ECONOMETRIC ANALYSIS OF ECONOMIC AND ENVIRONMENTAL EFFICIENCY OF DUTCH DAIRY FARMS

Promotor:	Dr.ir. A.J. Oskam Hoogleraar in de agrarische economie en plattelandsbeleid
Co-promotor:	Dr. G.J. Thijssen Universitair Hoofddocent bij de leerstoelgroep agrarische economie en plattelandsbeleid

Stijn Reinhard

ECONOMETRIC ANALYSIS OF ECONOMIC AND ENVIRONMENTAL EFFICIENCY OF DUTCH DAIRY FARMS

Proefschrift

ter verkrijging van de graad van doctor
op gezag van de rector magnificus
van de Wageningen Universiteit,
dr. C.M. Karssen,
in het openbaar te verdedigen
op woensdag 27 oktober 1999
des namiddags te vier uur in de Aula

Abstract

Econometric analysis of economic and environmental efficiency of Dutch dairy farms
Reinhard, Stijn, 1999

The Dutch government aims for competitive and sustainable farms, that use marketable inputs efficiently as well as apply environmentally detrimental variables efficiently in the production process. The objective of this research is to define, to estimate and to evaluate environmental efficiency. Environmental efficiency is a measure that allows for the combination of a firm's environmental pressure with its economic performance. If the environmental efficiency could be improved, the emission of nitrogen into the environment will decrease without loss of production or additional costs.

Three econometric methods based on the neoclassical production theory (stochastic production frontier, output distance function and shadow cost system) are transformed to enable the definition and estimation of environmental efficiency. These methods are applied to a panel of Dutch dairy farms. Nitrogen surplus is the environmentally detrimental variable throughout this thesis. In the stochastic production frontier, nitrogen surplus is modelled as an environmentally detrimental input. In the distance function N surplus is applied as a bad output. Due to the materials balance definition of N surplus the shadow price of bad output is positive. A shadow cost system is used to compute the cost-efficient and the nitrogen-efficient production. The latter is based upon the input mix that minimises the nitrogen content of variable inputs. Finally the variation in efficiency is explained in a two-stage approach with characteristics that are hypothesised to influence environmental efficiency. The environmental efficiency measures are compared to alternative environmental indicators currently used.

Keywords: Environment; Agriculture; Efficiency; Environmental Efficiency; Stochastic Frontier Analysis; Data Envelopment Analysis; Distance Function; Cost Function; Materials Balance.

Econometric analysis of economic and environmental efficiency of Dutch dairy farms
Stijn Reinhard
Ph.D. Thesis, Wageningen Agricultural University, - With Ref –With Summary in Dutch
ISBN 90-5808-090-0

Preface

About six years ago, I noticed that in my day-to-day work at the Agricultural Economics Research Institute (LEI), I could not get the deepening of scientific knowledge and experience I was aiming for. This triggered the wish to do Ph.D. research. Luckily Arie Oskam, Geert Thijsen and Vinus Zachariasse were willing to help me to convert my plans into a research project. This thesis is the result of research I performed at the Agricultural Economics Research Institute in the period August 1995 – May 1999. The project was funded by LEI and the Mansholt Institute (LNV stimulans project).

I am indebted to my supervisors Geert Thijssen and Arie Oskam. Geert drew my attention to the subject of this thesis, after he met Knox Lovell in Wageningen in 1992. His stimulating comments and his realistic view on the feasibility of various ideas stimulated the progress of this project. His dedicated supervision shows in the co-authorship of chapters 2 to 6. Arie provided valuable and critical comments on earlier drafts. Knox Lovell was the great source of inspiration for the subject of this thesis. His contributions to chapter 2, 3 and 6 led to papers that can be easily read.

I also want to thank the following people at LEI for their support: Vinus Zachariasse for his effort to arrange the funding of the LEI and the confidence he had in the completion of this thesis. Floor Brouwer, Krijn Poppe and Jan Dijk shared their expertise in analysing (environmental) indicators using FADN data. Ton van Lierop assisted in drawing many versions of the figures in this thesis, and the secretary team at the Agriculture division (Brigitte van Oord, Iris van Es and Helga van der Kooij) transformed my text into a book. Zayd Abdulla and Ingrid Matser edited my English. I like to thank Caro Hummels for the challenge she offered me in our thesis race and for the cover design.

I also like to acknowledge the group of efficiency researchers who gather at the annual efficiency workshops. They have been very helpful in sharing their ideas with newcomers to this topic. George Battese, Scott Atkinson, Hal Fried, Shawna Grosskopf and Spiro Stefanou, among others, were so kind to supply me with (draft versions of) their papers. The Dutch efficiency research group, Bert Balk, Rene Goudriaan and Jos Blank, has been helpful in commenting on portions of this thesis.

Finally, I like to mention the women at home base (Beatrice, Arlet and Jitte) for distracting my mind and showing me that there are other valuable things on earth than Ph.D. research.

Stijn Reinhard
The Hague, August 1999

Contents

Page

1. Introduction

1.1 Definition of empirical problem

For a long time, the objective of policies regarding the Dutch agricultural sector was to increase agricultural productivity. This increase was necessary to ensure a fair standard of living for the agricultural community (Tracy, 1989). Agricultural productivity has increased rapidly in the Netherlands since World War II; technological development enabled the substitution of variable inputs (fertiliser, feed and pesticides) for labour (Oskam, 1991; Rutten, 1992). This increased use of variable inputs led to environmental side effects, which became apparent in the seventies. In the dairy sector of the Netherlands the focus has mainly been on environmental pollution due to excess application of nutrients (RIVM, 1988). For instance acid rain was related to emission of ammonia, nitrates were found in drinking water and phosphate was found in surface water. These environmentally detrimental effects are all related to excess fertilisation (nitrogen and phosphorus). The input of nutrients (feed and fertiliser) in agriculture is much larger than the output of nutrients in desirable products. To reduce the nutrient surplus accumulated in the environment the government has put forward environmental objectives and it has formulated regulations.

