Alvarez et al. (2006) and Dinar et al. (2007), $u_i^I$ is modeled as:

$$u_i^I = g(z_i; \delta) + \varepsilon_i, \quad (7)$$

where $z$ is a vector of explanatory variables which includes an output specialization index, interactions between this index and the elements of $x_i$, and farm-specific characteristics (e.g. demographic, socio-economic, etc.) (Dinar et al. 2007; Huang and Liu, 1994); $\delta$ is a vector of parameters to be estimated and $\varepsilon$ is a random error referring to the unexplained or residual technical efficiency. The requirement that $u_i^I = g(z_i; \delta) + \varepsilon_i \geq 0$ is met by truncating $\varepsilon_i$ from below such that $\varepsilon_i \geq -g(z_i; \delta)$, and $\varepsilon_i$ is assumed to be an independently, but not identically distributed random variable with $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$[1]. Substituting equation (7) into equation (6) yields:

$$-lnx_1 = lnD^I(x_i^*, y_i) + v_i - [g(z_i; \delta) + \varepsilon_i], \quad (8)$$

[1] In the spirit of Huang and Liu (1994), $\varepsilon_i$ is assumed to follow a normal distribution with zero mode, truncated from below at a variable truncation point $[-g(z_i; \delta)]$, which allows $\varepsilon_i \leq 0$, but enforces $u_i^I \geq 0$.

The specification of the efficiency model allows for a non-neutral shift of observed input from the frontier. The assumptions imposed on $u_i^I$ and $\varepsilon_i$ are consistent with $u_i^I \sim N^+(g(z_i;\delta), \sigma_u^2)$ (Battese and Coelli, 1995), and that $v_i$ and $u_i^I$ are distributed independently (Kumbhakar and Lovell, 2003, p. 267). The first term on the right-hand side of equation (8) is the change in the frontier quantity of inputs; the g(·) function gives the change in the distance to the frontier i.e. technical efficiency. The information contained in the first right-hand side term can be used to test whether economies of scope exist. The log likelihood function of the above model is a straightforward extension of the Huang and Liu (1994) and can be found in Kumbhakar and Lovell (2003, p. 270).

A few comments are in place here. First, the model in (8) yields two effects of crop specialization on input uses. The first partial derivative of the input distance function defined in (8) with respect to one output is assumed to be negative, implying that an extra unit of output *ceteris paribus* reduces the amount by which the input vector has to be deflated to reach the production frontier (Coelli and Fleming, 2004). The dual relation between cost function and the input distance function can be exploited to derive a measure of economies of scope (or cost complementarities) without requiring estimates of the parameters of the cost function (Hajargasht et al. 2008). This approach has the advantages that the estimation of an input distance function does not require behavioral assumptions, such as cost minimization, nor does it require access to input price data, which are not available in our case (especially capital and land).

Second, the non-neutral specification gives a marginal contribution of output specialization on technical efficiency and varies with the farm's input utilization. It is important to indicate that the model is different from the one used by Rahman (2009) to explain the effect of diversification on technical efficiency. Rahman assumed a neutral specification where the marginal effect of crop diversification on technical efficiency is constant. Since the Huang and Liu (1994) paper, in which a neutral specification is demonstrated to suffer from misspecification, the non-neutral stochastic frontier model is preferred to a neutral model in many empirical applications (Alvarez et al. 2006; Dinar et al. 2007; Karagiannis and Tzouvelekas, 2009). These authors argued that the conventional formulation and estimation of the stochastic frontier production function may not be appropriate in identifying the sources of technical inefficiency in production. Also, Dinar et al. (2007) have shown that the hypothesis of a neutral shift in the production frontier is strongly rejected.

For the empirical implementation, we assume that the input distance function is approximated by a Translog. The Translog is a flexible functional form which approximates any twice differentiable function without imposing a priori restrictions on the production technology. However, a complication arises with the 'traditional' Translog specification because some producers in the sample are perfectly specialized in one category of vegetables (i.e. traditional or non-traditional vegetables). For this reason a modified Translog function is used in which vegetable outputs are adjusted according to the Battese (1997) transformation (see Tsekouras et al. 2004). Moreover, variables related to production conditions are included in the production frontier model (see e.g. Dinar et al. 2007; Sherlund et al. 2002). The empirical model is given by:

$$ln\, D_i^I/x_{1,i} = \beta_0 + \sum_d^D \beta_d F_{di} + \beta_1 D_{1i} + \beta_2 D_{2i} + \sum_k^K \beta_{k^*} lnx_{ki}^* + \frac{1}{2}\sum_k^K \sum_l^K \beta_{k^*l^*} lnx_{ki}^* lnx_{li}^* + \sum_m^M \beta_m lny_{mi} + \frac{1}{2}\sum_m^M \sum_n^M \beta_{mn} lny_{mi}\, lny_{ni} + \frac{1}{2}\sum_k^K \sum_m^M \beta_{km} lnx_{ki}^*\, lny_{ni} \quad (9)$$

where $x^*s$ are input quantities normalized by $x_1$, $ys$ are outputs, $Fs$ are physical production variables, and $i$ indexes farms. $D_1$ is a dummy variable for traditional vegetable production with $D_1 = 1$ if $y_{Trad} = 0$ and $D_1 = 0$ if $y_{Trad} > 0$; and $y_1 = Max(y_{Trad}, D_1)$. Similarly, $D_2$ is a dummy variable for non-traditional vegetable production with $D_2 = 1$ if $y_{NTrad} = 0$ and $D_2 = 0$ if $y_{NTrad} > 0$; and $y_2 = Max(y_{NTrad}, D_2)$. Using (8), we obtain the following estimable form:

$$-lnx_{1,i} = \beta_0 + \sum_d^D \beta_d F_{di} + \beta_1 D_{1i} + \beta_2 D_{2i} + \sum_k^K \beta_{k^*} lnx_{ki}^* + \frac{1}{2}\sum_k^K \sum_l^K \beta_{k^*l^*} lnx_{ki}^* lnx_{li}^* + \sum_m^M \beta_m lny_{mi} + \frac{1}{2}\sum_m^M \sum_n^M \beta_{mn} lny_{mi}\, lny_{ni} + \frac{1}{2}\sum_k^K \sum_m^K \beta_{km} lnx_{ki}^*\, lny_{ni} - u_i^I + v_i \quad (10a)$$

The modified non-neutral efficiency regression with interactions is given by ,

$$u_i^I = \delta_0 + \delta_I Spe_i + \sum_k^K \delta_{Ik} Spe_i lnx_{ki}^* + \sum_j^J \delta_{Ij} Spe_i A_{ji} + \varepsilon_i \quad (10b)$$

$Spe$ refers to specialization index and $As$ are farm characteristics; $x^*s$ are the same as defined in (9).

From (10b), the marginal effect of output crop specialization on the expected production efficiency is a function of the normalized inputs, farm characteristics and environmental variables. The marginal effect is given in Huang and Liu (1994), Kumbhakar and Lovell (2003, p. 270) and Wang (2002), and is:

$$\frac{\partial lnE(-u_i^I|\varepsilon_i)}{\partial Spe} = \psi\left[\delta_I + \textstyle\sum_k^3 \delta_{Ik} lnx_{ki}^* + \sum_j^4 \delta_{Ij} A_{ji}\right] E(exp\{-u_i^I\}|\varepsilon_i) \quad (11)$$

where

$$\psi = \left[\sigma_\varepsilon + \frac{\phi(\xi)}{1-\Phi(\xi)} - \frac{\phi(\sigma_\varepsilon+\xi)}{1-\Phi(\sigma_\varepsilon+\xi)}\right]\frac{1}{\sigma_\varepsilon},$$

$$\xi = \frac{\delta_0+\delta_I Spe_i + \sum_k^3 \delta_{Ik} Spe_i lnx_{ki}^* + \sum_j^4 \delta_{Ij} Spe_i A_{ji}}{\sigma_\varepsilon},$$

$$E(exp\{-u_i^I\}|\varepsilon_i) = exp\left[\sigma_\varepsilon\left(\xi + \frac{1}{2}\sigma_\varepsilon\right)\right]\frac{1-\Phi(\sigma_\varepsilon+\xi)}{1-\Phi(\xi)},$$

where $E$ is the expectation operator, $\phi$ and $\Phi$ are the probability and cumulative density functions of a standard normal distribution, respectively.

### 4.2.2. Economies of Scale and Scope

From equation (10a), the input elasticity for output $y_m$, $-\varepsilon_{D^I,y_m} = -\partial lnD^I/\partial lny_m = \partial lnx_1/\partial lny_m = \varepsilon_{x,y_m}$, represents the percent change in $x_1$ from a 1% change in $y_m$, holding all input ratios $x^*$ (and thus input composition) constant. The scale elasticity can be calculated as the negative sum of the input-output elasticities; that is, $-\varepsilon_{D^I,y} = -\sum_1^M \partial lnD^I/\partial lny_m = \sum_1^M \partial lnx_1/\partial lny_m = \sum_1^M \varepsilon_{x,y_m} = \varepsilon_{x,y}$. The measure of scale economies is indicated by the short-fall of $\varepsilon_{X,Y}$ from unity.

In a multiproduct production technology, economies of scope exist when for outputs $y_1$ and $y_2$, the average cost of joint production is less than the cost of producing each output separately (Cowing and Holtmann, 1983; Panzar and Willig, 1981; Teece, 1980). That is, economies of scope are measured by:

$$EOS = C(y_1, 0) + C(0, y_2) - C(y_1, y_2) \quad (12)$$

where $C(y_1, y_2)$ is the variable cost of producing both outputs simultaneously and $C(y_1, 0)$ and $C(0, y_2)$ denote the variable costs of producing the two outputs separately. Economies of scope exist if *EOS* > 0, in which case the costs of producing both outputs separately is higher than the cost of producing them jointly.

More generally, a sufficient condition for the presence of economies of scope between outputs $i$ and $j$ is:

$$\frac{\partial^2 C(\cdot)}{\partial y_i \partial y_j} < 0, \text{ for } i \neq j \tag{13}$$

where $C(\cdot)$ is the variable cost function. This expression implies that the cost function exhibits cost complementarities.

The input distance function and the cost function are dual to one another, meaning that the information contained in the input distance function about the production technology is identical to the cost function (Färe and Primont, 1995, p. 47-48). In this study, economies of scope are measured using a primal input distance function. Consequently, we use the dual measure of economies of scope approach developed by Hajargasht et al. (2008). In this chapter, the derivative-based measure of economies of scope is obtained by exploiting the duality between the shadow cost function and the input distance function. Focusing on the sufficient condition in (13), they derived a general expression to calculate the economies of scope between outputs $i$ and $j$ using the derivatives of the input distance function as follows:

$$C_{yy} = C\left\{D_y^I D_y^{I\prime} - D_{yy}^I + D_{yx}^I [D_{xx}^I + D_x^I D_x^{I\prime}]^{-1} D_{xy}^I\right\} \tag{14}$$

where subscripts denote partial differentiation.

From this equation, one can see that information on the sign of the second cross partial derivatives of outputs, $D_{yy}^I(i,j)$, is not sufficient to conclude if scope economies exist or not. As shown by Hajargasht et al. (2008), if the technology satisfies certain restrictions, such as input homotheticity or global constant returns to scale, simpler expressions are obtained. A value of (14) less than zero (i.e., $C_{yy}/C < 0$) indicates the presence of economies of scope, meaning that the vegetable producer has an incentive to diversify. In contrast, a value greater than zero (i.e., $C_{yy}/C > 0$) represents diseconomies of scope, implying that the producer has an incentive to specialize in the production of one output category.

## 4.3. Data and Specification of the Model

Data used in this chapter are part of a broader survey on the structural characteristics of the vegetable sector in southern Benin. The survey is based on farm-level cross-section data for the agricultural year 2009/2010. A multistage stratified random sampling technique was employed to locate the departments, the cities/towns in each of the four departments, and the sample households. Data are available for a total of 239 households[2]. Vegetable producers are usually involved in producing two categories of vegetables, i.e. traditional vegetables and non-traditional vegetables. The data set contains 23 non-traditional ($y_{NTrad}$) vegetable crops and 10 traditional ($y_{Trad}$) vegetable crops (see Achigan-Dako et al. 2009 for detail on vegetables grouping). Four inputs are distinguished: material cost ($x_{Mat}$) that include fertilizer, pesticides, seeds, and other miscellaneous expenses; farm labor in hours ($x_{Lab}$); capital ($x_{Cap}$) measured in replacement cost and farmland in hectares ($x_{Land}$). Two soil fertility indicators (dummy) variables are used as additional variables in the specification of the distance function.

The specialization variable is specified as a normalized Hirschman index of the concentration of output shares for each vegetable crop. This index discriminates between producers who are relatively more specialized. It is a widely used measure of concentration and was used, for example, by Al-Marhubi (2000) to specify the concentration of output shares in his analysis of export diversification and growth. Following Al-Marhubi (2000, p. 561), the normalized Hirschmann index is defined as follows:

$$H_i = \frac{\sqrt{\sum_j^{33}\left(\frac{q_j}{\sum_j^{33} q_j}\right)^2} - \sqrt{1/33}}{1-\sqrt{1/33}} \tag{15}$$

where i is the producer index, $q_j$ represents the producer output quantity of vegetable crop j, and 33 is the number of vegetables produced in the data set. The Hirschmann index is normalized to assume values ranging from 0 to 1. Note that a normalized Hirschmann index of 1 indicates perfect specialization. Likewise, a value closer to 0 signifies a more diversified vegetable crop production.

[2] The sample producers were selected based on the information on the total number of vegetable producers including their farms size categories, which were obtained from a census survey in each city/town. Then a stratified random sampling procedure was applied using a formula from Whitley and Ball (2002) with a 5% error limit.

Based on the existing literature, farmers' socio-economic characteristics are included in the model. These are: producers' education ($EDUC$), and farming experience ($EXP$). Most empirical studies found that farm experience and producer education have the strongest impact on the producer management practices. For example, Pope and Prescott (1980) found that less experienced farmers (or younger farmers) are more specialized as they may start small and specialized operations, and perhaps become more diversified as they expand their operations. Katchova (2005) found that more educated farmers have higher excess farm values. The ratios of the amount of credit received by producer over total revenue ($MCRED$), and the proportion of vegetables sold to wholesaler ($WHOLE$) are included to represent socioeconomic characteristics of farms. Vegetable cultivation requires more purchased inputs such as fertilizers, pesticides, and irrigation water, increasing the need for liquidity in hand. Vegetable cultivation also demands more labor than field crops, such as cereals and a large proportion of labor in vegetable cultivation is hired labor (Ali and Abedullah, 2002). All these conditions increase the demand for liquidity in vegetable production. Consequently, more loans are required to finance vegetable production. Vegetables have a shorter shelf life than cereal crops, so strong relationships between producers and buyers are essential to ensure a timely delivery to the market. Hence, the proportion of vegetable output sold to wholesaler is included in the model as an explanatory variable. Table 4.1 presents summary statistics for all farms. Aggregate non-traditional vegetable outputs represent 55% of the total vegetable output share, meaning that producing non-traditional vegetables is one of the strategic decisions made by producers.

In our model specification (10a), capital is set as the normalizing input $x_1$ so that all other inputs are represented relative to capital. All input and output variables were mean-corrected prior to estimation, so that the coefficients of the first-order terms can be directly interpreted as distance elasticities evaluated at the geometric mean of the data. That is, each output and input variable has been divided by its geometric mean.

## 4.4. Empirical Results

### 4.4.1. Economies of Scale and Scope

The parameter estimates of the Translog specification of the input distance are presented in Table 4.2. The results show that all elasticities (first-order terms for input and output variables) are between zero and one and possess the expected signs at the geometric mean.

**Table 4.1. Descriptive Statistics of the Variables[a] ($n = 239$)**

| Variable | Variable | Mean[b] | St. dev. | Min. | Max. |
|---|---|---|---|---|---|
| **Economic data** | | | | | |
| Aggregate output for traditional vegetables[c] ($10^3$ F CFA) | $y_{Trad}$ | 2,269 | 3,767 | 5.136 | 2.40E+4 |
| Aggregate output for non-traditional vegetables[c] ($10^3$ F CFA) | $y_{NTrad}$ | 1,574 | 3,386 | 24.355 | 3.42E+4 |
| Total output ($10^3$ FCFA) | - | 3,818 | 6,585 | 141.70 | 4.67E+4 |
| Materials ($10^3$ F CFA) | $x_{Mat}$ | 367.431 | 488.614 | 14.750 | 4,712 |
| Labor (Hours) | $x_{Lab}$ | 314.861 | 125.472 | 83.294 | 912.307 |
| Capital ($10^3$ F CFA) | $x_{Cap}$ | 465.844 | 525.613 | 1.350 | 2,739 |
| Land area (ha) | $x_{Land}$ | 0.4879 | 0.9824 | 0.0048 | 10.5 |
| Specialization index | $SPE$ | 0.5748 | 0.1677 | 0.2407 | 1 |
| Dummy for traditional vegetables | $d\_Trad$ | 0 = 02.09%<br>1 = 97.91% | | | |
| Dummy for non-traditional vegetables | $d\_NTrad$ | 0 = 18.83%<br>1 = 81.17% | | | |
| **Farm characteristics** | | | | | |
| Years of management experience in vegetables production (Year) | $EXP$ | 14.0042 | 9.2757 | 1 | 40 |
| Number of years spent in formal education by the producer (Year) | $EDUC$ | 6.9539 | 5.2574 | 0 | 21 |
| Ratio of credit received over revenue (Ratio) | $MCRED$ | 0.0758 | 0.1372 | 0 | 0.8241 |
| Fraction of vegetables output sold to Wholesaler | $WHOLE$ | 0.39361 | 0.4470 | 0 | 1 |

[a] Descriptive statistics calculated for non-zero output observations.
[b] Frequencies are reported for dummy variables.
[c] Aggregate output consists of the average price of crops times the quantity produced.
$1US = 494.030 F CFA in 2010 or 1 Eur = 655.957 F CFA.