Policy with respect to agriculture has changed into a set of broader objectives in the Netherlands. Nowadays it aims for a competitive and sustainable agriculture and for safe food (MLNV, 1990). These objectives have been elaborated in subsequent governmental reports as a sustainable and environmentally efficient economy (MVROM et al., 1997:5). In 1984 the first restriction with respect to nutrients was implemented. Intensive livestock farms were no longer allowed to build new production capacities for hogs and poultry any more. Since 1987, farmers have been allowed to apply only a fixed maximum quantity of manure (measured in kg phosphate) on their farms. Any surplus manure must be removed from the farm. Also legislation came into effect with respect to the method (mandatory low emission slurry application) and timing (not allowed in winter) of manure application [1]. Since 1998, nutrient standards have been related to the farm level. To accomplish this, mineral accounting was made mandatory for livestock farms with more than 2.5 animals (units) per ha. For every kg of phosphate and nitrogen surplus above the levy free surpluses a levy has to be paid (NLG 2.50 per kg phosphate per ha and NLG 1.50 per kg nitrogen surplus per

[1] Additional background information on the Dutch environmental policy as it applies to agriculture is available in OECD (1994) and Brouwer and van Berkum (1998).

ha in 1998). These regulations will gradually become stricter to allow agriculture to adapt itself (MVROM and MLNV, 1995). The levy free surplus will be decreased in stages, so that by 2008/2010, fertilisation will be almost in balance with the extraction of minerals by crops.

In line with the traditional policy on agriculture, the technical and economic efficiency of dairy farms has been researched intensively (see appendix A). This provided valuable measures for evaluating the productive performance of farms in the context of production possibilities and cost minimisation. With the increasing consciousness about the environmental problems caused by agriculture and the newly formulated policy, the environmental performance of farms has become increasingly important (Färe et al., 1996). At present, the supply of quantitative information about agri-environmental linkages is inadequate. Without such information, governments and other users cannot adequately identify, prioritise and measure the environmental impacts associated with agriculture, which makes it difficult to improve the targeting of agricultural and environmental programmes and to monitor and assess policies (OECD, 1997:3). Nutrient balances are available as indicators for agricultural nutrient use (OECD, 1997:25). Although indicators are available for both the economic and environmental objectives of the government, a comprehensive performance measure that combines economic and environmental performance has not yet been developed.

1.2 Indicators and the definition of the methodological problem

An indicator can be defined as 'a parameter, or value derived from parameters, which points to, provides information about, describes the state of a phenomenon/environment/area, with a significance extending beyond that directly associated with a parameter value' (Brouwer and Crabtree, 1999). Indicators always imply a compromise. Their design needs to optimise between relevance to the user, scientific validity and measurability (Bakkes, 1997:379). Desirable indicators are variables that summarise or otherwise simplify relevant information, make visible or perceptible phenomena of interest, and quantify, measure and communicate relevant information (Gallopin, 1997). Two important features of indicators are quantification of information as well as simplification of complex phenomena (Hammond et al., 1995). Agri-environmental indicators are intended to: (i) Provide information to policy-makers on the current state of the environment in agriculture; (ii) Help policy-makers understand the links between causes and effects and the impact of agricultural policies on the environment; (iii) Contribute to monitoring and evaluating policy effectiveness in promoting sustainable agriculture (Parris, 1999). The PSR-framework (Pressure on the environment, State of the environment, Response from society to change pressure on and state of the environment) has been used often to develop environmental indicators (e.g. Bakkes et al., 1994). The OECD (1997) modified this framework to analyse agri-environmental linkages and develop agri-environmental indicators into the Driving force-State-Response (DSR) framework [2]. A specific agri-environmental indicator often covers only a portion of this framework. The manure surplus per ha can be regarded as a Driving force indicator. Corresponding State indicators are for instance the amount of nitrate in ground water or the ammonia content in the air. If policy is formulated to reduce the emission of nitrogen surplus, nitrogen surplus per ha can be viewed as a Response indicator for environmental policy effects. No scientific consensus exists as to the appropriate linkages among DSR framework components (Billharz and Molden, 1997:392). Oskam and Vijftigschild (1999) put forward that due to its strong focus on policy issues, the conceptual framework of the OECD may provide only limited indications of the state of the environment. They prefer the term 'agri-environmental pressure indicators' for indicators that reflect the relation pressure - state. They propose an alternative indicator that is a weighed summation of underlying environmental indicators. Further work is identified by the OECD to combine information about nutrient balances with knowledge about the production system. If nutrient balance is used alongside of other indicators, the understanding of the linkages between agriculture and environment will be enhanced (OECD, 1997:25).

The standard approach to combine nutrient balances with knowledge about the production system is to use relative performance measures (e.g. nitrogen surplus per ha, cows per ha). These relative performance measures have a serious flaw, in that they only consider the land input and ignore all other inputs, such as labour, machinery, fuel, fertiliser, pesticides, etc. The use of partial measures in the formulation of management and policy advice is likely to result in excessive use of those inputs, which are not included in the performance measure. Similar problems occur when other simple measures of efficiency, such as litres of milk per cow or output per unit of labour, are used (Coelli, 1995b).

Tyteca (1996) defines environmental performance indicators as analytical tools that allow comparisons between various firms in an industry, with each other and with respect to certain environmental characteristics. The environmental performance indicator that is to be developed in this Ph.D.-thesis will relate the technical and economic performance of farms to their environmental pressure.

The standard efficiency methodology is an attractive framework to analyse the (comprehensive) environmental performance of (dairy) farms. Efficiency scores are performance measures on the basis of which production units are evaluated. In efficiency measurement observations are compared with optimal production conditional on inputs (or outputs, depending on the definition used). Efficiency scores readily show the potential improvements. Technical efficiency measures do not need price information nor do they require the specifi-

[2] The DSR framework addresses the following questions: (i) what driving force is causing environmental conditions in agriculture to change; (ii) what effect does this have on the state of the environment; (iii) what actions are being taken to respond to changes in the state of the environment?

cation of any a priori weight on the environmental impacts that are being aggregated (Tyteca, 1996). Another advantage of efficiency methodology is that it fits in with the expression 'environmental efficiency' or 'eco-efficiency' that is frequently used in policy reports [3] (e.g. MVROM et al., 1997). One of the challenges for Dutch agriculture as identified by MVROM et al., (1997:24) is to improve efficiency in production and farm processes in order to optimise inputs and emission. Environmental efficiency has so far not been estimated econometrically.