Hence, the input distance function satisfies the property of monotonicity, i.e. the input distance function is non-decreasing in inputs and non-increasing in outputs.

The two output dummy variable parameters are both statistically significant at the 5% critical level, showing that the hypothesis that the intercepts are equal for both types of vegetable producers (specialized in one output and not) is rejected. This result implies that a considerable bias would be introduced in the parameter estimates if the distance function was estimated without addressing explicitly this “zero” observation problem (Battese, 1997; Tsekouras et al. 2004).

The returns to scale calculated as the negative of the sum of the first-order output coefficients is 0.23, indicating possible presence of increasing returns to scale economies at the sample mean. The null hypothesis of constant returns to scale (CRS) is tested using a Wald test on the sum of the two output coefficients. The resulting $\chi^2$ statistic shows that the null hypothesis of CRS is rejected at the 1% critical level.

**Table 4.2. MLE estimates of the Translog input distance function frontier**

| Coefficients[a] | Estimates | S.E. | $P > \|z\|$ | Coefficients | Estimates | S.E. | $P > \|z\|$ |
|---|---|---|---|---|---|---|---|
| $\beta_0$ | 0.7321*** | 0.1547 | 0.000 | $\beta_{Trad\_NTrad}$ | -0.0256 | 0.0247 | 0.300 |
| $\beta_{Mat}$ | 0.1613** | 0.0642 | 0.012 | $\beta_{Trad\_Mat}$ | 0.1196*** | 0.0327 | 0.000 |
| $\beta_{Lab}$ | 0.6954*** | 0.0655 | 0.000 | $\beta_{Trad\_Lab}$ | -0.1261*** | 0.0313 | 0.000 |
| $\beta_{Land}$ | 0.1237* | 0.0647 | 0.056 | $\beta_{Trad\_Land}$ | 0.0108 | 0.0209 | 0.604 |
| $\beta_{Mat\_Mat}$ | 0.0423 | 0.0279 | 0.129 | $\beta_{NTrad\_Mat}$ | -0.0257 | 0.0351 | 0.465 |
| $\beta_{Lab\_Lab}$ | -0.04756 | 0.0355 | 0.181 | $\beta_{NTrad\_Lab}$ | -0.0016 | 0.0427 | 0.969 |
| $\beta_{Land\_Land}$ | 0.0012 | 0.0186 | 0.947 | $\beta_{NTrad\_Land}$ | 0.0809** | 0.0336 | 0.016 |
| $\beta_{d\_Trad}$ | -0.3316*** | 0.1274 | 0.009 | $\beta_{Mat\_Lab}$ | 0.0533 | 0.0496 | 0.283 |
| $\beta_{d\_NTrad}$ | -0.2095*** | 0.0642 | 0.001 | $\beta_{Mat\_Land}$ | -0.1987*** | 0.0606 | 0.001 |
| $\beta_{Trad}$ | -0.1379*** | 0.0221 | 0.000 | $\beta_{Lab\_Land}$ | 0.1804*** | 0.0491 | 0.000 |
| $\beta_{NTrad}$ | -0.0878*** | 0.0250 | 0.000 | $\beta_{B\_Soil}$ | 0.0016 | 0.0591 | 0.978 |
| $\beta_{Trad\_Trad}$ | -0.0337*** | 0.0112 | 0.003 | $\beta_{M\_Soil}$ | 0.0119 | 0.0429 | 0.780 |
| $\beta_{NTrad\_NTrad}$ | -0.0056 | 0.0191 | 0.770 | | | | |
| ***Model diagnostic*** | | | | | | | |
| Log likelihood | -2.5714 | | | | | | |
| Wald $\chi^2_{24}$ | 3506.26*** | | | | | | |
| $RTS = \|\beta_{Trad} + \beta_{NTrad}\|$ | 0.2257 | | | | | | |
| Number of obs. | 239 | | | | | | |

[a] RTS stands for the returns to scale; veg. for vegetables.
*** Significance at 1% level, ** Significance at 5% level, * significance at 10% level.

Additionally, the inverse of this sum is equal to 4.43, providing a measure of Ray scale economies, suggesting the presence of increasing returns to scale. Thus, the transformation process described in our model may be thought of as exhibiting increasing returns to scale. This is important for computing the economies of scope in the next paragraph as the calculation of economies of scope are based on an input distance function that exhibits variable returns to scale. This finding is consistent with results in many other empirical analyses of small-scale farms (e.g. Coelli and Fleming, 2004) and implies that vegetable farms are likely to benefit from scale increases. The individual output contributions underlying the scale elasticity show that both categories of output contributed significantly to input use. The result indicates that traditional vegetables require a greater input share than non-traditional vegetables. However, both outputs appear to have almost similar output share (45% for traditional vegetables and 55% for non-traditional vegetables) (Table 4.1). The Pearson correlation test indicates that the two outputs are not correlated. However, the theory of diversification pointed out that even though a Pearson correlation test shows that two outputs are not correlated, the production of one can be reduced if uncertainty over the second output rises (Just and Pope, 1978).

To further investigate the implications of our estimates about output complementarities, we focus on the economies of scope equation in (14). Since the data are mean-corrected prior to the estimation of the distance function, the presence of economies of scope is evaluated at the means of the sample data. The expression of $C_{yy}(1{,}2)/C$ evaluated at the sample means of the data is equal to 0.085. This value implies that vegetable producers have 8.5 per cent higher costs by producing traditional vegetables together with non-traditional vegetables compared to producing the two categories of outputs separately. Therefore, vegetable producers have a strong incentive for specialization in the production of one of the two outputs defined in this study. This result is in line with the finding of Oude Lansink and Stefanou (2001) who found substantial diseconomies of scope in the Dutch arable farms when considering dynamic adjustments of areas of crops. The incentive for specialization in traditional vegetables is relatively higher than the incentive for specialization in non-traditional vegetables, since the scale effect of traditional vegetables is higher than the scale effect of non-traditional vegetables (Table 4.2). An explanation of the presence of diseconomies of scope is that the two groups of outputs are produced in the same period and have the same input requirements.

### 4.4.2. Impact of specialization on technical efficiency

Table 4.3 provides the results of the estimation of the non-neutral technical efficiency effect model. The estimated variances $\sigma^2$ and $\sigma_u^2$ are 0.086 and 0.047, respectively. The parameter $\gamma$ is positive and significant at the 5% critical level, indicating that technical inefficiency is likely to have an important role in explaining variability in performance among vegetable producers in the sample. The value of $\gamma$ in Table 4.3 indicates that about 54.2% of the variability of the disturbances is due to technical inefficiency.

Table 4.4 reports the results of the likelihood-ratio (LR) test of several hypotheses on the technology and technical efficiency. First, the null hypothesis that a distribution of $u^I$ has a mode at zero, that is $\delta_0 = \delta_{Spe} = \delta_{Spe\_Mat} = \delta_{Spe\_Lab} = \delta_{Spe\_Land} = \delta_{Spe\_Exp} = \delta_{Spe\_Educ} = \delta_{Spe\_Mcred} = \delta_{Spe\_Whole} = 0$ is rejected at the 5% critical level. This implies that the technical efficiency specification in (10b) cannot be reduced to the half-normal model as proposed by Aigner et al. (1977). Second, we tested for the effect of output specialization on technical efficiency. The null hypothesis is, $\delta_{Spe} = \delta_{Spe\_Mat} = \delta_{Spe\_Lab} = \delta_{Spe\_Land} = \delta_{Spe\_Exp} = \delta_{Spe\_Educ} = \delta_{Spe\_Mcred} = \delta_{Spe\_Whole} = 0$ (i.e. the specification is truncated normal stochastic frontier model with constant mode $\delta_0$). This hypothesis is rejected at the 5% critical level implying that technical inefficiency follows a truncated normal distribution with variable mode depending on vegetable crop specialization. Third, in specifying the model we assumed that specialization in output production has a non-neutral effect on technical efficiency. The null hypothesis is, $\delta_{Spe\_Mat} = \delta_{Spe\_Lab} = \delta_{Spe\_Land} = \delta_{Spe\_Exp} = \delta_{Spe\_Educ} = \delta_{Spe\_Mcred} = \delta_{Spe\_Whole} = 0$, is rejected at the 5% critical level indicating that the non-neutral effect of specialization on technical efficiency in (10b) cannot be reduced to a neutral specification that was used by e.g. Coelli and Fleming (2004) and Rahman (2009). This outcome implies that crop specialization does not have a constant impact on technical efficiency.

**Table 4.3. MLE estimates of the efficiency effect model (Non-neutral specification)[3]**

| Variables[a] | Coefficients | Estimates | S.E. | $P > \|z\|$ |
|---|---|---|---|---|
| Constant | $\delta_0$ | 0.1985 | 0.2211 | 0.369 |
| Specialization | $\delta_{Spe}$ | -0.7449* | 0.4493 | 0.097 |
| Specialization × ln(Materials/Capital) | $\delta_{Spe\_Mat}$ | -0.2422 | 0.2525 | 0.338 |
| Specialization × ln(Labor/Capital) | $\delta_{Spe\_Lab}$ | -0.0430 | 0.1622 | 0.791 |
| Specialization × ln(Land/Capital) | $\delta_{Spe\_Land}$ | 0.4258** | 0.1689 | 0.012 |
| Specialization × Experience | $\delta_{Spe\_Exp}$ | 0.0023 | 0.0077 | 0.770 |
| Specialization × Education | $\delta_{Spe\_Educ}$ | 0.0244* | 0.01269 | 0.054 |
| Specialization × Credit | $\delta_{Spe\_Mcred}$ | 0.00067 | 0.00086 | 0.438 |
| Specialization × Wholesaler | $\delta_{Spe\_Whole}$ | 0.5883** | 0.27489 | 0.032 |
| $\sigma^2 = \sigma_v^2 + \sigma_u^2$ | | 0.08646 | 0.0282 | |
| $\gamma = \sigma_u^2/\sigma^2$ | | 0.5416 | 0.2536 | |
| $\sigma_u^2$ | | 0.0468 | 0.0364 | |
| $\sigma_v^2$ | | 0.0396 | 0.0112 | |

[a] Specialization stands for Specialization index; Experience for Years of management experience in vegetable production; Education for Number of year spent in formal education by the producer; Credit for ratio of amount of credit received over total revenue; Wholesaler for fraction of vegetable sold to wholesaler.
*** Significance at 1% level, ** Significance at 5% level, * significance at 10% level.

**Table 4.4. Tests of hypotheses for parameters of the efficiency frontier model for vegetable producers in Benin**

| No. | Hypothesis | LR-test | Critical value at 0.05 |
|---|---|---|---|
| 1. | Ho. Aigner et al. (1977) formulation (i.e. $\delta_0 = \delta_{Spe} = \delta_{Spe\_Mat} = \delta_{Spe\_Lab} = \delta_{Spe\_Land} = \delta_{Spe\_Exp} = \delta_{Spe\_Educ} = \delta_{Spe\_Mcred} = \delta_{Spe\_Whole} = 0$) | 42.77 | $\chi_9^2 = 16.27^*$ |
| 2. | Ho. Stevenson. (1980) formulation (i.e. $\delta_{Spe} = \delta_{Spe\_Mat} = \delta_{Spe\_Lab} = \delta_{Spe\_Land} = \delta_{Spe\_Exp} = \delta_{Spe\_Educ} = \delta_{Spe\_Mcred} = \delta_{Spe\_Whole} = 0$) | 21.93 | $\chi_8^2 = 15.51$ |
| 3. | Ho. Coelli and Fleming (2004) neutral specification (i.e. $\delta_{Spe\_Mat} = \delta_{Spe\_Lab} = \delta_{Spe\_Land} = \delta_{Spe\_Exp} = \delta_{Spe\_Educ} = \delta_{Spe\_Mcred} = \delta_{Spe\_Whole} = 0$) | 31.13 | $\chi_7^2 = 14.07$ |

* The critical value is obtained from Kodde and Palm (1986, Table 1) as the LR-test statistic follows a mixed chi-squared distribution.

[3] We have also experimented an alternative model by adding the four farm characteristics variables standing alone into the above model to check the individual effects of these variables and encounter omitted variable bias. But this model couldn't converge because of high multicollinearity problems.

The result shows that specialization has a positive effect on vegetables farmers' technical efficiency. These results are consistent with the results of Alvarez et al. (2006) and Dinar et al. (2007) who found that restrictions on the general non-neutral model are rejected.

Column 2 of Table 4.5 shows the average technical efficiency and its quartile distribution. The result reveals a positive skewness in the distribution of technical efficiency. The average technical efficiency of the sample is 79.40%, implying that the same output can be produced with 79% of the observed inputs. In addition, Table 4.5 reports the quartile distribution of the marginal effects of crop specialization on the technical efficiency, (computed using (11)). The results suggest a positive effect of specialization on technical efficiency. As indicated by Wang (2002), the opposite marginal effects in these two quartiles show that specialization in vegetable outputs production affects technical efficiency non-monotonically in the sample. Consequently, the results cannot tell more about when the impact of crop specialization turns from negative to positive. Since we cannot interpret directly the meaning of the marginal effects, we also compute the elasticity of technical efficiency with respect to specialization using the method described in Cameron and Trivedi (2009, p. 335). On average, the contribution of vegetable output specialization to technical efficiency is found to be quite low, but different from zero at the 5% level of significance. Specifically, the result shows that a 1% increase in specialization is associated with a 0.02% increase in technical efficiency. The result implies that, on average, specialization generates gains in technical efficiency. This suggests that the costs of diversifying outweigh the benefits, and specializing is the preferred strategy. The results are consistent with the findings in many empirical works, indicating that diversification often requires specialized equipment and that diversified farms accumulates fewer assets than specialized farms (Harwood et al. 1999). In line with Katchova (2005), the results suggest that diversified vegetable farms had a lower excess value than specialized farms. The results are also in line with the finding of

**Table 4.5. Distribution of technical efficiency and the marginal effect and elasticity of technical efficiency with respect to specialization**

| | Mean efficiency (TE) | Marginal effect of Specialization (ME) | Elasticity with respect to Specialization (EL)[a] |
|---|---|---|---|
| First Quartile | 0.3458 | -0.1941 | -0.1405 |
| Median | 0.8514 | 0.0281 | 0.2035 |
| Third Quartile | 0.9086 | 0.0580 | 0.4200 |
| Mean | 0.7940 | 0.0169 | 0.0123 |

[a] $EL = ME \times \frac{\overline{TE}}{\overline{Spe}}$, where $\overline{TE}$ refers to mean of technical efficiency; $\overline{Spe}$ mean of specialization index (Cameron and Trivedi, 2009, p. 335)

Llewelyn and Williams (1996) for irrigated farms in Indonesia, that greater diversification is associated with lower technical efficiency. Since vegetables are cash crops, the result stresses that diversification increases costs by the presence of diseconomies of scope and by decreasing technical efficiency. The reason for our finding is that the two categories of vegetables are grown in the same period and compete for the same inputs (labor, pesticides, fertilizers and water) and require similar managerial skills. Like in Rahman's (2009) study of smallholders in Bangladesh, the worsening evidence of diversification economies observed between traditional and non-traditional vegetables is largely due to the practice of producing both categories of crops. From the survey results, it turns out that vegetable production is generally input intensive regardless of the type of vegetable in consideration. However, this result is in contrast with Coelli and Fleming (2004) who found that greater specialization leads to lower technical efficiency.

## 4.5. Conclusion and Implications

This chapter provides an empirical evaluation of the impact of crop specialization on vegetable producers' economic performance in Benin. The challenge in this chapter was to assess whether changes in farm orientation through diversification or specialization can be attributed to the search for greater performance. We based our estimation on a non-neutral stochastic frontier model to test and consider the adjustment of input utilization with output choices and estimate the effect of specialization on production technology and producer management performance. The study employs a parametric method in estimating an input distance function using a modified Translog specification and a truncated efficiency regression, representing efficiency in production. The results show a prevalence of increasing returns to scale. Compared to non-traditional vegetables, traditional vegetables have greater returns to scale. The results also provide evidence for diseconomies of scope, indicating that vegetable producers have a strong incentive for specialization in either traditional or non-traditional vegetables. The production of traditional and non-traditional vegetables jointly at the farm-level induces 8.5 per cent higher costs compared to producing the two output categories separately. The contribution of vegetable output specialization to technical efficiency is found to be quite low, but significant. Specifically, a 1% increase in crop specialization is associated with a 0.02% increase in technical efficiency.

Our results suggest that policy makers aiming at food security and agricultural growth may enhance specialization. The policy implication of this chapter is that the current government agricultural policy to encourage diversification may lead to larger costs and greater technical inefficiency of production.

## CHAPTER 5

# Efficiency analysis of pesticide use in vegetable production in Benin


## Abstract

This chapter analyzes the efficiency of pesticide use in vegetable production in Benin. A bootstrap DEA technique is applied to estimate the mean and 95% confidence interval of technical efficiency and the value of the marginal product of pesticides. Technical efficiency measures show that the initial DEA estimators are biased upward. The bias-corrected efficiency estimator indicates that vegetable producers are less efficient in terms of pesticide use than in the use of other inputs. Also, results suggest that along with pesticides, land and fertilizer are overused. The findings imply that efforts should be made to enhance the market of approved pesticides and that the training of vegetable producers could be appropriate in order to limit the overuse of pesticides. Special attention should be paid to a coordinate policy between different actors that aims at reducing structural dependence on pesticide use.



*Keywords*: vegetables, pesticides, efficiency, shadow prices, smooth bootstrap, Benin.