The basis of standard efficiency methodology was developed by Farrell (1957). He proposed that the efficiency of a firm consists of two components: (i) technical efficiency, which reflects the ability of a firm to obtain maximum output from a given set of inputs, and (ii) allocative efficiency, which reflects the ability of a firm to use the inputs in the optimal proportions, given their respective prices. These two components are then combined to provide a measure of total economic efficiency (overall efficiency). Farrell also introduced an input-oriented technical efficiency measure, defined as the ratio of minimum potential to observed input required to produce the given output. Thus the analysis of technical efficiency can have an input-conserving orientation or an output-augmenting orientation. Efficiency is a relative measure; efficiency scores depend on the firms that are compared.

In the efficiency literature, methods to estimate the technical or economic performance are readily available. The two important methods to compute technical efficiency scores are (i) mathematical programming methods (e.g. Data Envelopment Analysis, DEA) and (ii) econometric methods (Stochastic Frontier Approach, SFA, cost functions and distance functions). According to Lovell (1993) there are two essential differences between the econometric approach and mathematical programming methods in the calculation of a frontier function. The econometric approach is stochastic, and so attempts to distinguish the effects of noise from the effects of inefficiency. DEA is non stochastic, and lumps noise and inefficiency together, calling the combination inefficiency. The econometric approach is parametric, and confounds the effects of misspecification of functional form (of both technology and inefficiency) with inefficiency. The mathematical programming approach is non parametric and less prone to this type of specification error. DEA is extensively described by Charnes et al. (1995). Hjalmarsson et al. (1996) argue that one of the main appeals of the stochastic frontier approach is the possibility it offers for a specification in the case of panel data. It also allows for a formal statistical testing of hypotheses. Coelli (1995b) concluded that if one is using farm-level data where measurement errors, missing variables, the weather etc. are likely to play a significant role, then the assumption that all deviations from the frontier are due to inefficiency, (an assumption made by mathematical programming techniques) may be too bold. There is a long history of the econometric approach to efficiency

[3] These environmental efficiency measures are not defined in the policy reports.

measurement in agriculture, see Battese (1992) and Coelli (1995b) for an overview. In this thesis, we focus on econometric methods to compute environmental efficiency.

The Stochastic Frontier Approach (SFA) is motivated by the idea that deviations from the frontier might not be entirely under the control of the firm studied. The stochastic frontier approach was introduced by Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977) and was later extended to panel data by Pitt and Lee (1982) and Battese and Coelli (1988, 1992). An alternative representation of production technology is the cost function. The cost function was adapted to estimate input-oriented technical efficiency and allocative efficiency (Schmidt and Lovell, 1979). This approach corresponds to Farrell's (1957) original efficiency measure. Kopp and Diewert (1982) approach the measurement of allocative inefficiency by analysing the cost-minimising demands implied by Shephard's lemma. Atkinson and Cornwell (1994a) adapted this approach into a shadow cost system and computed allocative inefficiency based on the difference between shadow prices and observed prices. In a shadow cost system deviations from optimal ratios of inputs are explicitly modelled by a price distortion factor (Kumbhakar, 1996; Atkinson and Cornwell, 1994a). Although distance functions have been available since they were developed by Shephard (1953, 1970), it was only recently that applications involving distance functions appeared (Färe et al., 1993; Lovell et al., 1994, Grosskopf et al., 1997). The principal advantage of the distance function representation is that it allows for the possibility to specify a multiple-input, multiple-output technology when price information is not available or, alternatively, when price information is available but cost, profit or revenue representations are precluded because of violations of the required behavioural assumptions (Färe and Primont, 1995). Distance functions also provide performance measures, by providing a measure of the distance between each producer and the frontier technology. Econometric methods were recently applied to estimate distance functions (Lovell et al., 1994; Coelli and Perelman, 1996; Grosskopf et al., 1997). In fact, the econometric estimation method for distance functions is still being developed (Atkinson et al., 1998; Atkinson and Primont, 1998). Overviews of econometric methods for efficiency estimates can be found in Greene (1997), Coelli et al. (1998) and Kumbhakar and Lovell (1999).

The determinants of inefficiency are exogenous variables, which are neither inputs to the production process nor outputs of it, but which nonetheless influence the process (Simar et al., 1994). In the literature various methods are being developed based on the error component that describes efficiency (e.g. Reifschneider and Stevenson, 1991; Huang and Liu, 1994; Battese and Coelli, 1995; Kumbhakar and Lovell, 1999).

Recently the efficiency methodology was applied to environmental problems. Färe et al. (1989) computed an environmental performance measure based on the firm's efficiency in the restricted situation (because of environmental legislation) and the unrestricted situation. Ball et al. (1994) and Tyteca (1997) define and compute various environmental performance measures for agriculture and the paper sector respectively. One of their measures compares observed emission to minimum emission of bad output. The aforementioned studies all use mathematical programming methods. Hetemäki (1996) applied econometric efficiency methods to estimate technical efficiency based on bad outputs and conventional inputs and output. He computes shadow prices, but he neither defines nor estimates a measure of environmental efficiency.

The impact of pollution on the production process of the firm is modelled in several ways into the conventional neoclassical framework. Most models do not directly incorporate pollution into the models of production technology but enter the costs of abatement into a cost function (e.g. Conrad and Morisson, 1989; Barbera and McConnell, 1990) or a profit function (Oude Lansink and Peerlings, 1997). When the pollution is incorporated directly in the neoclassical framework the effluent is either specified in a production function (e.g. Pittman, 1981; Cropper and Oates, 1992) or in a profit function as an additional fixed input (Fontein et al., 1994). When pollution is incorporated in the neoclassical production model, the underlying assumptions have to be tested [4].

Nitrogen emission is a non-point source pollution and can hardly be measured directly. Therefore, nutrient balances are computed with the materials balance condition. The discharge of nutrients into the environment is computed as the difference between nutrients in inputs and nutrients in desired outputs. The link between production theory and materials balance is rarely touched upon in the literature. Some theoretical and conceptual steps in this direction were taken set out by Anderson (1987), Smith and Weber (1989) and Van den Bergh and Nijkamp (1994).

1.3 Objective of this thesis

The objective of this research is to define, to estimate and to evaluate environmental efficiency. Environmental efficiency is a measure that allows for the combination of a firm's environmental pressure with its (economic) performance. Econometric models, based on the neoclassical production theory, are adapted to enable the definition and estimation of a farm's technical (and allocative) efficiency and environmental efficiency. Three different econometric methods (stochastic production frontier, distance function and cost function) are analysed in this thesis on their possibilities to compute environmental efficiency. These methods are applied to a panel of Dutch dairy farms. Pollution is incorporated in this framework in various ways. Nitrogen surplus is the environmentally detrimental variable throughout this thesis, and it is computed with the materials balance condition. Finally, the variation in efficiency is explained based on characteristics that are hypothesised to influence environmental efficiency.