*JEL Classifications*: C6, D49, Q0, Q1

## 5.1. Introduction

In Sub-Saharan Africa, both domestic and international demand for vegetables is showing upward trends. In recent years increasing attention has been directed towards vegetable production and consumption. Vegetables are essential for a healthy and balanced diet and add variety, interest and flavor to the menu. Vegetable crops are, however, susceptible to pests and diseases. High-value vegetables are sensitive to pest pressure and subject to intensive application of pesticides. To prevent and cure from pests and diseases, farmers use a large amount of pesticides on vegetables such as insecticides, fungicides and herbicides. In contrast to traditional food crops like cereals, cassava and rice, several authors found that farmers in Sub-Saharan Africa use a large amount of pesticides on vegetables and the use is exacerbated by insecticide resistance (Dinham, 2003; Martin et al. 2006).

Pesticide use has been standard practice in vegetable production for several decades and an increase in intensity is due to higher pest pressure reported by producers in recent years. For example, Williamson et al. (2008) found that vegetable producers in Benin used larger volumes of pesticides than vegetable farmers in Ghana and Ethiopia and reported higher frequency of application (every 3-5 days insecticides spraying) than cotton farmers. Previous research also showed that small scale vegetables farmers did not receive adequate agricultural extension services and were lacking knowledge in pesticide use (Ngowi et al. 2007). There is evidence that the pesticide use in the vegetable production in urban and peri-urban areas is much more intensive than in the rural areas.

The problems associated with pesticide use in developing countries have been widely documented (see Dinham, 2003 for an overview). Inappropriate use of pesticides has consequences not only for the effectiveness of the intended pest control but also for operator and consumer health, farm livestock, soil organisms, wildlife and vegetation and may lead to contamination of soil, water and air (Williamson et al. 2008). Consequently, much of the interest in pesticide use in vegetable production in West Africa has focused on alternative methods to control pest attacks. In fact, various policies aiming at reducing the use and dependence of vegetables on synthetic pesticides are encouraged and tested in West Africa, including classical biological control, resistant varieties, crop rotation, recycling of organic matter and biopesticide use (Martin et al. 2006). On the other hand, availability and affordability of pesticides was a major concern for many vegetable producers. The market of pesticides in Benin is composed of formal and informal markets where both approved and banned pesticides are sold. Williamson et al. (2008) indicated that the relative costs of pesticides have risen sharply in recent years, implying that insight into the value of the marginal product of pesticides in vegetable production could help to determine the optimal level of pesticide use.

The empirical economics literature on pesticide use in vegetable production in Benin, however, has paid little attention to the value of the marginal product of pesticides. Most farm-level economic analysis of pesticide use has focused on cost-benefit analysis and the willingness to pay for biopesticides or organically grown vegetables (Adégbola and Singbo, 2001; Coulibaly et al. 2006, 2011; Martin et al. 2006; Singbo et al. 2008). A major limitation of these studies is that they did not investigate the technical interdependence between pesticides and other productive inputs. Biological evidence supports the importance of allowing for interactions among inputs, practices and outputs when non-experimental data are used. Furthermore, these previous studies treated pesticides as an output expanding input, while agronomic evidence suggest that pesticides reduce crop damage (Lichtenberg and Zilberman, 1986). Thus, ignoring the interaction between productive and damage abatement inputs may bias the estimation of technical efficiency and value of marginal product of pesticides.

The literature uses two alternative frameworks for incorporating pesticides as a damage control input into a production function: the abatement function (Lichtenberg and Zilberman, 1986) and the output damage function (Fox and Weersink, 1995). In the former, it is assumed that the abatement function is independent of the initial infestation, implying that the abatement function approach is an appropriate modeling method when pesticides are applied in a prophylactic way to prevent infestation or diseases. The other specification, i.e. the output damage function assumes that the effect of pesticides on the effective output is the result of a process involving two stages: (a) the effect of the damage control input on the damage agent (abatement), and (b) the effect of the remaining damage agent on the effective output. In the first stage, pest incidence depends on the untreated pest population and on the proportion of it controlled by the abatement activities. In the second stage, effective output is indirectly affected by abatement through the loss caused by the remaining damage agent incidence. The output damage function approach is more appropriate when pesticides are applied once pest incidence is realized (Karagiannis and Tzouvelekas, 2011).

Parametric and non-parametric approaches have been used to study the value of the marginal product of pesticides. A limitation of most studies using the parametric approach is the assumption of asymmetry between damage abatement and productive inputs, i.e. homothetic separability of productive inputs and damage abatement inputs. This implies that the asymmetric specification fails to recognize the interactions and interdependencies across inputs, field practices, pest population and pest treatments. Oude Lansink and Carpentier (2001) adopted a parametric approach based on Carpentier and Weaver (1997), that treating damage abatement inputs and productive inputs symmetrically. More recently, Oude Lansink and Silva (2004) provided an empirical application of a non-parametric data envelopment analysis (DEA) model in an effort to investigate the technical interdependence between productive inputs and pesticides[1]. Like all non-parametric approaches, their approach is attractive because no functional form needs to be assumed to represent the production technology. Furthermore, the non-parametric DEA approach allows for simultaneously measuring the technical efficiency of inputs. Moreover, bootstrap methods have been proposed to assess the uncertainty due to sample variation by estimating bias, confidence intervals and testing hypotheses.

The objective of the chapter is threefold. First, we use a multiple-output, multiple-input technology framework to estimate technical efficiency and the value of the marginal product of pesticides and other inputs. The effect of pesticides on the value of the marginal product of other inputs is investigated in order to analyze the technical interdependence between damage abatement and productive inputs. Second, we propose a bootstrap method for obtaining confidence intervals of technical efficiency and the value of the marginal product. The application focuses on a sample of vegetable producers in Benin.

The remainder of this chapter is organized as follows. Section 5.2 presents DEA models and the bootstrap technique to correct for bias and determine confidence intervals of technical efficiency and the value of the marginal product. The data

[1] Technical interdependence relates to the impact of an input on the value of the marginal product of another input. If the value of the marginal product of an input increases (decreases) as the other input increases, then the two inputs are complements (substitutes) (Beattie and Taylor, 1993; Oude Lansink and Silva, 2004).

employed in the chapter is described in section 5.3, followed by the presentation of the empirical results in section 5.4. Concluding remarks follow in the last section.

## 5.2. Input Distance Function with Damage Abatement Inputs

### 5.2.1. DEA Models Incorporating Damage Abatement Inputs

Consider a sample of $N$ farms which produce $Q$ marketed outputs from $P$ purchased productive inputs and $A$ purchased damage abatement inputs. Let $y \in \Re_+^Q$, $x \in \Re_+^P$, and $z \in \Re_+^A$ denote vectors of non-negative outputs, non-negative productive inputs and non-negative damage abatement inputs, respectively. The production technology for a decision making unit (DMU) is fully represented by the input requirement set:

$$L(y) = \{(x, z) \in \Re_+^P \times \Re_+^A | (\boldsymbol{x}, \boldsymbol{z}) \text{ can produce } \boldsymbol{y}\} \tag{1}$$

which represents the set of all feasible combinations of vectors of productive and damage abatement inputs given a vector of output $y$. A non-parametric representation of $L(y)$ is:

$$L(y) = \{(x, z): Y'\lambda \geq y_i, X'\lambda \leq x_i, Z'\lambda \leq z_i, \mathbf{I}'\lambda = 1, \lambda \geq 0\} \tag{2}$$

where $Y$ is the $(N \times Q)$ matrix of observed outputs, $y_i$ is the vector of observed outputs of farm $i$, $X$ is the $(N \times P)$ matrix of observed productive inputs, $x_i$ is the vector of productive inputs used by farm $i$, $Z$ is the $(N \times A)$ matrix of observed damage abatement inputs, $z_i$ is the vector of damage abatement inputs (pesticides) used by farm $i$; $\lambda$ is a $(N \times 1)$ vector of intensity variables (farm weights) and **I** is the $(N \times 1)$ unitary vector. We assume that (1) satisfies the standard regularity conditions: possibility of inaction, no free lunch, strong input and output disposability, closedness of $L(y)$ and variable returns to scale (VRS) (Färe, 1988, p. 35; Färe and Grosskopf, 1990; Fukuyama and Weber, 2002). The VRS condition ($\mathbf{I}'\lambda = 1$) ensures that increased amounts of inputs do not necessarily lead to a proportional increase of the amount of outputs. Technical efficiency is defined as the ability of a farm to use the minimum feasible amounts of productive and damage abatement inputs to produce a given level of output. Hence technical efficiency is measured relative to production possibilities characterized by $L(y)$. The Shephard input distance function is defined as:

$$D^I(x, z, y) = sup\{\gamma > 0: (x/\gamma, z/\gamma) \in L(y)\} \quad (3)$$

The input distance function can reflect joint production of multiple outputs and the duality between the input distance function and the cost function allows to retrieve the input shadow prices. In order to compute the technical efficiency of an individual input, sub-vector technical efficiency measures are introduced to generate technical efficiency measures of a subset of inputs rather than for the entire vector of inputs, holding all other inputs and outputs constant. Four input-oriented models are constructed for measuring technical efficiency, i.e. they contract inputs in four different directions.

The first model measures technical efficiency by radially contracting all productive and damage abatement inputs equiproportionately while keeping the outputs constant. This standard radial measure is incapable of identifying the technical efficiency of individual input use, since such a measure treats the contribution of productive and abatement inputs to technical efficiency equally. The second model measures technical efficiency by radially contracting only productive inputs equiproportionately, given the damage abatement inputs and outputs. The third model measures technical efficiency by radially contracting all damage abatement inputs with an equal proportion, given the productive inputs and the output level. The fourth model is a variation of the Russell technical efficiency measure that allows for non-proportional contractions in each input. This model allows for non-proportional reductions in each subset of inputs, allowing for different technical efficiency scores of productive inputs and damage abatement inputs (Ball et al. 1994; Oude Lansink and Silva, 2004). This is equivalent to the non-radial notion of input technical efficiency, as discussed by Kopp (1981). The general form of the four models is given by:

$$\min_{\gamma_{ji},\lambda} \gamma_{ji}$$

s.t.

$$\begin{aligned}
&Y\lambda \geq y_i \\
&X\lambda \leq \gamma_{ki} x_i \\
&Z\lambda \leq \gamma_{li} z_i \qquad (4) \\
&\mathbf{I}\lambda = 1 \\
&\lambda \geq 0
\end{aligned}$$

where $\gamma_k$ and $\gamma_l$ are the input sub-vector space technical efficiency scores for farm $i$. The specification of each of the four models is summarized in Table 5.1.

A set of dual variables for each observation is obtained from each model. These dual variables are used to generate the value of the marginal product (shadow price) of each input. The value of the marginal product of each input for output $q$ is given by (Ball et al. 1994; Oude Lansink and Silva, 2004):

$$MP_{pqi}^{m} = \frac{\partial y_{qi}}{\partial x_{pi}} = -\frac{\partial \gamma_{mi}/\partial x_{pi}}{\partial \gamma_{mi}/\partial y_{qi}},\ m = 1, \ldots, 4;\ p = 1, \ldots, P;\ q = 1, \ldots, Q;\ i = 1, \ldots, N,$$

$$MP_{aqi}^{m} = \frac{\partial y_{qi}}{\partial z_{ai}} = -\frac{\partial \gamma_{mi}/\partial z_{ai}}{\partial \gamma_{mi}/\partial y_{qi}},\ m = 1, \ldots, 4;\ a = 1, \ldots, A;\ q = 1, \ldots, Q;\ i = 1, \ldots, N, \quad (5)$$

where $MP_{pqi}^{m}$ is the marginal product of the productive input $p$ for output $q$ and for observation $i$ estimated from model $m$, $MP_{aqi}^{m}$ is the marginal product of the damage

**Table 5.1. Specification of the models**

| Models | Technical efficiency choice variables | Objective function |
|---|---|---|
| **Model 1**: Radial technical efficiency in the full input space | $\gamma_{ki} = \gamma_{li} = \gamma_{1i}$ | $\min_{\gamma_{1i},\lambda} \gamma_{1i}$ |
| **Model 2**: Radial technical efficiency in the productive input subspace | $\gamma_{li} = 1, \gamma_{ki} = \gamma_{2i}$ | $\min_{\gamma_{2i},\lambda} \gamma_{2i}$ |
| **Model 3**: Radial technical efficiency in the damage abatement input subspace | $\gamma_{ki} = 1, \gamma_{li} = \gamma_{3i}$ | $\min_{\gamma_{3i},\lambda} \gamma_{3i}$ |
| **Model 4**: Non-radial technical efficiency using Russell-type measure | $\gamma_{ki} \neq \gamma_{li}$ | $\min_{\gamma_{ki},\gamma_{li},\lambda} (\gamma_{ki} + \gamma_{li})/2$ |

abatement input $a$ for output $q$ and for observation $i$ estimated from model $m$ and $\gamma_{mi}$ is the technical efficiency score for the $ith$ observation in model $m(= 1, \ldots ,4)$. The quantities $\partial\gamma_{mi}/\partial x_{pi}$, $\partial\gamma_{mi}/\partial z_{ai}$ and $\partial\gamma_{mi}/\partial y_{qi}$ are the dual variables in model $m(= 1, \ldots ,4)$ associated with the constraints on the productive input $p$, the damage abatement input $a$ and the output $q$. The value of the marginal product of each input is obtained as:

$$SV_{pqi}^{m} = w^{q} MP_{pqi}^{m},$$

$$SV_{aqi}^{m} = w^{q} MP_{aqi}^{m}, \quad (6)$$

where $w^{q}$ is the observed price of output $q$. Each model provides an estimate of the shadow prices of each input at a particular point on the frontier. Since our model includes multiple outputs, the values of the marginal product are calculated for each output separately. If farmers maximize profits, then the shadow prices of a given input is the same across the two outputs (Varian, 2002, p. 566). However, in practice the shadow prices computed from the two outputs will not coincide. To circumvent this problem, revenue shares of the $Q$ outputs are used to compute a weighted (using revenue shares as weight) average of the shadow prices for each input of observation $i$ in each model as follows:

$$SV_{pi}^{m} = \sum_{q=1}^{Q}\left(\rho_{qi} \times SV_{pqi}^{m}\right),$$

$$SV_{ai}^{m} = \sum_{q=1}^{Q}\left(\rho_{qi} \times SV_{aqi}^{m}\right), \quad (7)$$

where $\rho_{qi}$ is the revenue share of output $q$ for observation $i$.

The extent to which damage abatement inputs are underused or overused is inferred from a comparison of the shadow prices and the market prices. Shadow prices are greater (lower) than market prices for inputs that are underused (overused).

Technical interdependence between damage abatement inputs and productive inputs is investigated using the four previous models. First, a set of shadow prices of the productive inputs is generated for each model. Second, one damage abatement input constraint is increased by one unit and new shadow prices of the productive inputs are generated for each model. This constraint perturbation is done for each of $A$ damage abatement inputs. Comparison of the shadow prices of the productive inputs from the perturbed model and the original set of shadow prices provides information on the local technical interdependence between these inputs and a particular damage abatement input (Oude Lansink and Silva, 2004). If increasing a damage abatement input increases (reduces) the shadow price of another input, then the two inputs are local complements (substitutes). Furthermore, increasing the pesticides constraint is expected to decrease the shadow price of pesticides.

### 5.2.2. Smooth Bootstrap Procedure

Simar and Wilson (1998 and 2000) methodologically studied the statistical properties of nonparametric envelopment estimators and developed a single-smooth bootstrap algorithm which can be used to examine the statistical properties of technical efficiency scores generated through DEA. As statistical properties of the frontier are obtained from finite samples, the corresponding measures of technical efficiency are sensitive to the sampling variations of the obtained frontier. Hence, the DEA estimators could be biased upwards (Simar and Wilson, 1998 and 2008).

The full-sample homogenous smooth bootstrap is a consistent way to analyze the sensitivity of technical efficiency scores relative to the sampling variations of the estimated frontier. As stated by Simar and Wilson (1998 and 2000), we assume a data-generating process where farms randomly deviate from the underlying true frontier in a radial direction. We apply the full-sample homogenous smooth bootstrap to overcome the possible statistical noise that may affect the measurement of technical efficiencies and shadow price of pesticides. Therefore, the model accounts for the effects of statistical noise due to measurement error and other causes. In this chapter, we subsequently estimate the bias-corrected technical efficiency scores along with the shadow prices from the bootstrap sample. 95% confidence intervals are also generated for technical efficiency scores and shadow prices.

## 5.3. Data Description

The data used in this chapter were obtained through a survey among specialized vegetable producer in southern Benin in the agricultural production years 2009-2010.

The sample was selected based on the proportion of traditional and non-traditional vegetable farms in each administrative region and the sample is representative of the urban and peri-urban vegetable producers in Benin. The primary focus of this survey was to understand the production and cost structure in vegetable production. Each individual farmer in this survey was requested to report details on the outputs produced and inputs used. The vast majority of producers in the area are on-farm decision-makers vis-à-vis pesticide applications. A sample of 136 vegetable producers is obtained which includes a range of farm sizes. All producers face the same productive process, i.e. they produce both traditional and non-traditional vegetables. Table 5.2 reports the descriptive statistics of key variables.