[4] Pittman (1981) found that the quasi-convexity of the translog production function is not strictly satisfied.

The following research questions are deduced:

1 How to define environmental efficiency?
A definition of environmental efficiency is not yet agreed upon in the literature.

2 How to compute environmental efficiency econometrically?
Three different econometric methods (stochastic frontier analysis, distance function and cost function) are identified to estimate technical (and allocative) efficiency. These methods have not yet been applied to compute environmental efficiency scores.

3 How to model pollution in the neoclassical framework?
A standard way to model pollution in the neoclassical framework is not available. The way to incorporate pollution appropriately into econometric efficiency models has to be determined.

4 How to deal with the materials balance condition?
Nitrogen surplus is measured with a materials balance definition. This characteristic of the environmentally detrimental variable has not yet been incorporated in the efficiency framework.

5 How to explain environmental efficiency differences across farms?
Various methods are available to explain efficiency differences. The method, that best suits the developed environmental efficiency scores, has to be selected and developed.

6 What is the best method to compute environmental efficiency scores with?
In this thesis three environmental efficiency measures are computed econometrically. They need to be compared to alternative environmental indicators to select the best measure for analysing environmental performance.

In the next section 1.4, these six research questions are elaborated into the research objectives of the following chapters.

1.4 The models

The next paragraphs introduce the chapters of this thesis and elaborate the research questions addressed in these chapters.

Environmental efficiency in SFA methodology

The objective of chapter 2 (in the context of this thesis) is to address the question: how to incorporate environmental effects in SFA and how to compute environmental efficiency? The stochastic production frontier approach allows only one (aggregated) output to be modelled. To incorporate environmental efficiency into a description of the production process of dairy farming, the environmentally detrimental variable has to be specified as an input. Nitrogen surplus is modelled as a conventional input. The SFA technical efficiency measure is output-augmenting and has to be transformed to allow minimisation of the environmentally detrimental input.

Multiple environmentally detrimental variables in SFA and DEA
The objective of chapter 3 is first to analyse whether the method we put forward in chapter 2 can be extended to multiple environmentally detrimental inputs and second to investigate the strengths and weaknesses of SFA and DEA for estimating environmental efficiency. We define and estimate environmental efficiency scores based on multiple environmentally detrimental variables (nitrogen surplus, phosphorus surplus and energy). The differences between SFA and DEA are evaluated on the basis of the magnitude and ranking of the efficiency scores and the ability to impose or test theoretical restrictions.

Environmental efficiency in distance function methodology
In the chapters 2 and 3 we treat the environmentally detrimental variable as an input. Distance functions allow the modelling of environmentally detrimental variables as outputs, because they can handle multiple-output, multiple-input production technologies (Färe and Primont, 1995). The objective of chapter 4 is to research whether the econometric approach to distance functions can be applied to model nitrogen pollution as an output, and to analyse the consequences of the materials balance definition of nitrogen surplus. Distance functions have been used before to incorporate bad outputs (Färe et al., 1993; Coggins and Swinton, 1996) in a non parametric context and in an econometric model by Hetemäki (1996). They did not compute environmental performance measures because at the technically efficient point both good and bad outputs are maximised. Therefore this point is not optimal from an environmental perspective. We use the definitions of allocative and total efficiency to estimate environmental and resource use efficiency.

Environmental efficiency in a cost function methodology
The methods to estimate the frontier in the previous chapters did not require behavioural assumptions (profit maximisation or cost minimisation). However, Dutch agricultural policy has two objectives in this context: (i) minimisation of costs at farm level and (ii) minimisation of nitrogen emission. The objective of chapter 5 is to determine the possibilities a cost system offers to incorporate the materials balance definition and to estimate environmental efficiency. A shadow cost system is used to compute nitrogen efficiency, because it allows farmers to deviate from cost-minimising behaviour with respect to market prices. In this framework, the cost-efficient and nitrogen-efficient production are identified.

Explaining the variation in environmental efficiency
The objective of chapter 6 is to explain the variation found in environmental efficiency scores. The environmental efficiency scores computed in chapter 2 are explained by way of

example. We assume that efficiency scores originate from omitted variables in the (first stage) frontier analysis. A model of dairy farming is exploited to determine the explanatory variables. A two-stage method is applied, in which stochastic frontier analysis is used again in the second stage to regress estimated environmental efficiency scores against explanatory variables.

Selecting the best method to compute environmental performance measures with
In chapter 7 the developed environmental efficiency measures are compared with alternative environmental indicators. Currently partial indices (e.g. nitrogen surplus per ha) are used to indicate environmental pressure of the firm. The criteria for the evaluation of the distinguished measures are extracted from the literature. This evaluation provides the preferred indicator given the available data and the objective.

1.5 Data

In this study we utilise data describing the production activities of highly specialised dairy farms [5] that were included in the Dutch Farm Accountancy Data Network (FADN) for part or all of the 1985-1995 period [6]. Farms normally remain in this panel for 5 to 7 years (Bouwman et al., 1997:27). 20-25% of participating farms is replaced with new farms every year (Poppe, 1992:17), so this panel is incomplete. The FADN is a stratified random sample. Stratification is based on farm size, age of the farmer, region and type of farm. The FADN covers 99% of milk production, and no systematic errors due to non-response are found (Dijk, 1990). Thus the FADN is representative of highly specialised dairy farms. The FADN panel data set also contains environmentally detrimental variables such as nitrogen surplus, phosphorus surplus and (direct and indirect) energy use. The aggregation of FADN data into variables of the data set, applied in this thesis is described in appendix B.