The variable list contains two aggregate outputs (traditional vegetables and non-traditional vegetables), six productive inputs (N-fertilizer, other variable inputs, land, labor, capital and water) and two damage abatement inputs (insecticides and

**Table 5.2. Descriptive Statistics**

| **Variable** | Unit | Mean | St. Deviation |
|---|---|---|---|
| *Quantities* | | | |
| Aggregate output for traditional vegetables | $10^6$ FCFA | 2.521 | 6.519 |
| Aggregate output for non-traditional vegetables | $10^6$ FCFA | 1.203 | 2.016 |
| N-Fertilizer | $10^5$ FCFA | 2.342 | 4.209 |
| Other Inputs | $10^5$ FCFA | 1.049 | 1.702 |
| Land area | ha | 0.638 | 1.509 |
| Labor | $10^2$ Man-hour | 3.195 | 1.156 |
| Capital | $10^5$ FCFA | 6.034 | 9.423 |
| Water | $10^6$ Liter | 5.124 | 12.287 |
| Insecticides | $10^4$ FCFA | 3.328 | 4.795 |
| Other Pesticides | $10^4$ FCFA | 4.134 | 10.372 |
| *Prices* | | | |
| Laspeyeres weigthed average price index for traditional vegetables | Index | 1.004 | 0.448 |
| Laspeyeres weigthed average price index for non-traditional vegetables | Index | 0.873 | 0.590 |

*Note:* \$1US = 494.030 FCFA in 2010 or 1 Eur = 655.957 FCFA.

other pesticides). Traditional vegetables consist of tomato, solanum plants, okra, pepper, amaranth, corchorus, bitterleaf, African basil, cockscomb and onion. Non-traditional vegetables consist of lettuce, cabbage, courgette, cucumber, beet, carrot, radish, turnip, french bean, melon, squash, watermelon, celery, chicory, chives, coriander, dill, fennel, garden mint, leek, overripe, parsley, rocket and thyme. The quantity of output is measured as the sum of the revenues from traditional and non-traditional crops, respectively. Other variable input consists of seeds and other miscellaneous expenses. Land represents the total area under vegetable crops and is measured in hectares. Labor consists of family labor and hired labor and is measured in man-hours. Capital consists of machinery and equipment and is measured in replacement cost. In the study area, insecticides dominated chemical pest management, reflecting not only the serious problems of insect attack in vegetable production, but also the availability and relatively low cost of many older generation insecticides. Other pesticides consist of fungicides, herbicides, nematicides, acaricides, fumigant, rodenticides and biopesticides. As found by Williamson et al. (2008), the most encountered active ingredients were the insecticides endosulfan, dimethoate, cypermethrin, chlorpyrifos, fenitrothion, malathion, profenofos, lambda-cyhalothrin and delthamethrin. We limit our study to two categories of pesticides to avoid zero values in the damage abatement inputs. The data set exhibits considerable variation, especially with respect to the quantity of damage abatement inputs where standard deviations exceed the means and the difference between the minimum and maximum is relatively large.

## 5.4. Results and Discussion

### 5.4.1. Technical Efficiency Analysis

The results of each model for the smoothed bootstrap with 2,000 bootstrap replications for each observation are reported in Table 5.3. The results consist of the average initial technical efficiency scores, the average bias-corrected technical efficiency estimates and the lower and upper bounds of the 95% confidence intervals of the average technical efficiency. The technical efficiency scores generated from the four models suggest a significant amount of technical inefficiency. Since the initial DEA estimates in all models are outside the 95% confidence intervals (meaning that the bias estimates are large relative to the standard error estimates), the bias-corrected technical efficiency estimates are preferred over the initial estimates (Simar and Wilson, 2008). In each model, the initial technical efficiency scores for the 136 units yield an average uncorrected technical efficiency score of 0.635 (Model 3) to 0.879 (Model 4), while the bootstrap model generates an average bias-corrected score of 0.314 (Model 3) to 0.787 (Model 4). The 95% confidence intervals are of moderate length. The average bias-corrected technical efficiency score of model 3 suggests a relatively higher amount of technical inefficiency than models 1 and 2. Since model 3 measures technical efficiency in the use of pesticides, this indicates that vegetable farms in the sample are less efficient in the use of pesticides. This implies that by using pesticides efficiently, the vegetable producers would be able to reduce their pesticide use by almost 69%, on average, keeping output and productive inputs constant. Also, the bias-corrected technical efficiency score of model 4 indicates, on average, a higher amount of technical inefficiency in the use of pesticides than in the use of productive inputs, given the output level. Since the estimated technical efficiency score of pesticides in models 3 and 4 is lower than the technical efficiency in model 1, the results suggest that the application of pesticides is more difficult to manage for vegetable producers than the use of productive inputs such as fertilizers, labor, land, capital and water. These findings can be explained by the fact that in the conventional agricultural production system, the technical efficiency of pesticides is generally more dependent on weather, soil conditions and pest incidence than the technical efficiency of productive inputs (Oude Lansink and Silva, 2004). The

**Table 5.3. Average technical efficiency scores and confidence intervals ($n = 136$; $B = 2,000$)**

| Models | | Initial Eff. Scores | Bias corrected Eff. Scores | 95% Confidence interval | |
|---|---|---|---|---|---|
| | | | | Lower bound | Upper bound |
| **Model 1**: Radial measure of productive inputs and pesticides abatement technical efficiency | | 0.849 | 0.724 | 0.716 | 0.726 |
| **Model 2**: Radial measure of productive inputs technical efficiency | | 0.652 | 0.362 | 0.341 | 0.371 |
| **Model 3**: Radial measure of pesticides abatement technical efficiency | | 0.635 | 0.314 | 0.297 | 0.327 |
| **Model 4**: Russell-type measure of productive inputs and pesticides abatement technical efficiency | Productive | 0.879 | 0.787 | 0.779 | 0.789 |
| | Pesticides | 0.656 | 0.439 | 0.412 | 0.454 |

formulation and the method of application also have greater influence on the technical efficiency of pesticides on the size of the target pest population than the choice of active ingredient (van Emden and Service, 2004).

### 5.4.2. Analysis of Shadow Values and Input Interdependences

The estimation of the input distance function allows us to generate shadow prices of damage abatement inputs for each producer, along with their confidence intervals. In order to get the shadow values of each productive unit, we use expressions (6) and (7) under the hypothesis that the shadow prices of outputs are equal to their observed market prices as suggested by Ball et al. (2004) and Färe and Grosskopf (1990). Table 5.4 reports the bootstrap sample average of the shadow values of all productive and damage abatements and the corresponding 95% confidence intervals. Shadow values of productive inputs (pesticides) in model 2 are smaller (larger) than their values in models 1 and 3. The differences between the shadow values of model 2 versus models 1 and 3 reflect the different points at the frontier at which the shadow prices are evaluated. This is because shadow prices in model 2 are evaluated at the point on the frontier that reflects the minimum quantity of productive inputs required for producing a given bundle of vegetable outputs and the quantity of pesticide use. Overall, shadow prices of productive inputs in model 4 are larger than their respective values in the other models.

In models 1, 2 and 3, the shadow price of fertilizer was found to be lower than the market price, which suggests overuse of fertilizer. For example, in model 2, where performance was evaluated in the productive input subspace, vegetable producers' return for each additional FCFA of fertilizer use was 0.70 FCFA, which suggests that fertilizer is less productive. An explanation of the low shadow price of fertilizer is that a continuous and intensive vegetable production practice is observed on poor sandy soils with a large use of nutrients (Drechsel et al. 2006). The policy implication is that excessive use of fertilizer (manure) should be restricted. An additional hectare of land yielded at least 2.00 $10^6$ FCFA of revenue, which suggests a high competition for urban and peri-urban farmland. However, the shadow prices of land are significantly lower than the market price, which implies overuse of land in vegetable farming.

The average shadow price of labor in all models was found to be significantly higher than the market price, implying underuse of labor. For each additional hour of labor, producers' return ranged from 3.06 $10^2$ FCFA (model 3) to 3.92 $10^2$ FCFA (model 2).

The shadow price of water in all four models is higher than the market price, indicating underuse of water. This result implies that the value of the marginal product of irrigation exceeds the cost of irrigation, meaning that water was not optimally used at the farm level. This result is consistent with the finding of Danso et al. (2003) in West Africa showing that manual irrigation (the most common method of irrigation) in vegetable production needs to be carried out with high frequency, leading to underuse. However, the increased use of irrigation in vegetable production may be attributed to risk aversion by producers related to the probability of droughts (Henry and Bowen, 1981), as access to water is a crucial requirement for year-round vegetable production.

From an additional FCFA of insecticides, producers' return ranged from 0.0006 FCFA (model 4) to 0.43 FCFA (model 2). The return from each additional FCFA of other pesticides was 0.0025 FCFA (model 4) to 0.47 (model 1). The results imply that insecticides and other pesticides were less productive for vegetable producers. The shadow prices of insecticides and other pesticides are lower than their average market prices in all models, suggesting overuse of insecticides and other pesticides. This means that vegetable producers could increase their profitability by decreasing the use of insecticides and other pesticides. This result implies that producers are allocatively inefficient in damage abatement input use. This finding is in line with the conventional wisdom in the agricultural community that farmers overuse pesticides (Macharia et al. 2011; Sexton et al. 2007). An explanation for excessive use of pesticides is an intensive growing systems with high yields, short rotations and thus a high use of insecticides, herbicides, fungicides, nematicides as well as pest resistance against pesticides (de Kort, 1993; Kortenhoff, 1993). As pesticides are used in a prophylactic way to prevent anticipated infestations, the overuse of pesticides may kill pest species as well as beneficial species. Destruction of a pest's natural enemies often leads to rapid resurgence of the pest or to introduction of secondary pests, which necessitates more treatments (de Kort, 1993). In all four models the results also show that more than 97% of vegetable producers in the sample overuse the damage abatement inputs (insecticides and other pesticides).

**Table 5.4. Average Shadow values of inputs and 95% Bootstrap confidence intervals ($n = 136$; $B = 2,000$)**

| Inputs | Market Price | Model 1 | | Model 2 | | Model 3 | | Model 4 | |
|---|---|---|---|---|---|---|---|---|---|
| | | Shadow Price | 95% CI | Shadow Price | 95% CI | Shadow Price | 95% CI | Shadow Price | 95% CI |
| ***Productive inputs*** | | | | | | | | | |
| N-Fertilizer | 1[(1)] | 0.83 | [0.28;2.61] | 0.70 | [0.27;2.57] | 0.68 | [0.28;2.67] | 1.07 | [0.42;2.82] |
| Other Inputs | 1[(1)] | 0.54 | [0.22;1.40] | 0.60 | [0.26;1.47] | 0.62 | [0.26;1.41] | 0.73 | [0.22;1.99] |
| Land area | 5.00[(2)] | 2.00 | [0.53;7.35] | 2.21 | [0.57;7.21] | 2.17 | [0.55;7.48] | 2.86 | [0.51;8.76] |
| Labor | 1.19[(3)] | 3.24 | [1.36;6.26] | 3.92 | [1.42;6.62] | 3.06 | [1.42;6.34] | 3.64 | [1.54;7.42] |
| Capital | - | 1.43 | [0.18;3.90] | 1.41 | [0.19;3.55] | 1.97 | [0.19;6.32] | 3.30 | [1.06;6.11] |
| Water | 0.00[(4)] | 0.52 | [0.09;1.63] | 0.92 | [0.13;1.68] | 0.54 | [0.13;1.37] | 1.07 | [0.28;3.56] |
| ***Damage abatement inputs*** | | | | | | | | | |
| Insecticides | 1[(1)] | 0.36 | [0.21;0.71] | 0.43 | [0.21;0.75] | 0.36 | [0.22;0.62] | 0.0006 | [0.00;0.004] |
| Other Pesticides | 1[(1)] | 0.47 | [0.13;1.27] | 0.45 | [0.14;1.33] | 0.43 | [0.15;1.31] | 0.0025 | [0.00;0.012] |

*Note.* CI: Confidence Intervals, \$1US = 494.030 FCFA in 2010 or 1 Eur = 655.957 FCFA

(1) Prices of N-Fertilizer, Other Inputs, Insecticides and Other Pesticides are set to one because these inputs are aggregated and measured in FCFA. For instance, if a producer wants to buy 1 FCFA of fertilizer, he/she has to pay 1 FCFA.
(2) Land Price is based on the state land price per ha (Law No.164/PC/MFAEP-EDT of 11th of September 1964) since the majority of land cultivated in urban and peri-urban areas is the property of the state ($10^6$ FCFA). In fact, Benin is still a transition country in terms of its land policy with heterogeneous nature of land tenure arrangements (Le Meur, 2008).
(3) Labor price per man-hour is the price for permanent hired labor (FCFA) and is calculated from the survey data.
(4) Water price is set to be zero as the cost for irrigation equipment is included in capital and the labor used for irrigation is included in labor.

Based on the estimation results of the linear programming problem in (4), we performed a further analysis of technical interdependence of inputs. Table 5.5 reports the differences in the shadow values of productive and damage abatement inputs resulting from increasing separately by one unit the constraint of each pesticide. The 95% confidence intervals are also presented in Table 5.5. In general, the impact of an increase in each damage abatement input on the shadow value of a productive input is not significant at the critical 5% level. This result implies that there is no evidence for technical interdependence between productive and damage abatement inputs. This result contrasts with Oude Lansink and Silva (2004) who found evidence of strong technical relationships between both types of inputs. The difference with Oude Lansink and Silva (2004) may be explained by the failure of Oude Lansink and Silva to account for sampling variation in the estimated frontiers.

As expected, in all four models, the shadow price of insecticides decreases significantly when the insecticide constraint is increased by one unit. The same result is found for other pesticides.

In sum the result in Table 5.5 indicates no evidence of technical interdependence between pesticide use and productive inputs. This is the challenge in most of empirical analysis of the economics of pesticides where the estimated form of such relationships can be critical for farm-level decision making (Hall and Moffitt, 2002; Marsh et al. 2000; Saphores, 2000; Sexton et al. 2007).

These results could be of interest in defining an efficient point of pesticide use in vegetable production. From the above results, the main problem with the use of pesticides could be related to the mix of approved and banned pesticides. As indicated by Snelder et al. (2008) in the case of Philippines, a mechanism is needed to control the use and sale of restricted and banned pesticides as most of the pesticides used in vegetable production are freely sold in stores and markets. Since, the market of approved pesticides (selective pesticides) for vegetable production is missing, policy makers should make such products available to producers, a distribution is required for low-cost application products. Due to lack of training in pesticide use, vegetable producers do not always respect the re-entry periods after spraying and essential harvest intervals are not known. In this respect, integrated pest management addressing the issues of pesticides usage and alternatives must be adjusted and reinforced to the case of vegetable products with emphasis on cost-effective pest-control methods for covering the investment risks. However, its success is strongly related to a good extension service in the early stage (van Lenteren, 1993).

## 5.5. Conclusions

This chapter provides valuable information on the pesticides used in pest control in vegetable production. As pesticide application in vegetable production systems of Benin are applied prophylactically to prevent from the occurrence of an infestation or diseases, the input function is used to study the value of the marginal product of pesticides. Shadow prices of two categories of pesticides are determined using four input-oriented models, each measuring the shadow price at different subspaces of the frontier. The homogenous smoothed bootstrap technique is used to determine confidence intervals of technical efficiency scores and shadow prices.

Results show that vegetable producers have a lower technical efficiency in the use of pesticides. Also, results suggest that vegetable producers overuse insecticides and other pesticides. The overuse of pesticides means that the actual market prices of pesticides are higher than the value of the marginal product of pesticides in the production process. The overuse of pesticides can be attributed to the characteristics of the vegetables production system and may also point at risk aversion of farmers, i.e. farmers overuse pesticides in order to reduce the risks of pests and diseases. The study shows that there is no evidence of technical interdependence between pesticides and productive inputs. The overuse of pesticides may result in contamination of vegetable products and have adverse effects on the health of both producers and consumers. The results indicate the need for producers to apply rational methods for pesticide use. The implication is that the government may support producers by providing better information through extension services. The government may pay special attention to a policy that aims at the reduction of structural dependence of producers on pesticides. Integrated pest management addressing the issues of pesticides usage and alternatives may be adjusted and reinforced to the case of vegetable products with emphasis on cost-effective pest-control methods.

**Table 5.5. Average differences in the shadow values of inputs and the corresponding 95% Bootstrap confidence intervals when the insecticides and other pesticides constraints change by one unit ($n = 136$; $B = 2,000$)**

| Inputs | Model 1 | | Model 2 | | Model 3 | | Model 4 | |
|---|---|---|---|---|---|---|---|---|
| | Difference | 95% CI | Difference | 95% CI | Difference | 95% CI | Difference | 95% CI |
| ***Insecticides*** | | | | | | | | |
| N-Fertilizer | 0.157 | [-1.80;2.04] | 0.165 | [-1.63;1.93] | 0.187 | [-1.81;1.81] | -0.026 | [-1.90;1.86] |
| Other Inputs | -0.002 | [-0.91;1.08] | -0.024 | [-1.00;0.95] | -0.048 | [-1.03;0.91] | -0.044 | [-1.43;1.28] |
| Land area | -0.31 | [-6.19;5.34] | -0.047 | [-5.84;4.72] | 0.039 | [-6.15;4.75] | -0.017 | [-6.13;5.88] |
| Labor | 0.540 | [-2.78;3.58] | -0.709 | [-3.74;3.78] | 0.514 | [-3.60;3.69] | -0.283 | [-3.57;2.73] |
| Capital | 0.815 | [-1.93;3.70] | -0.034 | [-2.26;2.58] | -0.702 | [-5.07;2.24] | -0.378 | [-3.57;2.50] |
| Water | 0.308 | [-1.08;1.43] | -0.128 | [-0.92;1.63] | 0.268 | [-77;1.55] | -0.212 | [-2.07;1.14] |
| Insecticides | -0.344** | [-0.70;-0.19] | -0.402** | [-0.68;-0.18] | -0.323** | [-0.58;-0.17] | -0.0004[a] | [-0.004;0.0003] |
| Other Pesticides | 0.067 | [-0.76;0.86] | 0.046 | [-0.80;0.96] | 0.028 | [-0.90;0.90] | 0.0003 | [-0.009;0.008] |
| ***Other Pesticides*** | | | | | | | | |
| N-Fertilizer | -0.060 | [-1.93;1.82] | 0.005 | [-1.57;1.77] | 0.002 | [-1.87;1.82] | -0.049 | [-1.56;1.83] |
| Other Inputs | 0.31 | [-0.74;1.03] | 0.025 | [-0.85;0.75] | 0.006 | [-1.01;0.84] | -0.057 | [-1.37;1.17] |
| Land area | 0.101 | [5.31;5.26] | -0.042 | [-5.46;5.75] | 0.206 | [-5.60;4.97] | 0.348 | [-5.81;6.12] |
| Labor | 0.435 | [-2.73;3.34] | -0.652 | [-3.19;3.81] | 0.215 | [-3.48;3.81] | 0.099 | [-3.12;3.06] |
| Capital | 0.843 | [-2.18;3.10] | -0.031 | [-2.33;2.52] | -0.589 | [-4.97;2.39] | 0.170 | [-3.10;3.44] |
| Water | 0.33 | [-0.95;1.55] | -0.005 | [-84;1.46] | 0.452 | [-0.62;1.77] | 0.19 | [-1.73;1.92] |
| Insecticides | 0.032 | [-0.31;0.34] | -0.088 | [-0.38;0.21] | -0.019 | [-0.30;0.21] | -0.00001 | [-0.0025;0.002] |
| Other Pesticides | -0.465** | [-1.27;-0.12] | -0.448** | [-1.34;-0.13] | -0.426** | [-1.30;-0.14] | -0.00252[a] | [-0.012;0.0.00007] |

*Legend.* ** Significance at 5% level, * Significance at 10% level, [a] Significance at 20% level.

## CHAPTER 6

# General Discussion and Conclusions

## 6.1. Introduction

The overall objective of this thesis was to analyze the production technology and the performance of vegetable producers in Benin. This was done by investigating the level of, and factors that determine marketing, allocative, technical and scale efficiency of these producers. The thesis focuses on the supply-side of vegetable production and targets farm-level decision making. While pursuing the main objective, this research also paid special attention to the development of methodologies for implementing the theory in empirical studies.

This final chapter reviews the scientific implications of the present thesis, provides a general discussion on the methodology and empirical results and gives policy implications and suggestions for future research. This chapter is organized as follows. Section 6.2 reviews the theoretical and methodological issues. Section 6.3 summarizes the main findings. Section 6.4 develops the policy implications of the thesis. Section 6.5 provides suggestions for future research and Section 6.6 the main conclusions of the thesis.

## 6.2. Theoretical and Methodological Issues

### 6.2.1. Theoretical Issues

This thesis employs the neo classical production theory as the basis for the empirical models. The primal approach based on the distance function is used in Chapters 2, 3, 4 and 5 of the thesis. In the context where there is no particular orientation and the profit maximization problem must be solved by choosing inputs and outputs simultaneously, the directional distance function introduced by Chambers et al. (1996 and 1998) is shown to have its dual representation in the profit function. The directional distance function treats outputs and inputs as endogenous and so, is consistent with the economic objective of profit maximization. The dual relation between the directional distance function and the profit function was the basis of Chapter 2. The primal approach using the input distance function, where one is interested in reducing input usage while keeping outputs fixed, is employed in Chapters 4 and 5. In these chapters, we exploit the duality between the input distance function and the cost function to examine economies of scope and the efficiency and interdependency of specific inputs, respectively.

A producer has three non-exclusive ways to increase competitiveness: decrease production costs; increase market share; and adjust the prices to the state of the market (Dolgui and Proth, 2010). Whereas decreasing production costs is achieved by the improvement of technical, scale and allocative efficiency, maximising output prices (i.e. a pricing strategy) is achieved by improving marketing efficiency. Additionally, from the farm management perspective, producers are involved in three basic activities: production, marketing and investment (i.e. financial activities) (Kay et al. 2008, p. 42). However, in developing countries, including Benin, the investment activities in the agricultural sector (mainly for small scale farmers) are problematic due to the lack of a financial market. In this thesis, as we do not have data on farms' investment activities, the analysis related to investment activities is ignored. The outcome is that producers need not only decide how much to produce and how much inputs to use, but also at what price to sell the output. In other words, producers must optimize both their productive and marketing performance. Thus, an integrated microeconomic framework was developed in Chapter 3 to assess the efficiency with which vegetable producers allocate their resources to production and marketing activities. Therefore, output prices are no longer exogenous, but the outcome of producers' marketing efforts and skills.

Chapter 4 extended the analysis to horizontal crop diversification (mainly for small-scale producers). By diversifying, farmers can benefit from economies of scope (or cost complementarities) that are associated with the use of inputs common to a number of production processes. Besides this, diversification requires giving up the benefits of specializing in one enterprise, like scale economies. Hence, the direction in which diversification affects producer performance is not clear. The stochastic production frontier forms the basis for analyzing the direct and indirect impact of vegetable crops diversification on producer performance. The objective in this chapter, from a theoretical perspective, is to develop a model for measuring economies of scope and technical efficiency from the primal perspective.

Another issue is the role of some inputs in the production process from an agronomic point of view. Most importantly, pesticides are a damage control input rather than a productive input (labor, fertilizers, capital and other materials). In fact, pesticides are used to reduce damage rather than increasing output directly. This agronomic fact is the core of Chapter 5 that examines the efficient use of pesticides in vegetable production, both technically and allocativelly.

### 6.2.2. Methodological Issues

This section discusses the methodological issues in the empirical applications of Chapters 2-5.

The first issue is the level of aggregation of outputs. By incorrectly treating vegetable production as a homogenous product, estimation of efficiency may be biased and policy conclusions likely in error. One approach to allow flexibility in the assumptions is the use of a multiproduct technology. In this thesis, we do allow for the multi-output technology, but there are several limitations for adding more outputs (see Chapters 3, 4 and 5). Increasing the number of outputs may lead to the occurrence of zero values, as the likelihood of a farm not producing a particular output increases. That is problematic in non-parametric applications. It also results in a situation where many farms will be located at the frontier.

The second issue is the choice between parametric econometric techniques and non-parametric mathematical programming techniques for measuring efficiency. Developments in comparing both techniques concluded that the overall results drawn by the two approaches are similar (Greene, 2008, p. 114). Consequently, the objective of the study and the data available are the main criteria one can use to make a choice. In Chapters 2, 3 and 5 of this thesis, we use the non-parametric data envelopment analysis (DEA) technique since the primary objective in these chapters was to estimate different efficiency measures (technical, allocative, scale, output, input and marketing) in the case of a multiple output technology. In Chapter 4, the parametric stochastic frontier approach is used because the objective of this chapter was to estimate not only technical efficiency and scale economies but also to assess the presence or absence of economies of scope. Therefore, in Chapter 4, the characteristics of the production function is of particular interest.

When dealing with the non-parametric DEA, one has a choice between radial and non-radial measures of efficiency. The non-radial models are useful in situations where both inputs and outputs are controllable and we seek their improvement. For instance, they reflect the potential for improvement in desired input and output directions. In Chapters 2 and 3, the directional distance function and its dual profit function (Chambers et al. 1996 and 1998) form the basis for the analysis of technical, scale and allocative efficiency. Specifically, in Chapter 2 the directional distance function allows for measuring output and input technical inefficiency of lowland farming. In the context where the same resources are used in the production of outputs and in marketing outputs, a Russell-type efficiency measure is appropriate. The Russell efficiency measure allows for non-proportional increases in output quantity and output price, allowing for different scores of technical and marketing efficiency.

In Chapter 3, the Russell-type measure is used to derive technical and marketing inefficiency of vegetable producers. Also, in Chapter 5, the Russell-type measure is employed to measure different technical efficiency scores of productive inputs and damage abatement inputs.

Although the non-parametric efficiency analysis is appealing in many ways, the fundamental practical problem is that any measurement error and any other outcome of stochastic variation is embedded in the inefficiency estimates. In any sample, a single extreme observation can have profound effects on the estimates. Hence, it is important to find an appropriate method to deal with the stochastic nature of production and sampling process. In Chapter 5, the homogenous smooth bootstrap technique developed by Simar and Wilson (1998 and 2000) was used to provide statistical inference for the technical efficiency scores. For the directional distance function, the implementation of the bootstrap technique is very complex and not yet well developed. In Chapter 3, therefore, we rely on outlier detection techniques to examine the sensitivity of the technical and marketing inefficiency estimates.

In Chapter 4, we analyzed scale economies, economies of scope and the direct effect of vegetable crop specialization on technical efficiency. In a multiple-output production technology, the effects of specialization on technical efficiency may be related to input use, indicating that the effect of crop composition on technical efficiency is non-neutral. The non-neutral frontier assumes that the method of application of inputs and the level of inputs (i.e. scale of operation) determine the potential output level. The model developed in this chapter allows for computing a primal measure of economies of scope and for determining the impact of specialization on technical efficiency.

Moreover, in all efficiency analysis frameworks, it is attractive to separate factors that can be controlled by producers and those that producers cannot control, i.e. exogenous variables. To that end, appropriate models for incorporating exogenous variables are needed. In the case of the stochastic frontier analysis (SFA), the one-step method that estimates the frontier and the relationship of technical inefficiency to exogenous variables is shown by Schmidt (2011) to be consistent. Chapter 4 dealt with this issue and used a flexible production functional form and a modified non-neutral method to investigate the impact of specialization on vegetable producers' performance. The two-stage approach is shown to be valid in the case of the non-parametric DEA approach. The potentially serious problem that DEA efficiency estimates are serially correlated is addressed by using a truncated bootstrap technique (see Chapters 2 & 3).

## 6.3. Synthesis of Results

The purpose of this section is to synthesize the main findings across Chapters 2-5.

Chapter 2 investigates the performance of vegetable producers in the lowlands. The comparison of three lowland farming systems provides useful information on technical, allocative, scale, output and input inefficiency differences. Overall, vegetable producers are found to have a low technical inefficiency. This result is consistent with the findings in Chapters 3, 4 and 5 for vegetable producers in urban and peri-urban areas. Table 6.1 summarizes the technical inefficiency results in Chapters 2-5. According to the technical inefficiency results, producers are found to be less than 27% inefficient.

The results in Chapters 2 and 5 provide evidence that producers are allocatively inefficient. The returns to scale results in Chapters 2 and 4 provide evidence that the production technology exhibits increasing returns to scale. On top of technical, scale and allocative inefficiency, other sources of efficiency are analyzed such as marketing, input and output inefficiency.

The results in Chapter 4 indicate that vegetable producers in urban and peri-urban areas have a strong incentive for specialization. This chapter suggests gains in technical efficiency that follow from specialization. This result is consistent with the result of increasing returns to scale of the integrated rice-vegetable farming system in lowlands in Chapter 2. This is because by specializing, producers can take advantage of scale economies.

The analysis of Chapter 5 indicated that vegetable producers are technically less efficient in the use of pesticides than in the use of other inputs. The cost (input) inefficiency result in Chapter 2 of lowland farms is manifested in the high shadow prices of some productive variable inputs in Chapter 5. Therefore, the results show that urban and peri-urban vegetable producers rely substantially on pesticides and some productive inputs while lowland producers are constrained by access to input use. On the other hand, the results in Chapter 5

**Table 6.1. Summary of technical inefficiency results by Chapters**

| Chapter | Technical inefficiency scores |
|---|---|
| 2. Lowland farming systems analysis(1) | 0.20 |
| 3. Technical and marketing analysis | 0.14 |
| 4. Impact of specialization on performance | 0.21 |
| 5. Pesticide use analysis(2) | 0.27 |

*(1)The result of Chapter 2 presented here is related to Integrated Rice and vegetable farming system.*
*(2)The result of Chapter 5 presented here is related to overall inefficiency measure (model 1)*

suggest that urban and peri-urban vegetable producers face managerial problems in the use of pesticides.

## 6.4. Policy Implications

The results in Chapter 2 pointed out that producers could benefit by cultivating in the lowlands throughout the year. The final result in Chapter 2 shows that there are economic and food security gains in promoting lowland development strategies within the integrated rice-vegetable farming system. The policy implication of this result is that the government can promote lowland production by enhancing the use of appropriate technology and management techniques. Since the market of seeds, fertilizers and pesticides is not functioning well, the government may facilitate supply of these inputs.

In Chapter 3 of the thesis, it was found that vegetable producers are more marketing inefficient than they are technically inefficient. The policy implication of this result is that producers can get higher prices by obtaining better information through different marketing channels. As it was shown in Kenya by Ngugi et al. (2007), farmers organized in groups are able to realize higher profits compared to farmers not organized in groups. As stated by Barrett (2010), the interventions aimed at facilitating smallholder organization, at reducing the costs of selling and perhaps, especially at improving poorer household's access to improved technologies and productive assets are central to stimulating smallholder market participation. Given the past experience of failure in most of farmer organizations in Africa, however, more homogeneity and optimal group size and market orientation can enhance the role of producer organizations in improving access to markets. These producer organizations need to prioritise agribusiness opportunities over social welfare objectives even though this may mean that some households are unable to take advantage of them (Shiferaw et al. 2011).

The results in Chapter 4 suggested the presence of diseconomies of scope and that the degree of specialization has a positive effect on technical efficiency. In other words, the government should change its current policy of enhancing diversification to enhancing specialization.

The results in Chapter 5 of the thesis suggest that pesticides are overused in vegetable production. Hence, there is a potential for pesticide use reduction in the vegetable production. The policy implication is that the government may support producers by providing better information through extension services. The government may introduce measures that reduce structural dependence of producers on pesticides. Integrated pest management addressing the reduction of pesticide use and the promotion of alternatives may be applied to vegetable production.

## 6.5. Suggestions for Future Research

Our empirical analysis has focused on static models of farm performance. If we had panel data at our disposal, further methodological advances could be achieved by fixed and random effects stochastic frontier models accounting for unobserved heterogeneity (Emvalomatis et al. 2011). Meanwhile, the absence of panel data in our study limits the dynamic analysis of efficiency for vegetable producers, e.g. by accounting for costs in adjusting quasi-fixed inputs such as investment in capital and change in labor. The dynamic efficiency of vegetable production can be assessed using a model based on the adjustment of quasi-fixed inputs to their long-run equilibrium and time interdependence of production decisions (Emvalomatis et al. 2011; Serra et al. 2011). Therefore, even though the construction of panel data sets is costly, researchers in developing countries should pay special attention to collecting these data.

The uncertainty around the level of output prices could also be incorporated in the models in chapter 4 by adding the price variability attached to different crops. The seasonality effect of output prices is another issue to search for in the model to analyze whether a producer's marketing inefficiency varies across seasons.

## 6.6. Main Conclusions

The objective of this thesis is to investigate the production technology and the performance of vegetable producers in Benin. We arrive at the following conclusions:

i) The analysis of different lowland farming systems indicated that scale inefficiency, allocative inefficiency and output inefficiency are the main sources of overall economic inefficiency (Chapter 2).

ii) Increasing returns to scale prevailed in the integrated rice-vegetable farming system. Allocative and scale inefficiency are significantly smaller in the rice or the integrated rice-vegetable farming systems than the vegetable farming system (Chapter 2).

iii) Urban and peri-urban vegetable producers are more marketing inefficient than they are technically inefficient (Chapter 3).

iv) Vegetable producers in urban and peri-urban areas using retailer marketing arrangements are more marketing efficient than those selling to wholesalers (Chapter 3).

v) The production technology of vegetable producers in urban and peri-urban areas exhibits increasing returns to scale (Chapter 4).

vi) The study among urban and peri-urban vegetable producers provides evidence for diseconomies of scope, indicating that vegetable producers have a strong incentive for specialization in either traditional or non-traditional vegetables (Chapter 4).

vii) An increase in crop specialization at the farm level is associated with an increase in technical efficiency of vegetable producers in urban and peri-urban areas (Chapter 4).

viii) Vegetable producers in urban and peri-urban areas are less technically efficient in the use of pesticides than in the use of other inputs and also overuse pesticides (Chapter 5).

## References


Abbott, J.C., and Markeham, J.P., 1981. Agricultural economics and marketing in the tropics, Longman Group Limited, Burnt Mill, Harlow, Essex, Uk. 168 p.

Abdulai, A., and Huffman, W., 2002. Structural Adjustment and Economic Efficiency of Rice Farmers in Northern Ghana. *Economic Development and Cultural Change* 48(3), 503-520.

Achigan-Dako, E.G., Pasquini, M.W., and Assogba Komlan, F., 2009. Inventory and use of traditional vegetables: methodological framework. *In Traditional vegetables in Benin: Diversity, distribution, ecology, agronomy, and utilization. Achigan-Dako et al. (ed).* 9-51.

Adégbola, P.Y., and Singbo, A.G., 2003. Compétitivité de la filière riz du Bénin dans l'économie internationale, PAPA/INRAB, Porto-Novo. Communication de la 24ème session du Conseil des Ministres de l'ADRAO tenue du 17 au 19 septembre 2003, Cotonou. 20 p.

Adégbola, Y.P., and Singbo, A.G., 2001. Analyse socio-économique de la filière des biopesticides en cultures maraîchères au Bénin. PAPA/INRAB and IITA-Cotonou, Benin. 30 p.

Adesina, A.A., and Djato, K.K., 1997. Relative efficiency of women as farm managers: Profit function analysis in Côte d'Ivoire. *Agricultural Economics* 16, 47-53.

Agli, C., 2000. Etude de la filière cultures-maraîchères dans les zones humides du sud-Bénin: circuits de commercialisation et faisabilité économique de la relance de la filière. Agence Béninoise pour l'environnement, Ministère de l'environnement, de l'habitat et de l'urbanisme, Bénin. 28 p.

Aigner, D.J., Lovell, C.A.K., and Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* 6, 21-37.

Akoègninou, A., van der Burg, W.J., van der Maesen, L.J.G., Adjakidjè, V., Essou, J.P., Sinsin, B., Yédomonhan, H. (ed), 2006. Flore analytique du Benin. Backhuys Publishers. 1034 p.