Highly specialised dairy farms were chosen for the estimation in this thesis of environmental performance measures for (i) data reasons (ii) methodology reasons and (iii) policy relevance. Ad (i) For the first empirical research with the newly developed performance measures in this thesis, it is preferred to avoid problems that might be related to the data or to the sector being modelled. Dairy farms are represented best in the Dutch FADN, since it provides the most observations. Highly specialised dairy farms have a similar production structure. The results can be compared with the literature (e.g. Elhorst, 1990; Thijssen, 1992; Boots et al., 1997; Berentsen, 1999). Ad (ii) The number of different nutrient flows at farm level is larger for dairy farms than for other specialised farms, because dairy farming con-

[5] Two-thirds of the total amount of size units of these farms are from dairy cows.
[6] A description of the data set is given in each chapter.

sists of two components: roughage production and livestock production (Dijk et al., 1996). If the environmental aspects of dairy farming can be modelled in this Ph.D.-thesis, the method can also be used to describe the simpler production processes in the hog and poultry sectors. Ad (iii) The dairy sector is the largest specialised sector in Dutch agriculture (with respect to the produced value) and covers two thirds of all agricultural land. The dairy sector (including beef and veal production) had the biggest share (72%) in Dutch manure production in 1994. The share of cattle farms in agricultural ammonia emission is 62% (CBS, 1995).

2. Econometric estimation of technical and environmental efficiency: an application to Dutch dairy farms [1]

Abstract

In this article we estimate the technical and environmental efficiency of a panel of Dutch dairy farms. Nitrogen surplus, arising from the application of excessive amounts of manure and chemical fertiliser, is treated as an environmentally detrimental input. A stochastic translog production frontier is specified to estimate the output-oriented technical efficiency. Environmental efficiency is estimated as the input-oriented technical efficiency of a single input, the nitrogen surplus of each farm. The mean output-oriented technical efficiency is rather high, 0.894, but the mean input-oriented environmental efficiency is only 0.441. Intensive dairy farms are both technically and environmentally more efficient than extensive farms.

2.1 Introduction

The agricultural policy objective of the Dutch government, as in most Western European countries, has evolved from one of concentrating on increasing agricultural productivity into one of enhancing the sustainable development of a competitive agriculture. In recent years increasing attention has been directed toward the livestock sector, in which nitrogen pollution has been particularly severe. Nitrogen pollution comes from two sources, and it has three adverse environmental consequences. It arises from the application of chemical fertilisers and, increasingly, from the application of manure produced by cows and pigs, well in excess of amounts needed by plants for their growing process. Manure has evolved from what was once a valuable (and virtually free) input into what has become a waste product whose disposal is costly. Disposal in the form of transportation to shortage areas, or in the form of delivery to processing plants, is privately costly, while disposal on cropland is environmentally costly. The environmental problems created by nitrogen pollution include the eutrophication of surface water, which endangers plant and fish life; the leaching of nitrates into the groundwater aquifers, which contaminates the major source of Dutch drinking water; and the evaporation as ammonia, which contributes to acid rain. These

[1] Article by Stijn Reinhard, C. A. Knox Lovell and Geert Thijssen; published in the *American Journal of Agricultural Economics* 81:1 (February 1999), 44-60. Reprinted with permission of the American Agricultural Economics Association.

problems are particularly severe in the south and east of the country, where livestock farms are concentrated. The soil in this region is sandy, which facilitates leaching of nitrates into the groundwater, and nearby forests are damaged by the acid rain.

To deal with these problems the Dutch have implemented a three-phase National Environmental Policy Plan (NEPP). The first two phases concluded in 1994. Among other things, they established increasingly restrictive farm manure quotas, they levied fees on manure surpluses, and they imposed restrictions on the spreading of manure. A new feature of the NEPP is a requirement that intensive livestock farms maintain nutrient balance sheets from 1998 onward. These balance sheets permit an accurate calculation of farm-level nitrogen surplus, the difference between nitrogen in inputs and nitrogen in desirable output. Anticipating this legislation, the Agricultural Economics Research Institute computes the nitrogen surplus of the Dutch Farm Accountancy Data Network farms. The value of having a measure of nitrogen surplus is that it provides a reasonably accurate measure of input use which contributes directly to environmental degradation. While the environmental effects themselves are difficult to quantify, the input use which creates these effects can be quantified, and used to conduct an analysis of the economic and environmental performance of Dutch dairy farms [2].

Farms have to apply marketable inputs as efficiently as possible to achieve a competitive agricultural sector, and they have to deal efficiently with the environment to create the environment-friendly agriculture decreed by NEPP. This raises the aggregate questions of how technically efficient and environmentally efficient Dutch dairy farming is, and whether each type of efficiency has improved or deteriorated during the first two phases of NEPP. It also raises the disaggregate questions of which farms are relatively technically efficient and relatively environmentally efficient, and whether or not the two types of efficiency are compatible. To answer these questions an environmental efficiency measure must be developed.

A variety of environmental performance indices have been proposed in the past, and they can be grouped into two categories: those which adjust conventional indices of productivity change, and those which adjust conventional measures of technical efficiency. In both cases the adjustment has taken the form of incorporating quantifiable environmental effects into the output vector. The indices can also be categorised into those which are calculated using deterministic techniques, which can be either parametric or non parametric, and those which are estimated using stochastic techniques, which are exclusively parametric.

Pittman (1983) was perhaps the first to develop an index of productivity change which takes environmental effects into account. He developed an adjusted Törnqvist productivity index in which environmental effects are treated as additional undesirable outputs whose

[2] Additional background information on the Dutch environmental policy as it applies to agriculture is available in Dietz (1992) and Brouwer and van Berkum (1998).

disposability is costly. However, since undesirable outputs are not generally priced on markets, this approach is feasible only if the undesirable outputs can be valued by their shadow prices. Pittman (1983) used econometric techniques to estimate the shadow price of a single undesirable output, biochemical oxygen demand, generated in the process of converting wood pulp to paper in a sample of 30 Michigan and Wisconsin mills in 1976, where this shadow price was constrained to be constant across all observations.

Färe et al. (1989) also treated environmental effects as undesirable outputs, and they developed an 'enhanced hyperbolic productive efficiency measure' that evaluates producer performance in terms of the ability to obtain an equiproportionate increase in desirable outputs and reduction in undesirable outputs. They developed their measure on a strongly disposable technology (applicable if undesirable outputs are freely disposable) and on a weakly disposable technology (applicable when it is costly to dispose of undesirable outputs, due perhaps to regulatory action). They proposed using a non parametric mathematical programming technique known as Data Envelopment Analysis (DEA) to construct strong-disposal and weak-disposal best-practice production frontiers, and to calculate their enhanced efficiency measure. A comparison of the two values of their measure provides a measure of the cost (in terms of foregone revenue) of a lack of free disposability. They applied their techniques to Pittman's data. Their approach was later applied to US electricity generation data (including SO_2 emissions as the undesirable output) by Yaisawarng and Klein (1994), who calculated adjusted measures of efficiency and productivity change, and by Turner (1995), who calculated adjusted efficiency measures and marginal abatement costs. This DEA approach has also been applied to aggregate OECD data including CO_2 emissions by Zofio and Prieto (1996).