Akplogan, F., Adégbola, P., and Assogba-Komlan, F., 2007. Production et commercialisation des légumes locaux dans les zones urbaines et peri urbaines au Bénin. Working paper, Programme Analyse de la Politique Agricole de l'Institut National des Recherches Agricoles du Bénin (PAPA/INRAB). 45 p.

Ali, M., and Abedullah, 2002. Nutritional and economic benefits of enhanced vegetable production and consumption. *Journal of Crop Production: innovations in practice, theory & research* 6(1-2), 145-176.

Allen, D.W., and Lueck, D., 1998. The nature of the farm. *Journal of Law and Economics* XLI, 343-386.

Al-Marhubi, F., 2000. Export diversification and growth: an empirical investigation. *Applied Economics Letters* 7, 559-562.

Alvarez, A., Amsler, C., Orea, L., and Schmidt, P., 2006. Interpreting and testing the scaling property in models where inefficiency depends on firm characteristics. *Journal of Productivity Analysis* 25, 201-212.

Assogba-Komlan, F., Singbo, A., and Adégbola, P., 2002. Agriculture urbaine: cas de la ville de Cotonou. Rapport, INRAB, Benin. 30 p.

Audibert, M., 1997. Technical inefficiency effects among paddy farmers in the villages of the 'Office du Niger', Mali, West Africa. *Journal of Productivity Analysis* 8, 379–394.

Ball, V.E., Lovell, C.A.K., Luu, H., and Nehring, R.F., 2004. Incorporating environmental impacts in the measurement of agricultural productivity growth. *Journal of Agricultural and Resource Economics* 29(3), 436-460.

Ball, V.E., Lovell, C.A.K., Nehring, R.F., and Somwaru, A., 1994. Incorporating undesirable outputs into models of production: an application to US agriculture. *Review of Agricultural and Environmental Studies. Cahiers d'Economie et Sociologie Rurales* 31, 60-74.

Barghouti, S., Kane, S., Sorby, K., and Ali, M., 2004. Agricultural diversification for the poor: guidelines for practitioners. *Agricultural and Rural Development Discussion Paper 1, The World Bank* 48 p.

Barrett, C., 2010. Smallholder market participation: concepts and evidence from Eastern and Southern Africa. *In Food Security in Africa. Sarris, A., and Morrison, J. (ed).* Food and Agriculture Organization of the United Nations and Edward Elgar, 41-75.

Barrett, C.B., 1997. How credible are estimates of peasant allocative, scale, or scope efficiency? A commentary. *Journal of International Development* 9, 221-229.

Barrett, C.B., Sherlund, S.M., and Adesina, A.A., 2008. Shadow wages, allocative inefficiency, and labor supply in smallholder agriculture. *Agricultural Economics* 38, 21-34.

Battese, G.E., 1997. A note on the estimation of the Cobb-Douglas production function when some explanatory variables have zero values. *Journal of Agricultural Economics* 48(2), 250-252.

Battese, G.E., and Coelli, T.J., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics* 20, 325-332.

Beattie, B.R., and Taylor, C.R., 1993. The economics of production. New York: Wiley. 276 p.

Becker, M., and Johnson, D.E., 1999. Rice yield and productivity gaps in irrigated systems of the forest zone of Côte d'Ivoire. *Field Crops Research* 60, 201–208.

Becker, M., Johnson, D.E., 2001. Improved water control and crop management effects on lowland rice productivity in West Africa. *Nutrient Cycling in Agroecosystems* 59, 119–127.

Binam, N.J., Tonye, J., Wandji, N., Nyambi, G., and Akoa, M., 2004. Factors affecting the technical efficiency among smallholder farmers in the slash and burn agriculture zone of Cameroon. *Food Policy* 29, 531–545.

Bravo-Ureta, B.E., and Pinheiro, A.E., 1993. Efficiency analysis of developing country agriculture: a review of the frontier function literature. *Agricultural and Resource Economics Review* 22(1), 88–101.

Bravo-Ureta, B.E., and Pinheiro, A.E., 1997. Technical, economic and allocative efficiency in peasant farming: evidence from the Dominican Republic. *The Developing Economics* xxxv-1, 48–67.

Byerlee, D., de Janvry, A., and Sadoulet, E., 2009. Agriculture for development: toward a new paradigm. *The Annual Review of Resource Economics* 1, 15-31.

Cameron, A.C., and Trivedi, P.K., 2009. Microeconometrics using Stata. A Stata Press Publication, StataCorp LP, College Station, Texas. 692 p.

Cellule Bas-fond, 2002. Inventaire et mise en valeur des bas-fonds au Bénin. Direction du Génie Rural/ MAEP, Porto-Novo, Bénin. 70 p.

Chambers, R.G., Chung, Y., and Färe, R., 1996. Benefit and distance functions. *Journal of Economic Theory* 70, 407-419.

Chambers, R.G., Chung, Y., and Färe, R., 1998. Profit, Directional Distance Functions, and Nervolian Efficiency. *Journal of Optimization Theory and Applications* 98(2), 351-364.

Charnes, A., Cooper, W.W., and Rhodes, E., 1978. Measuring the efficiency of decision-making units. *European Journal of Operational Research* 2, 429-444.

Charnes, A., Cooper, W.W., Learner, D.B., and Phillips, F.Y., 1985. Management science and marketing management. *The Journal of Marketing* 49(2), 93-105.

Chavas, J-P., 2011. Agricultural policy in an uncertain world. *European Review of Agricultural Economics* 38(3), 383-407.

Coelli, T., and Fleming, E., 2004. Diversification economies and specialization efficiencies in a mixed food and coffee smallholder farming system in Papua New Guinea. *Agricultural Economics* 31, 229-239.

Coelli, T., and Perelman, S., 1996. Efficiency measurement, multiple-output technologies and distance functions: with application to European railways. *Working paper CREPP 96/05, Centre de Recherche en Economie Publique et en Economie de la Population, Université de Liège, Belgium*. 31 p.

Cole, S., 2009. Fixing market failures or fixing elections? Agricultural credit in India. *American Economic Journal: Applied Economics* 1(1), 219-250.

Coulibaly, O., Cherry, A., Nouhoheflin, T., Aitchedji, C.C., and Al-Hassan, R., 2006. Vegetable producer perceptions and willingness to pay for biopesticides. *Journal of Vegetable Science* 12(3), 27-42.

Coulibaly, O., Nouhoheflin, T., Aitchedji, C., Cherry, A., and Adégbola, P., 2011. Consumers' perceptions and willingness to pay for organically grown vegetables. *International Journal of Vegetable Science* 17(4), 349-362.

Cowing, T.G., and Holtmann, A.G., 1983. Multiproduct short-run hospital cost functions: empirical evidence and policy implications from cross-section data. *Southern Economic Journal* 49(3), 637-653.

Cox, T.L., and Wohlgenant, M.K., 1986. Prices and quality effects in cross-sectional demand analysis. *American Journal of Agricultural Economics* 68, 908-919.

Crawford, E., Kelly, V., Jayne, T.S., and Howard, J., 2003. Input use and market development in Sub-Saharan Africa: an overview. *Food Policy* 28, 277-292.

Danso, G.K., Drechsel, P., Akinbolu, S.S., and Gyiele, L.A., 2003. Review of studies and literature on the profitability and sustainability of urban and peri-urban agriculture. FAO Final Report, PR 25314, IWMI, Ghana.

Davidova, S., 2011. Semi-subsistence farming: an elusive concept posing Thorny policy questions. *Journal of Agricultural Economics* 62(3), 503-524.

de Janvry, A., 2010. Agriculture for development: new paradigm and options for success. *International Association of Agricultural Economics*, 17-36.

de Kort, C.A.D., 1993. Recent advances in insecticides and growth regulators. *In Modern crop protection: developments and perspectives, Zadoks, J.C. (ed)*, Wageningen Pers, The Netherlands, 37-51.

Dhungana, B.R., Nuthall, P.L., and Nartea, G.V., 2004. Measuring the economic inefficiency of Nepalese rice farms using Data Envelopment Analysis. *The Australian Journal of Agricultural and Resource Economics* 48, 347-369.

Dinar, A., Karagiannis, G., and Tzouvelekas, V., 2007. Evaluating the impact of agricultural extension on farms performance in Crete: a non-neutral stochastic frontier approach. *Agricultural Economics* 36, 133-144.

Dinham, B., 2003. Growing vegetables in developing countries for local urban populations and export markets: problems confronting small-scale producers. *Pest Management Science* 59, 575-582.

Dolgui, A., and Proth, J-M., 2010. Pricing strategies and models. *Annual Reviews in Control* 34, 101-110.

Drechsel, P., Graefe, S., Sonou, M., and Cofie, O.O., 2006. Informal irrigation in urban West Africa: an overview. Research Report 102, IWMI, Sri Lanka. 35 p.

Emvalomatis, G., Stefanou, S.E., and Oude Lansink, A., 2011. A reduced-form model for dynamic efficiency measurement: application to dairy farms in Germany and The Netherlands. *American Journal of Agricultural Economics* 93(1), 161-174.

Emvalomatis, G., Stefanou, S.E., and Oude Lansink, A., 2011. Estimation of stochastic frontier models with fixed effects through Monte Carlo Maximum Likelihood. *Journal of Probability and Statistics*, doi:10.1155/2011/568457. 13 p.

Erenstein, O., 2006. Intensification or extensification? Factors affecting technology use in peri-urban lowlands along an agro-ecological gradient in West Africa. *Agricultural Systems* 90, 132-158.

Erenstein, O., Sumber, J., Oswald, A., Levasseur, V., and Kore, H., 2006. What future for integrated rice-vegetable production systems in West African lowlands? *Agricultural System* 88(2-3), 376–394.

FAO, 2011. Food and Agriculture Organization of the United nations. http://www.fao.org/countries/55528/en/ben/.

Färe, R., 1988. Fundamentals of production theory. Lecture notes in economics and mathematical systems. Springer-Verlag, Berlin. 163 p.

Färe, R., and Grosskopf, S., 1990. A distance function approach to price efficiency. *Journal of Public Economics* 43, 123-126.

Färe, R., and Grosskopf, S., 2000. Theory and application of Directional Distance Functions. *Journal of Productivity Analysis* 13, 93–103.

Färe, R., and Grosskopf, S., 2004. New Directions: Efficiency and Productivity. Springer Verlag, Berlin, Germany. 174 p.

Färe, R., and Grosskopf, S., 2005. New directions: efficiency and productivity. Springer Science+Business Media; Inc. Kluwer Academic Publishers. Boston, Dordercht, London. 174 p.

Färe, R., and Primont, D., 1995. Multi-output and duality: theory and applications. Kluwer Academic Publishers, Boston, London. 172 p.

Färe, R., Grosskopf, S., and Lovell, K.C.A., 1994. Production frontiers. Cambridge University Press. 296 p.

Farrell, M., 1957. The measurement of productive efficiency. *Journal of the Royal Statistical Society A, General* 120, 253-281.

Farrell, M.J., and Fieldhouse, M., 1962. Estimating efficient production functions under increasing returns to scale. *Journal of the Royal Statistical Society. Series A (General)* 125(2), 252-267.

Fox, G., and Weersink, A., 1995. Damage control and increasing returns. *American Journal of Agricultural Economics* 77(1), 33-39.

Fried, H.O., Lovell, C.A.K., Schmidt, S.S., and Yaisawarng, S., 2002. Accounting for environmental effects and statistical noise in Data Envelopment Analysis. *Journal of Productivity Analysis* 17, 157–174.

Fuglie, K.O., 2008. Is a slowdown in agricultural productivity growth contributing to the rise in commodity prices? *Agricultural Economics* 39, 431-441.

Fukuyama, H., 2003. Scale characterizations in a DEA directional technology distance function framework. *European Journal of Operational Research* 144, 108–127.

Fukuyama, H., and Weber, W.L., 2002. Estimating output allocative efficiency and productivity change: application to Japanese banks. *European Journal of Operational Research* 137, 177-190.

Gattoufi, S., Oral, M., and Resiman, A., 2004. Data Envelopment Analysis literature: a bibliography update (1951–2001). *Socio-Economic Planning Sciences* 38, 159–229.

Gockowski, J., and Ndoumbe, M., 2004. The adoption of intensive monocrop horticulture in southern Cameroon. *Agricultural Economics* 30, 195-202.

Gockowski, J., Mbazo'o, J., Mbah, G., and Moulende, T.F., 2003. African traditional leafy vegetables and the urban and peri-urban poor. *Food Policy* 28, 221-225.

Greene, W. H., 2008. The econometric approach to efficiency analysis. *In The measurement of productive efficiency and productivity growth. Fried, H.O., Lovell, K.C.A., and Schmidt, S.S (ed).* Oxford University Press, 92–250.

Hajargasht, G., Coelli, T., and Rao, D.S.P., 2008. A dual measure of economies of scope. *Economic Letters* 100, 185-188.

Haji, J., 2006. Production efficiency of smallholder's vegetable-dominated mixed farming system in Eastern Ethiopia: A non-parametric approach. *Journal of African Economies* 16(1), 1-27.

Haji, J., and Andersson, H., 2006. Determinants of efficiency of vegetable production in smallholder farms: The case of Ethiopia. *Food Economics* 3, 125-137.

Hajivassiliou, V.A., 1993. Simulation estimation methods for Limited Dependent Variable models. *Cowles Foundation Paper 862*, 519-543.

Hall, D.C., and Moffitt, L.J., 2002. Modeling for pesticide productivity measurement. *In Economics of pesticides, sustainable food production and organic food markets, Hall, D.C., and Moffitt, L.J. (ed).* Elsevier Science Ltd 4, 21-35.

Harwood, J., Heifner, R., Coble, K., Perry, J., and Somwaru, A., 1999. Managing risk in farming: concepts, research, and analysis. *Market and Trade Economics Division and Resource Economics Division, Economic Research Service, U.S. Department of Agriculture. Agricultural Economic Report No. 774*. 125 p.

Henry, M.S., and Bowen, E., 1981. A method for estimating the value of water among sectors of a regional economy. *Southern Journal of Agricultural Economics* 12, 125-132.

Horowitz, J.L., 2001. The bootstrap and hypothesis tests in econometrics. *Journal of Econometrics* 100, 37-40.

Huang, C.J., and Liu, J-T., 1994. Estimation of a non-neutral stochastic frontier production function. *The Journal of Productivity Analysis* 5, 171-180.

Huffman, W.E., 1974. Decision making: the role of education. *American Journal of Agricultural Economics* 56, 85-97.

INSAE, 2003. Troisième recensement général de la population et de l'habitation, February, 2002. Synthèse des analyses. 47 p.

Iráizoz, B., Rapún, M., and Zabaleta, I., 2003. Assessing the technical efficiency of horticultural production in Navarra, Spain. *Agricultural Systems* 78, 387-403.

Irz, X., Lin, L., Thirtle, C., and Wiggins, S., 2001. Agricultural productivity growth and poverty alleviation. *Development Policy Review* 19(4), 449-466.

Jabbar, M.A., and Akter, S., 2006. Market and other factors affecting farm-specific production efficiency in poultry production in Vietnam. *Journal of Food Products Marketing* 12(2), 99-113.

Jabbar, M.A., and Akter, S., 2008. Market and other factors affecting farm specific production efficiency in pig production in Vietnam. *Journal of International Food & Agribusiness Marketing* 20(3), 29-53.

Jacoby, H.G., 1993. Shadow wages and peasant family labour supply: an econometric application to the Peruvian Sierra. *The Review of Economic Studies* 60(4), 903-921.

Jaleta, M., and Gardebroek, C., 2007. Farm-gate tomato price negotiations under asymmetric information. *Agricultural Economics* 36, 245–251.

Jayne, T.S., Kelly, V., and Crawford, E., 2003. Fertilizer consumption trends in Sub-Saharan Africa. *Policy Synthesis 69, Department of Agricultural Economics, Michigan State University, East Lansing*. *(http://www.aec.msu.edu/agecon/fs2/psynindx.htm)*.

Just, R.E., and Pope, R.D., 1978. Stochastic specification of production functions and economic implications. *Journal of Econometrics* 7, 67-86.

Karagiannis, G., and Tzouvelekas, V., 2009. Measuring technical efficiency in the stochastic varying coefficient frontier model. *Agricultural Economics* 40, 389-396.

Karagiannis, G., and Tzouvelekas, V., 2011. The damage-control effect of pesticides on total factor productivity growth. *European Review of Agricultural Economics* Doi: 10.1093/erae/jbr025, 1-21.

Katchova, A.L., 2005. The farm diversification discount. *American Journal of Agricultural Economics* 87(4), 984-994.

Kay, R.D., Edwards, W.M., and Duffy, P.A., 2008. Farm management. Sixth edition. McGraw-Hill, New York. 468 p.

Keatinge, J.D.H., Yang, R-Y., Hughes, J.d'A., Easdown, W.J., and Holmer, R., 2011. The importance of vegetables in ensuring both food and nutritional security in attainment of the Millennium Development Goals. *Food Security* 3, 491-501.

Kelly, V.A., 2005. Fertilizer demand in Sub-Saharan Africa: realizing the potential. *Policy Synthesis 77, Department of Agricultural Economics, Michigan State University, East Lansing*. *(http://www.aec.msu.edu/agecon/fs2/psynindx.htm)*.

Kodde, D.A., and Palm, F.C., 1986. Wald criteria for jointly testing equality and inequality restrictions. *Econometrica* 54(5), 1243-1248.

Kopp, R.J., 1981. The measurement of productive efficiency: reconsideration. *The Quarterly Journal of Economics* 96(3), 477-503.

Kortenhoff, A., 1993. Developments in the use of pesticides. *In Modern crop protection: developments and perspectives, Zadoks, J.C. (ed)*, Wageningen Pers, The Netherlands, 3-10.

Kostov, P., and Lingard, J., 2004. Subsistence agriculture in transitions economies: its roles and determinants. *Journal of Agricultural Economics* 55, 565-576.

Kuiper, E.W., Lutz, C., and van Tilburg, A., 2003. Vertical price leadership on local maize markets in Benin. *Journal of Development Economics* 71, 417-433.

Kumbhakar, S.C., and Lovell, K.C.A., 2003. Stochastic frontier analysis. Cambridge University Press. 333 p.

Kumbhakar, S.C., Lien, G., Flaten, O., and Tveteras, R., 2008. Impacts of Norwegian milk quotas on output growth: a modified distance function approach. *Journal of Agricultural Economics* 59(2), 350-369.

Lancioni, R.A., 2010. A strategic approach to industrial product pricing: the pricing plan. *Industrial Marketing Management* 34, 177-183.

Lavigne-Delville, P., and Boucher, L., 1998. Dynamiques paysannes de mise en culture des basfonds en Afrique de l'Ouest forestière. *In Les rizicultures de l'Afrique de l'Ouest. Cheneau-Loquay, A., and Leplaideur, A. (ed.).* CIRAD, Montpellier, France, 365-376.

Le Meur, P-Y., 2008. Information on land: a common asset and strategic resource, the case of Benin. Iied, Making decentralization work. Russell Press, UK, issue paper 147, 22 p.

Lewis, W., 2004. The power of productivity: wealth, poverty, and the threat to global stability. The University of Chicago Press, Chicago, Ltd., London. 339 p.

Lichtenberg, E., and Zilberman, D., 1986. The econometrics of damage control: why specification matters. *American Journal of Agricultural Economics* 68, 261-273.

Llewelyn, R.V., and Williams, J.R., 1996. Nonparametric analysis of technical, pure technical, and scale efficiencies for food crop production in East Java, Indonesia. *Agricultural Economics* 15, 113-126.

Macharia, I., Mithofer, D., and Waibel, H., 2011. Indirect and external costs of pesticide use in the vegetable sub-sector in Kenya. *In Vegetable production and marketing in Africa: socio-economic research. Mithöfer, D., and Waibel, D. (ed).* CAB International, 227-242.

MAEP, 2011. Plan stratégique de relance du secteur agricole. Benin. 135 p.

Marsh, T.L., Huffaker, R.G., and Long, G.E., 2000. Optimal control of vector-virus-plant interactions: the case of potato leafroll virus net necrosis. *American Journal of Agricultural Economics* 82(3), 556-569.

Martin, T., Assogba-Komlan, F., Houndete, T., Hougard, J.M., and Chandre, F., 2006. Efficacy of mosquito netting for sustainable small holders' cabbage production in Africa. *Journal of Economic Entomology* 99(2), 450-454.

Monroe, K.B., 2003. Pricing: making profitable decisions. 3rd edition, McGraw-Hill Higher Education. 658 p.

Morrison-Paul, C.J.M., and Nehring, R., 2005. Product diversification, production systems, and economic performance in U.S. agricultural production. *Journal of Econometrics* 126, 525-548.

Moustier, P., Mbaye, A., de Bon, H., Guerin, H., and Pages, J. (ed)., 1998. Agriculture periurbaine en Afrique subsaharienne. Actes de l'atelier international 20-24 avril 1998. Montpellier-France. CIRAD, CORAF, Montpellier-France.

Nagle, T.T., and Holden, R.K., 1995. The strategy and tactics of pricing; a guide to profitable decision making. Prentice-Hall, Inc. 409 p.

Nakano, Y., Bamba, I., Diagne, A., Otsuka, K., and Kajisa, K., 2011. The possibility of a rice green revolution in large-scale irrigation schemes in Sub-Saharan Africa. *Policy research working paper. WPS5560. The World Bank.* 33 p.

Ngowi, A.V.F., Mbise, T.J., Ijani, A.S.M., London, L., and Ajayi, O.C., 2007. Smallholder vegetable farmers in Northern Tanzania: pesticide use practices, perceptions, cost and health effects. *Crop Protection* 26, 1617-1624.

Ngugi, I.K., Gitau, R., and Nyoro, J.K., 2007. Access to high value markets by smallholder farmers of African indigenous vegetables in Kenya. IIED, London. 28 p.

OECD, 2008. Contribution to the United Nations Commission on sustainable development 16: towards sustainable agriculture. 53 p.

Oude Lansink, A., 2011. Public and private roles in plant health management. *Food Policy* 36, 166-170.

Oude Lansink, A., and Carpentier, A., 2001. Damage control productivity: an input damage abatement approach. *Journal of Agricultural Economics* 52(3), 11-22.

Oude Lansink, A., and Ondersteijn, C., 2006. Energy productivity growth in the Dutch greenhouse industry. *American Journal of Agricultural Economics* 88(1), 124-132.

Oude Lansink, A., and Silva, E., 2004. Non-parametric production analysis of pesticides use in the Netherlands. *Journal of Productivity Analysis* 21, 49-65.

Oude Lansink, A., and Stefanou, S., 2001. Dynamic area allocation and economies of scale and scope. *Journal of Agricultural Economics* 52(3), 38-52.

Oude Lansink, A., and Stefanou, S., 2007. The impact of inefficiency on diversification. Working paper. 21 p.

Owens, T., Hoddinott, J., and Kinsey, B., 2003. The impact of agricultural extension on farm production in resettlement area of Zimbabwe. *Economic Development and Cultural Change* 51, 337-357.

PADAP (Programme d'Appui au développement Agricole Périurbain Sud Bénin), 2003. Diagnostic, Demande, Offre et marchés, Systèmes de production. I*n Rapport définitif Etude de faisabilité.* MAEP, Bénin. Tome 2, 158 p.

Panzar, J.C., and Willig, R.D., 1981. Economies of scope. *The American Economic Review* 71(2), 268-272.

Pope, R.D., and Prescott, R., 1980. Diversification in relation to farm size and other socioeconomic characteristics. *American Journal of Agricultural Economics* 62(3), 554-559.

Rahman, S., 2009. Whether crop diversification is a desired strategy for agricultural growth in Bangladesh? *Food Policy* 34, 340-349.

Rahman, S., and Rahman, M., 2008. Impact of land fragmentation and resource ownership on productivity and efficiency: the case of rice producers in Bangladesh. *Land Use Policy* 26, 95-103.

Ray, S.C., 2004. The direction distance function and measurement of super-efficiency: an application to airlines data. *Working paper 2004-16, University of Connecticut, Department of Economics Working Paper Series*, 13 p.

Resti, A., 2000. Efficiency measurement for multi-product industries: a comparison of classic and recent techniques based on simulated data. *European Journal of Operational Research* 121, 559-578.

Richards, P., 1986. Coping with hunger: hazard and experiment in an African rice-farming system. *The London research series in geography 11*. Allen & Unwin, London. 176 p.

Rust, R.T., Ambler, T., Carpenter, G.S., Kumar, V., and Srivastava, R.K., 2004. Measuring marketing productivity: current knowledge and future directions. *Journal of Marketing* 68, 76-89.

Sabuhoro, J.B., and Larue, B., 1997. The market efficiency hypothesis: the case of coffee and cocoa futures. *Agricultural Economics* 16, 171-184.

Saphores, J-D.M., 2000. The economic threshold with a stochastic pest population: a real options approach. *American Journal of Agricultural Economics* 82(3), 541-555.

Schmidt, P., 2011. One-step and two-step estimation in SFA models. *Journal of Productivity Analysis* 36, 201-203.

Serra, T., Oude Lansink, A., and Stefanou, S.E., 2011. Measurement of dynamic efficiency: A Directional Distance Function parametric approach. *American Journal of Agricultural Economics* 93(3), 756-767.

Sexton, S.E., Lei, Z., and Zilberman, D., 2007. The economics of pesticides and pest control. *International Review of Environmental and Resource Economics* 1, 271-326.

Seyoum, E.T., Battese, G.E., and Fleming, E.M., 1998. Technical efficiency and productivity of maize producers in Eastern Ethiopia: A study of farmers within and outside the Sassakawa-Global 2000 Project. *Agricultural Economics* 19, 341-348.

Shephard, R.W., 1953. Cost and production functions. Princeton, NJ: Princeton University Press 104 p.

Shephard, R.W., 1970. The theory of cost and production functions. Princeton, NJ: Princeton University Press 308 p.

Sherlund, S.M., Barrett, C.B., and Adesina, A.A., 2002. Smallholder technical efficiency controlling for environmental production conditions. *Journal of Development Economics* 69, 85-101.

Shiferaw, B., Hellin, Jon, and Muricho, G., 2011. Improving market access and agricultural productivity growth in Africa: what role for producer organizations and collective action institutions? *Food Security* 3, 475-489.

Sidhu, S.S., and Baanante, C.A., 1979. Farm-level fertilizer demand for Mexican wheat varieties in the Indian Punjab. *American Journal of Agricultural* Economics 61(3), 455-462.

Simar, L., and Wilson, P.W., 1998. Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. *Management Science* 44(1), 49-61.

Simar, L., and Wilson, P.W., 2000. A general methodology for bootstrapping in non-parametric frontier models. *Journal of Applied Statistics* 27, 779-802.

Simar, L., and Wilson, P.W., 2007. Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics* 136, 31-64.

Simar, L., and Wilson, P.W., 2008. Statistical inference in nonparametric frontier models: recent developments and perspectives. *In The measurement of productive efficiency and productivity growth. Fried, H.O., Lovell, K.C.A., and Schmidt, S.S. (ed), Oxford University Press,* 421-521.

Singbo, A., Nouhoeflin, T., and Assogba-Komlan, F., 2008. Facteurs socio-économiques déterminant la lutte contre les ravageurs des légumes en zones urbaines au sud Bénin. *In Agricultures et développement urbain en Afrique subsaharienne : environnement et enjeux sanitaires, Parrot L. et al. (ed.). Paris: L'Harmattan,* 1-11.

Singbo, A.G., and Oude Lansink, A., 2010. Lowland farming system inefficiency in Benin (West Africa): Directional distance function and truncated bootstrap approach. *Food Security* 2, 367-382.

Snelder, D.J., Masipiqueña, M.D., and de Soo, G.R., 2008. Risk assessment of pesticide usage by smallholder farmers in the Cagayan Valley (Philippines). *Crop Protection* 27, 747-762.

Spencer, D.S.C., and Byerlee, D., 1976. Technical change, labor use, and small farmer development: evidence from Sierra Leone. *American Journal of Agricultural Economics* 58, 874-880.

Stefanou, S.E., and Saxena, S., 1988. Education, experience, and allocative efficiency: a dual approach. *American Journal of Agricultural Economics* 70, 338-345.

Stevenson, R.E., 1980. Likelihood functions for generalized stochastic frontier estimation. *Journal of Econometrics* 13, 57-66.

Tauer, L.W., 1993. Short-run and long-run efficiencies of New-York dairy farms. *Agricultural and Resource Economics Review* 22(1), 1-9.

Teece, D.J., 1980. Economies of scope and the scope of the enterprise. *Journal of Economic Behavior and Organization* 1, 223-247.

Thanassoulis, E., Portela, M.C.S., and Despić, O., 2008. Data Envelopment Analysis: The mathematical programming approach to efficiency analysis. *In The measurement of productive efficiency and productivity growth. Fried, H.O., Lovell, K.C.A., and Schmidt, S.S. (ed).* Oxford University Press, 251-420.

Tran, N.A., Shively, G., and Preckel, P., 2010. A new method for detecting outliers in Data Envelopment Analysis. *Applied Economics Letters* 17, 313-316.

Tschirley D., and Jayne, T.S., 2008. Food crises and food markets: implications for emergency response in Southern Africa. *Policy Synthesis* nº82, 6p. http://www.aec.msu.edu/agecon/fs2/psynindx.htm.

Tsekouras, K.D., Pantzios, C.J., and Karagiannis, G., 2004. Malmquist productivity index estimation with zero-value variables: the case of Greek prefectural training councils. *International Journal of Production Economics* 89, 95-106.

van Emden, H.F., and Service, M.W., 2004. Pest and vector control. Cambridge University Press, UK. 349 p.

van Lenteren, J.C., 1993. Integrated Pest Management: the inescapable trend. *In Modern crop protection: developments and perspectives, Zadoks, J.C. (ed).* Wageningen Pers, The Netherlands, 217-225.

Varian, H. R., 2002. Intermediate microeconomics: a modern approach. Six edition, W.W. Norton & Company, New York, US. 688 p.

Verlinden, E., and Soule, B. G., 2003. Etude de la filière riz au Bénin : Diagnostic-Plan d'Action. PADSE. SOFRECO. 102 p.

Wadud, A., and White, B., 2000. Farm household efficiency in Bangladesh: a comparison of stochastic frontier and DEA methods. *Applied Economics* 32, 1665-1673.

Wang, H-J., 2002. Heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model. *Journal of Productivity Analysis* 18, 241-253.

Weinberger, K., and Lumpkin, A.T., 2007. Diversification into horticulture and poverty reduction: a research agenda. *World Development* 35(8), 1464-1480.

Weinberger, K., and Pichop, G.N., 2009. Marketing of African indigenous vegetables along urban and peri-urban supply chains in Sub-Saharan Africa. *In African indigenous vegetables in urban agriculture, Shackleton, C., Pasquini, M.W., and Drescher, A.W. (ed).* Earthscan, London, UK., 225-244.

Weinberger, K., Pasquini, M., Kasambula, P., and Abukutsa-Onyango, M., 2011. Supply chains for indigenous vegetables in urban and peri-urban areas of Uganda and Kenya: a gendered perspective. *In Vegetable production and marketing in Africa: socio-economic research Mithöfer, D., and Waibel, D. (ed).* CAB International, 169-181.

Welch, F., 1970. Education in production. *The Journal of Political Economy* 78, 35-59.

White, F., 1983. The vegetation of Africa: a descriptive memoir to accompany the Unesco/AETFAT/UNSO vegetation map of Africa. Unesco. 356 p.

Whitley, E., and Ball, J., 2002. Statistics review 4: sample size calculations. *Critical Care 6*, 335-341.

Williamson, S., Ball, A., and Pretty, J., 2008. Trends in pesticide use and drivers for safer pest management in four African countries. *Crop Protection* 27, 1327-1334.

Wilson, P., Hadley, D., and Asby, C., 2001. The influence of management characteristics on the technical efficiency of wheat farmers in eastern England. *Agricultural Economics* 24, 329-338.

Wilson, P.W., 2003. Testing independence in models of productive efficiency. *Journal of Productivity Analysis* 20, 361-390.

Wohlgenant, M., and Mullen, J., 1987. Modeling the farm-retail price spread for beef. *Western Journal of Agricultural Economics* 1, 119-125.

Wollni, M., and Zeller, M., 2007. Do farmers benefit from participating in specialty markets and cooperatives? The case of coffee marketing in Costa Rica. *Agricultural Economics* 37, 243-248.

World Bank, 2007. World Development Report. Agriculture for Development. Washington, The world Bank. 317 p.

Xue, M., and Harker, P.T., 1999. Overcoming the inherent dependency of DEA efficiency scores: a bootstrap approach. Unpublished Working Paper, Wharton Financial Institutions Center, University of Pennsylvania. 32 p.

Zhu, X., and Oude Lansink, A., 2010. Impact of CAP subsidies on technical efficiency of crop farms in Germany, the Netherlands and Sweden. *Journal of Agricultural Economics* 61(3), 545-564.

## Summary

Productivity performance in the agricultural sector is important for the improvement in overall economic performance and can offer good opportunities for increasing food security and reducing poverty. The overall objective of this thesis is to analyze the production technology and the performance of vegetable producers in Benin. In each chapter, we use up-to-date methods for analyzing different efficiency notions.

Chapter 2 examines differences in economic inefficiency between three lowland farming systems. Several performance measures such as overall, technical, allocative, scale, input and output inefficiency are estimated. Moreover, the sources of inefficiency are analyzed to gain insight in the lowland production environment characteristics. This chapter employs a new robust two stage semi-parametric approach that consists of a directional distance function and a single truncated bootstrap. The first stage results provide evidence of significant technical, allocative and scale inefficiencies among producers, of which scale inefficiency, allocative inefficiency and output inefficiency are the main sources of overall economic inefficiency. Increasing returns to scale prevails in the integrated rice-vegetable farming system. Input inefficiency indicates that variable inputs (seed and fertilizers) are not used optimally, reflecting limited access to quality and quantity of seeds and fertilizers for most farms. The second stage results examine the influence of environmental and socio-economic factors on the technical, allocative and scale inefficiency of the lowland producers. There are substantial differences between the three lowland farming systems. Technical inefficiency is significantly smaller when farmers produce only rice in the rainy season. Allocative and scale inefficiency is significantly smaller in the rice and the integrated rice-vegetable farming systems. Water control, size of family workforce, years of management experience in lowland cultivation and the upland farm size held by households are other factors influencing technical, allocative and scale inefficiency. Formal education and experience are substitutes, whereas water control and lowland farming systems are complements, each having a significant effect on the level of technical, allocative and scale inefficiency. Finally, there is economic and food security gain in promoting lowland development strategies with integrated rice-vegetable farming systems.

Chapter 3 proposes an approach to measure technical and marketing inefficiency of a sample of urban vegetable producers. The study provides a Russell-type measure of inefficiency using a directional distance function that accounts simultaneously for the

expansion of output and output prices and the reduction of variable inputs. The results indicate that producers are more marketing than technically inefficient. The truncated bootstrap regression of the determinants of the two inefficiency terms shows that more specialized producers have lower marketing inefficiency and that soil fertility decreases technical inefficiency. Another finding is that producers using retailer marketing arrangements are more marketing efficient than those selling to wholesalers. The results imply that agricultural policies should improve the capacity of producers to apply the available technology more efficiently. In addition, public and private extension services must focus on the managerial skills and sales management to help producers implement a profitable pricing strategy, rather than focusing solely on the production process. In conclusion, even though it is important to reduce the technology gap and improve the managerial skills of producers, agricultural policy must be accompanied by increasing market participation of farmers and market access.