Färe et al. (1993) also treated environmental effects as undesirable outputs, and they used a parametric mathematical programming technique to calculate the parameters of a deterministic translog output distance function. This enabled them to calculate an enhanced hyperbolic efficiency measure, and also to calculate the shadow prices of the undesirable outputs. They used Pittman's data to illustrate their techniques. Although these shadow prices could have been used to construct Pittman's adjusted Törnqvist productivity index, they did not undertake such a construction.

Ball et al. (1994) provided an empirical application of the DEA model proposed by Färe et al. (1989), in which nitrogen surplus was modeled as an undesirable byproduct of US agricultural production. They calculated a variety of adjusted efficiency measures and the corresponding shadow prices of the undesirable output. The shadow prices were then used to calculate corresponding versions of Pittman's adjusted Törnqvist productivity index. They found rates of productivity growth to decline from 1.38% per year to anywhere from 1.22% per year to 0.99% per year over the period 1961-1988 when nitrogen surplus was included in the output vector.

Hetemäki (1996) used econometric techniques to estimate deterministic and stochastic variants of a translog output distance function, and to obtain estimates of technical efficiency and the shadow prices of undesirable outputs, in the Finnish pulp and paper industry.

The general strategy of the above studies has been to include environmental effects in the output vector, and then to obtain inclusive measures of technical efficiency, and occasionally productivity change, which incorporate the generation of one or more environmental effects as byproducts of the production process [3]. This is an accomplishment in itself - acknowledging that producers produce undesirable as well as desirable outputs when evaluating their performance. However in several of these studies the shadow prices of the undesirable outputs are also calculated or estimated. This is an additional accomplishment - shadow prices can be used to generate an adjusted index of productivity change, and they can also be interpreted as marginal abatement costs which can be compared with marginal benefit calculations. Although we follow both strands of this general line of research, our strategy is somewhat different.

First, we use econometric techniques to obtain efficiency estimates, which distinguishes our approach from all of those mentioned above except for Hetemäki (1996). Having only a single output, however, we estimate a stochastic production frontier rather than a stochastic distance function to relate the environmental performance of individual farms to the best practice of environment-friendly farming. To minimise misspecification error we use a stochastic translog production frontier.

Second, we model the environmental effect as a conventional input rather than as an undesirable output, which distinguishes our approach from all of those mentioned above. Cropper and Oates (1992) also followed this approach. They took a production function to include a vector of conventional inputs and the quantity of waste discharges. Waste emissions are treated simply as another factor of production. Reductions in these emissions result in reduced output. Pittman (1981) also modeled pollution as an input in the production function because the relation between an environmentally detrimental variable and output looks like the relation between conventional input and output [4]. Our reason for doing so is largely pragmatic. We are able to measure the environmentally detrimental input usage (excess nitrogen application), but we are unable to measure the environmental repercussions. Consequently, we cannot incorporate any undesirable outputs into our analysis and we assume that nitrogen surplus is a proxy for the undesirable environmental repercussions.

Third, and as a consequence of the second feature of our analysis, we provide separate estimates of technical efficiency and environmental efficiency. Technical efficiency is estimated in the conventional way, as the ratio of observed to maximum feasible output, where the latter is provided by the stochastic production frontier. Environmental efficiency is

---

[3] Tyteca (1996, 1997) provides an overview of these and other environmental performance indices.
[4] Haynes et al. (1993, 1994) and Boggs (1997) also treat environmental effects as inputs.

estimated as the ratio of minimum feasible to observed use of the environmentally detrimental input, where the former is provided by the stochastic production frontier. This requires a novel manipulation of the stochastic translog production frontier. Thus our measure of technical efficiency is an output-oriented measure, while our measure of environmental efficiency is a non-radial input-oriented measure since it focuses on just one of several inputs.

The article is organised as follows. We describe the production process of dairy farms, including the environmentally detrimental nitrogen surplus input, to provide the variables that have to be modeled. We elaborate on the concepts of technical and environmental efficiency and we model technical and environmental efficiency of each farm within the context of a stochastic translog production frontier containing the environmentally detrimental input. Farm-level estimates of technical and environmental efficiency are calculated, evaluated and compared.

2.2 Dutch dairy sector and the nitrogen problem

Milk production takes place on about 39,000 farms in the Netherlands. The majority (82%) of these farms specialise in dairy farming. In 1994 1.7 million dairy cows were kept. The average Dutch specialised dairy farm maintained about 49 cows on about 28 ha. The Dutch dairy sector has a rather intensive character, although the total number of cows has decreased since the implementation of a milk quota system in 1984. The relatively large number of cows per ha implies a large production of manure per ha. Together with a high level of fertiliser use, this leads to a large nitrogen surplus, and to correspondingly large flows of nitrogen into the soil. Part of the nitrogen is taken up by crops, but a large portion of these nutrients is emitted to the environment. Despite the declining trend in the use of nitrogen-generating inputs in the production process of the Dutch dairy sector, the surpluses of nitrogen that are emitted to the environment are still very high. In 1993 the average nitrogen surplus (in the form of inputs minus removal in the form of outputs) on specialised dairy farms was above 400 kg N per ha (Poppe et al., 1995). In our data set the average nitrogen surplus per farm is 416 kg N per ha. On average less than 25% of the nitrogen used is incorporated into desirable outputs.

A schematic representation of the main nitrogen flows is given in Figure 2.1. Variables that affect the nitrogen cycle directly are presented, along with the quantity of the corresponding nitrogen flow per ha between brackets. The production process on a dairy farm consists of two parts: (i) roughage production providing an intermediate input (grass and green maize) for the livestock; and (ii) animal production producing marketable outputs and manure, the latter providing an intermediate input for roughage production. Both processes are depicted in Figure 2.1. The inputs (including the intermediate input) are located on the left and the outputs (including the intermediate output) are on the right.

The nitrogen input per ha of the average farm represented by Figure 2.1 is 548 kg N (excluding intermediate input), and the nitrogen output per ha contains 548 kg N (excluding 'manure application'). The marketable output (milk, meat, livestock and roughage) contains 104 kg N per ha, and the nitrogen surplus (nitrogen exchange with soil, ammonia from land, manure sold [5] and ammonia from stable) consists of 444 kg N per ha. The nitrogen surplus of a farm is equal to the emission of nitrogen into the environment (namely soil, groundwater and air). The surplus is strictly positive in all cases.