A large majority of farms in Benin’s vegetable production subsector produce both traditional and non-traditional vegetables. By producing both categories of crops instead of only one, the farm may be able to reduce risk. Another benefit associated with diversification is the complementary use of inputs on the farm. Specialization in crops, however, allows operators to exploit scale economies. Moreover, specialized operators have better opportunities to fine-tune their skills. Chapter 4 provides an empirical evaluation of the impact of crop specialization on vegetable producers’ economic performance. The challenge in this study is to assess whether changes in farm orientation through diversification or specialization can lead to better performance. A non-neutral stochastic frontier model is used to test and consider the adjustment of input utilization with output choices and estimate the effect of specialization on production technology and producer management performance. An input distance function is estimated using a Translog specification and a truncated efficiency regression. The results suggest that the technology exhibits increasing returns to scale. Compared to non-traditional vegetables, traditional vegetables have larger contribution to returns to scale. The results also provide evidence for diseconomies of scope, indicating that vegetable producers have a strong incentive for specialization in either traditional or non-traditional vegetables. The contribution of vegetable output specialization to technical efficiency is found to be quite low, but statistically significant. An increase in crop specialization increases technical efficiency. The policy implication of this chapter is that the government has to change its policy towards enhancing specialization rather than diversification.

High-value vegetables are sensitive to pest pressure and subject to intensive application of pesticides. To prevent and cure from pests and diseases, producers use a large amount of pesticides on vegetables such as insecticides, fungicides and herbicides. Various policies aiming at reducing the use and dependence of vegetables on synthetic pesticide use are encouraged by public and private extension services. The market of pesticides in Benin is composed of formal and informal markets, where both approved and banned pesticides are sold. Therefore, the efficiency of the use of pesticides and other inputs of vegetable producers is analyzed in Chapter 5. As vegetable producers in Benin applied pesticides prophylactically to prevent from the occurrence of an infestation or diseases, the input function is used to study the value of the marginal product of pesticides. Shadow prices of two categories of pesticides are determined using four input-oriented models to measure technical efficiency in four different directions. Each model estimates the shadow price of damage abatement and productive inputs at different subspaces of the frontier. The homogenous smooth bootstrap technique is used to determine confidence intervals of technical efficiency scores and shadow prices. Results show that vegetable producers have lower technical efficiency in the use of pesticides than in productive inputs. Also, results suggest that vegetable producers overuse insecticides and other pesticides. The overuse of pesticides can be attributed to the characteristics of the vegetable production system and may also point at risk aversion of farmers. The study shows that there is no evidence of technical interdependence between pesticides and productive inputs. The implication is that the government may support producers by providing better information through extension services. The government may also take measures aiming at reducing the structural dependence on pesticides.

Based on the findings of this thesis, the main conclusions are:

i) The analysis of different lowland farming systems indicates that scale inefficiency, allocative inefficiency and output inefficiency are the main sources of overall economic inefficiency (Chapter 2).

ii) Increasing returns to scale prevails in the integrated rice-vegetable farming system. Allocative and scale inefficiency are significantly smaller in the rice or the integrated rice-vegetable farming systems than the vegetable farming system (Chapter 2).

iii) Urban and peri-urban vegetable producers are more marketing inefficient than they are technically inefficient (Chapter 3).

iv) Vegetable producers in urban and peri-urban areas using retailer marketing arrangements are more marketing efficient than those selling to wholesalers (Chapter 3).

v) The production technology of vegetable producers in urban and peri-urban areas exhibits increasing returns to scale (Chapter 4).

vi) The study among urban and peri-urban vegetable producers provides evidence for diseconomies of scope, indicating that vegetable producers have a strong incentive for specialization in either traditional or non-traditional vegetables (Chapter 4).

vii) An increase in crop specialization at the farm level is associated with an increase in technical efficiency of vegetable producers in urban and peri-urban areas (Chapter 4).

viii) Vegetable producers in urban and peri-urban areas are less technically efficient in the use of pesticides than in the use of other inputs and also overuse pesticides (Chapter 5).

## Samenvatting (Summary in Dutch)

Verbetering van productiviteit van de agrarische sector is een belangrijke voorwaarde voor de verbetering van de welvaart en voedselzekerheid en voor vermindering van armoede. De overall doelstelling van dit proefschrift is: het analyseren van de productie technologie en performance van groenteproducenten in Benin. In elk hoofdstuk worden up-to-date methode gebruikt voor het analyseren van verschillende efficiëntie concepten.

Hoofdstuk 2 onderzoekt verschillen in de economische inefficiëntie tussen drie verschillende laagland bedrijfssystemen. Verschillende performance maatstaven zoals overall, technische, allocatieve, schaal, input specifieke en output specifieke inefficiënties worden geschat. Tevens worden verschillende bronnen van inefficiëntie geanalyseerd om inzicht te krijgen in de rol van omgevingsfactoren in de laagland productie. Dit hoofdstuk gebruikt een nieuwe robuuste semi-parametrische methode die bestaat uit een directional distance functie en een truncated bootstrap regressie. De directional distance functie geeft informatie over technische, allocatieve en schaal inefficiënties van producenten. Schaal- en allocatieve inefficiëntie zijn de belangrijkste bronnen van overall economische inefficiëntie. De productietechnologie van geïntegreerde laagland rijstproductiesystemen wordt gekenmerkt door toenemende schaalopbrengsten. De input inefficiëntie laat zien dat variabele inputs (zaaizaden en kunstmest) niet optimaal worden gebruikt. Dit resultaat suggereert dat producenten beperkte toegang hebben tot de gewenste kwaliteit en hoeveelheid van deze inputs. De truncated bootstrap onderzoekt de invloed van omgevingsfactoren en sociaaleconomische variabelen op de technische, allocatieve en schaal inefficiëntie van laagland producenten. Technische inefficiëntie is significant lager voor producenten van uitsluitend rijst in het regenseizoen. Allocatieve en schaal inefficiëntie zijn significant lager in het rijst- en geïntegreerde rijst-groente systeem. Water management, aantal meewerkende familieleden, aantal jaren management ervaring in laagland systemen en de grootte van het hoogland areaal bepalen mede de technische, allocatieve en schaal inefficiëntie. Onderwijs en ervaring zijn substituten, terwijl water management en laagland bedrijfssystemen complementen zijn, elk met een significant effect op de inefficiëntie. Toepassing van geïntegreerde rijst-groente productiesystemen kan leiden tot verbeteringen van de welvaart en voedselveiligheid.

Hoofdstuk 3 introduceert een maatstaf van technische en marketing inefficiëntie van een steekproef van stedelijke groente producenten. Dit hoofdstuk gebruikt een Russell-type inefficiëntie maatstaf gebaseerd op een directional distance functie die gelijktijdig de

productie en output prijs maximaliseert en de variabele inputs minimaliseert. De resultaten geven aan dat producenten een grotere marketing inefficiëntie hebben dan technische inefficiëntie. De truncated bootstrap regressie van de factoren die deze inefficiëntie maatstaven verklaren, laat zien dat gespecialiseerde producenten een lagere marketing inefficiëntie hebben en dat bodemvruchtbaarheid de technische inefficiëntie doet afnemen. Producenten die gebruikmaken van retailer marketing arrangementen hebben een hogere marketing efficiëntie dan producenten die direct verkopen aan de groothandel. De resultaten impliceren dat landbouwbeleid de capaciteit om de technologie efficiënt te gebruiken, moet verbeteren. Daarnaast moeten publieke en private voorlichtingsdiensten zich meer focusen op het verbeteren van verkoop management, in plaats van zich uitsluitend te richten op de verbetering van het productieproces. Alhoewel het belangrijk is om de technologie gap te verminderen en management skills van producenten te verbeteren, moet landbouwbeleid samengaan met een grotere marktparticipatie van producenten en verbetering van markttoegang.

De meerderheid van de groenteproducenten in Benin produceren zowel traditionele als niet-traditionele groenten. Door beide typen groenten te produceren kunnen producenten de risico’s verminderen. Een ander voordeel van diversificatie is gelegen in complementariteit van inputs op het bedrijf. Specialisatie maakt het daarentegen mogelijk om schaalvoordelen te behalen en om de kennis van, en vaardigheden in het productieproces te maximaliseren. Hoofdstuk 4 analyseert de invloed van specialisatie op de economische performance van groenteproducenten. Een non-neutrale stochastische frontier wordt gebruikt om de verandering van het gebruik van inputs te testen en het effect van specialisatie op performance te meten. Een input distance functie wordt geschat op basis van een Translog specificatie, samen met een inefficiëntie model. De resultaten suggereren dat de productietechnologie wordt gekenmerkt door toenemende schaalopbrengsten. Traditionele groeten leveren een grotere bijdrage aan de schaalopbrengsten dan niet-traditionele groeten. De resultaten laten ook zien dat er sprake is van diseconomies of scope, wat impliceert dat groente producenten een sterke drijfveer hebben voor specialisatie in ofwel traditionele dan wel niet-traditionele groenten. Specialisatie in groenten heeft een klein maar significant positief effect op de technische efficiëntie. De beleidsimplicatie is dat de overheid haar beleid moet wijzigen en specialisatie in plaats van diversificatie moet bevorderen om de performance van groenteproducenten te vergroten.

Groenten met een hoge waarde zijn doorgaans gevoeliger voor ziekten en plagen; de productie gaat dan ook gepaard met een intensief gebruik van pesticiden zoals insecticiden, fungiciden en herbiciden. De publieke en private voorlichtingsdiensten promoten verschillende manieren om het gebruik en de afhankelijkheid van het gebruik van pesticiden in de groenteproductie te verminderen. Op de formele en informele markten van pesticiden in Benin worden zowel toegelaten middelen als verboden middelen verkocht. Daarom wordt de efficiëntie van het gebruik van pesticiden en andere inputs door groenteproducenten geanalyseerd in Hoofdstuk 5. De input distance functie wordt gebruikt omdat producenten pesticiden vooral preventief gebruiken. Schaduwprijzen van twee categorieën van pesticiden worden bepaald met behulp van vier verschillende input distance functies. Elk model schat de schaduwprijs op een ander deel van de frontier. De homogene smooth bootstrap techniek wordt gebruikt om betrouwbaarheidsintervallen van technische efficiëntie en schaduwprijzen te bepalen. De resultaten laten zien dat groente producenten pesticiden minder efficiënt gebruiken dan andere inputs. Ook laten de resultaten zien dat groente producenten insecticiden en overige pesticiden overmatig gebruiken. Het overmatig gebruik van pesticiden duidt op problemen bij de toepassing en op risico aversie van producenten. Hoofdstuk 5 laat zien dat er geen technische afhankelijkheid is tussen pesticiden en overige inputs. De beleidsimplicatie van deze resultaten is dat de overheid aan producenten betere informatie kan verschaffen over een doelmatig pesticidengebruik, b.v. via voorlichting. De overheid kan ook maatregelen treffen om de structurele afhankelijkheid van pesticiden te verminderen.

De belangrijkste conclusies van dit proefschrift zijn:

i) De analyse van verschillende laagland bedrijfssystemen laat zien dat schaal, allocatieve en output inefficiëntie de belangrijkste bronnen zijn van overall inefficiëntie (Hoofdstuk 2)

ii) Geintegreerde rijst-groente bedrijfssystemen worden gekenmerkt door toenemende schaalopbrengsten. Allocatieve en schaal inefficiëntie zijn significant kleiner in het rijst en het geïntegreerde rijst-groente systeem dan in het groente systeem (Hoofdstuk 2).

iii) Stedelijke en stedelijk-perifere groente producenten hebben een groter marketing inefficiëntie dan technische inefficiëntie (Hoofdstuk 3).

iv) Groente producenten in stedelijke en stedelijk-perifere gebieden die gebruikmaken van marketing arrangementen hebben een grotere marketing efficiëntie dan producenten die direct verkopen aan de groothandel (Hoofdstuk 3).

v) De productie technologie van groente producenten in stedelijke en stedelijk-perifere gebieden wordt gekenmerkt door toenemende schaalopbrengsten (Hoofdstuk 4).

vi) De productie technologie van stedelijke en stedelijk-perifere groente producenten wordt gekenmerkt door diseconomies of scope. Dit geeft aan dat groente producenten een sterke drijfveer hebben voor specialisatie in ofwel traditionele dan wel niet-traditionele groentes (Hoofdstuk 4).

vii) Een toename van de gewasspecialisatie op bedrijfsniveau gaat samen met een grotere technische efficiëntie van groente producenten in stedelijke en stedelijk-perifere gebieden (Hoofdstuk 4).

viii) Groente producenten in stedelijke en stedelijk perifere gebieden gebruiken pesticiden minder efficiënt dan andere inputs. Ook is er sprake van overmatig gebruik van pesticiden (Hoofdstuk 5).

## Training and Supervision Plan

Alphonse Gbèmayi Singbo
PhD candidate, Wageningen School of Social Sciences (WASS)
Completed Training and Supervision Plan

| Description | Institution | Year | ECTS[1] |
|---|---|---|---|
| **I. General Part** | | | |
| Techniques for Writing and Presenting a Scientific Paper | WGS, WU[2] | 2008 | 1.2 |
| **II. Graduate School Part** | | | |
| Mansholt Introduction Course | MG3S, WU[3] | 2008 | 1.5 |
| Research Proposal | MG3S, WU[3] | 2009 | 6.0 |
| **III. Discipline-Specific Courses** | | | |
| Economic Models | WUR[4] | 2008 | 6.0 |
| Advanced Econometrics | WUR[4] | 2008 | 6.0 |
| Organization of Agribusiness | WUR[4] | 2008 | |
| Advanced Macroeconomics | WUR[4] | 2008 | |
| Spatial Econometrics: Theory and Practices | MG3S, WU[3] | 2008 | 1.5 |
| Non-Parametric Methods for Efficiency Analysis | MG3S, WU[3] | 2008 | 4.0 |
| Dynamics Efficiency Analysis | MG3S, WU[3] | 2008 | 1.5 |
| The Bayesian Approach in Theory and Practice | MG3S, WU[3] | 2008 | 1.5 |
| Integrated Assessment of Agriculture and Sustainability Development (SEAMLESS) | PE&RC,WU[5] | 2008 | 2.0 |
| The Economic Institutions of Agriculture Food and Rural Areas: Institutional Dynamics, Organizations and Governance | MG3S, WU[3] | 2009 | 1.5 |
| Survival Analysis: Analysis of Individually Registered Time of Event Data | PE&RC,WU[5] | 2009 | 0.6 |
| Panel Data Analysis in Microeconomics | MG3S, WU[3] | 2009 | 4.0 |
| Advance Microeconomics | WUR[4] | 2009 | 6.0 |
| Panel Data Models for Limited Dependent Variable | Tilburg University (NAKE[6]) | 2009 | 3.0 |
| PhD Discussion Groups | BEC, WU[7] | 2008-12 | 3.0 |
| **III. Teaching Assistant** | | | |
| Agricultural Business Economics | BEC, WU[7] | 2012 | 0.5 |
| **IV. Conferences Presentations** | | | |
| The Fifth North American Productivity Workshop (NAPW-V), New York, USA | Stern School of Business of New York University | 2008 | 1.0 |
| The XI European Workshop on Efficiency and Productivity Analysis (EWEPA-XI), Pisa, Italy | School of Engineering, University of Pisa | 2009 | 1.0 |
| The XII European Workshop on Efficiency and Productivity Analysis (EWEPA-XII), Verona, Italy | School of Economics, University of Verona | 2011 | 1.0 |
| Efficiency Measurement: New Methods and Application to the Food Sector Analysis, Toulouse, France | Toulouse School of Economics | 2011 | 1.0 |
| **TOTAL[8]** | | | **53.8** |

[1] One ECTS on average is equivalent to 28 hours of course work.
[2] Wageningen Graduate School, Wageningen University.
[3] Mansholt Graduate School of Social Sciences, Wageningen University.
[4] Wageningen University and Research centre.
[5] Production Ecology and Resource Conservation Graduate School, Wageningen University.
[6] Netherlands Network of Economics.
[7] Business Economics Group, Wageningen University.
[8] Minimum of 30 ECTS are required.

## About the Author

Alphonse G. Singbo was born on March 27th, 1973 in Porto-Novo, Ouémé, Benin. He finished his primary education at the primary school of Accron, Porto-Novo in 1986. In the same year he began his second level of education at the secondary school of Akpassa, Porto-Novo. In 1991, he started his higher secondary education at the secondary school of Leon-Bourgine, Porto-Novo. In 1994, he began his study at University of Abomey-Calavi (known before as University of Benin). After one year in Physics and Chemistry specialization at the Faculty of Science and Techniques, he entered the Faculty of Agricultural Sciences of the same university in 1995. He obtained the degree of Agronomist in 1999. From 1999 to 2000 and based on his interest in agricultural economics, he obtained the Engineer Agronomist degree with specialization in rural economics at the same faculty. From January 2001 to September 2006, he was working at the National Agricultural Research Institute of Benin (INRAB), where he worked in the Agricultural Policy Analysis Unit. He started his MSc study in Rural Economics at the University of Louvain-La-Neuve (Belgium) and he obtained his MSc degree (High distinction) in September 2007. From January 2008 till June 2012 he was working in the Business Economics Group at Wageningen University on his PhD research project. He followed his PhD education program in the Wageningen School of Social Sciences of Wageningen University. During the period of his PhD, he worked as a Teaching Assistant in the course Agricultural Business Economics.

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**Cover design by**: The author

**Front side:** Three different methods (DEA, Smooth bootstrap and ML) of representing the production technology.

**Reverse side:** Pictures of vegetable and rice crops combined in pyramid to stress the structure of the population in Benin.