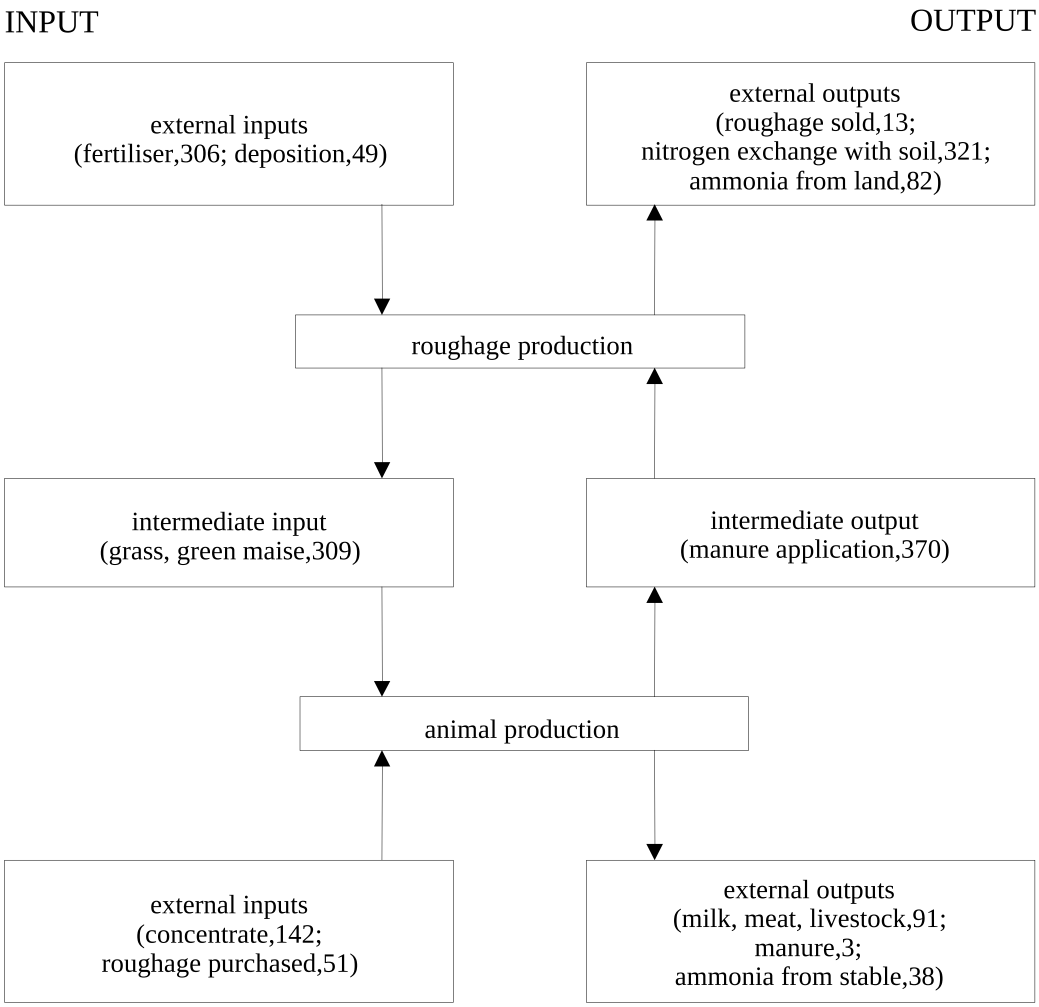

Figure 2.1 Specification of the average nitrogen flows of 3,919 strongly specialized dairy farms in the Dutch province Gelderland in 1988; the relevant variables and the corresponding N flows in kg N per ha are given between brackets

Source: Dijk, et al. (1996) adapted by the authors.

[5] In other research the 'manure sold' is often not part of the nitrogen surplus. We are interested in environmentally efficient production processes, and in our opinion the sale of manure is not part of the production process.

2.3 Definition and measurement of technical and environmental efficiency

Environmental efficiency is defined as the ratio of minimum feasible to observed use of an environmentally detrimental input, conditional on observed levels of the desirable output and the conventional inputs. So defined, environmental efficiency is an input-oriented single-factor measure of the technical efficiency of the environmentally detrimental input. This is a non-radial notion of input efficiency, as discussed by Kopp (1981). This efficiency measure allows for a differential reduction of the inputs applied [6]. The standard radial (equi-proportionate) measure is incapable of identifying the efficiency of individual input use, since such a measure treats the contribution of each input to productive efficiency equally.

The idea of environmental efficiency is illustrated in Figures 2.2-2.4. Figure 2.2 presents the best practice production frontier $F(\bullet)$, with output Y, conventional input X, environmentally detrimental input Z, and $Y \leq F(X,Z)$. The frontier is the increasing, quasi-concave surface $0X_R R^F Z_R$. Y_R is the observed output, produced using X_R of the conventional input and Z_R of the environmentally detrimental input. *ABCR* is the surface with identical output quantity, Y_R, as farm *R*. Figure 2.3 portrays the production frontier in conventional input and environmentally detrimental input space, holding output constant at its observed value, Y_R. Figure 2.4 provides another cross-section of Figure 2.2, holding the use of the conventional input constant at X_R. In Figure 2.3 and 2.4, a measure of environmental efficiency is provided by the non-radial input-oriented measure

$$EE_R = \min\{\theta : F(X_R, \theta Z_R) \geq Y_R\} = \left|OZ^F\right| / \left|OZ_R\right|, \tag{2.1}$$

where Z^F is the minimum feasible environmentally detrimental input use, given $F(\bullet)$ and the observed values of the conventional input X_R and output Y_R.

In Figure 2.2 the observed output $\mathrm{Y_R}$ is technically inefficient, since (Y_R, X_R, Z_R) lies beneath the best practice production frontier $F(\bullet)$. It is possible to measure technical efficiency using an input-conserving orientation, as the ratio of minimum feasible input use to observed input use, conditional on technology and observed output production. In Figure 2.3 this generates a radial technical efficiency measure $|0B|/|0R|$, and in Figure 2.2 this measure is reflected by $|Y_R B|/|Y_R R|$. It is also possible to measure technical efficiency using an output-expanding orientation, as the ratio of observed to maximum feasible output, conditional on technology and observed input usage. In Figures 2.2 and 2.4 this generates a technical efficiency measure of $|0Y_R|/|0Y^F|$. As Färe and Lovell (1978) have noted, only under

[6] One of the models specified by Ball et al. (1994) and Tyteca (1997) is similar to our definition of environmental efficiency.

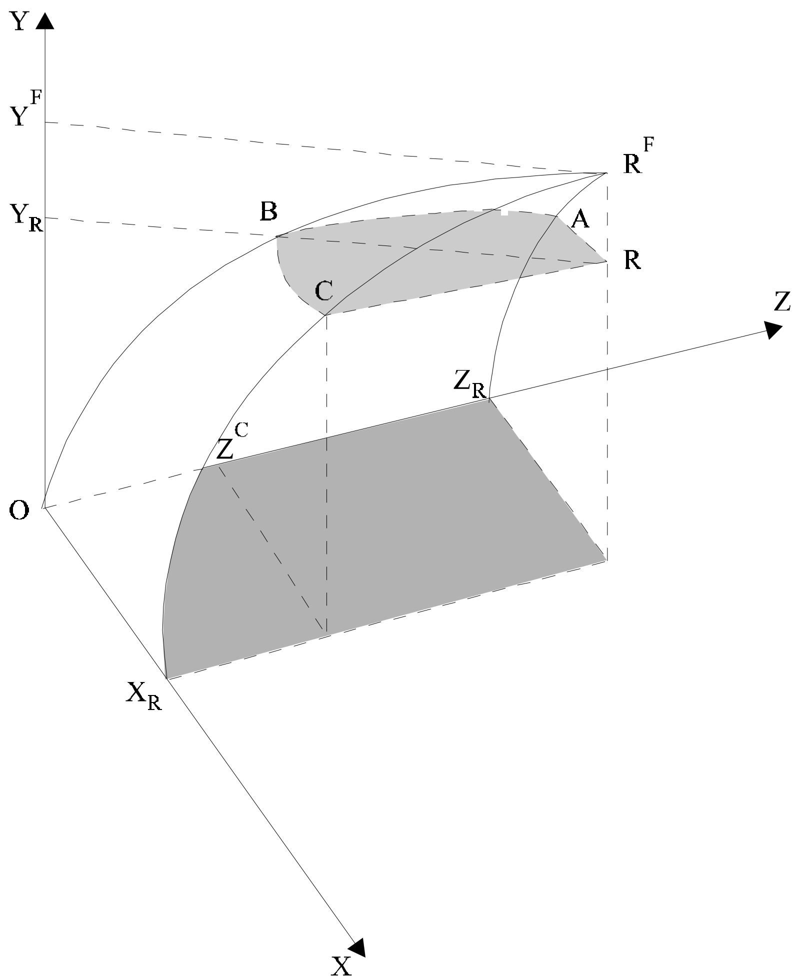

Figure 2.2 Production frontier in output, Y, conventional input, X, and environmentally detrimental input, Z, space

constant returns to scale do the two measures coincide for a technically inefficient producer. Not wishing to impose constant returns to scale on the structure of production technology, we need to select an orientation. We think an output orientation is more appropriate in the current context, and so our measure of technical efficiency is given by:

$$TE_R = [\max\{\phi : \phi Y_R \leq F(X_R, Z_R)\}]^{-1} = |0Y_R| / |0Y^F|, \tag{2.2}$$

where maximum feasible output Y^F is depicted in Figures 2.2 and 2.4, but not in Figure 2.3. Under weak monotonicity, environmental efficiency implies, and is implied by, output-oriented technical efficiency. Thus environmental efficiency can be achieved at high as well as low Z/X ratios along an isoquant.

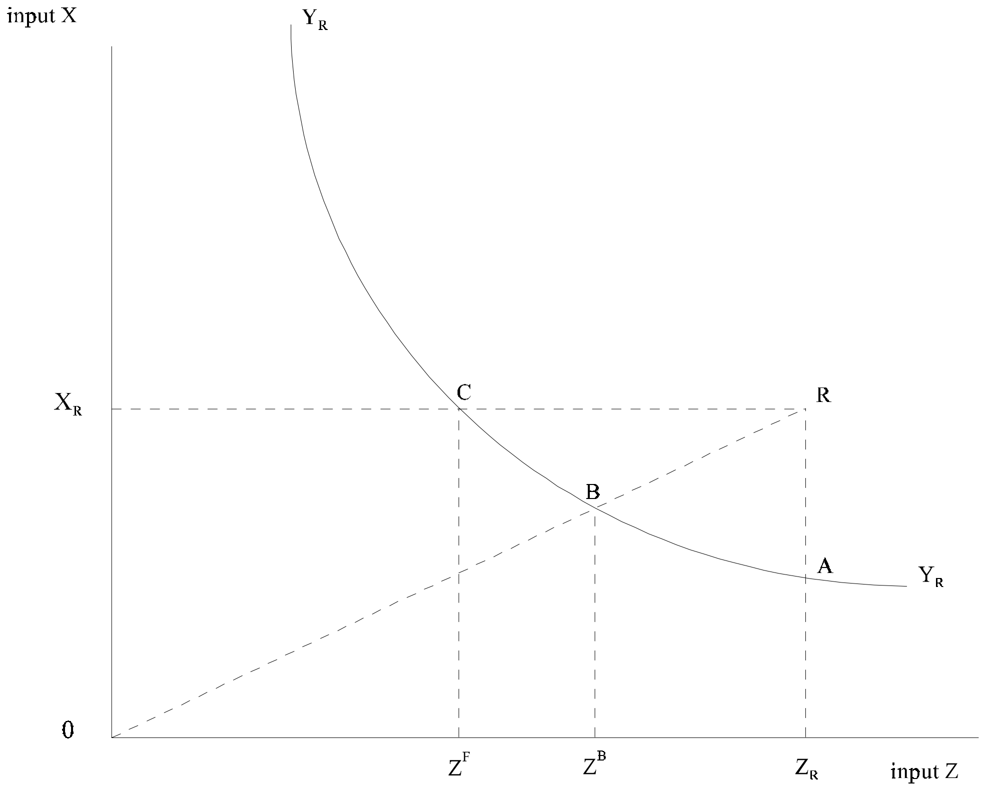

Figure 2.3 Production frontier in normal input, X, and environmentally detrimental input, Z space

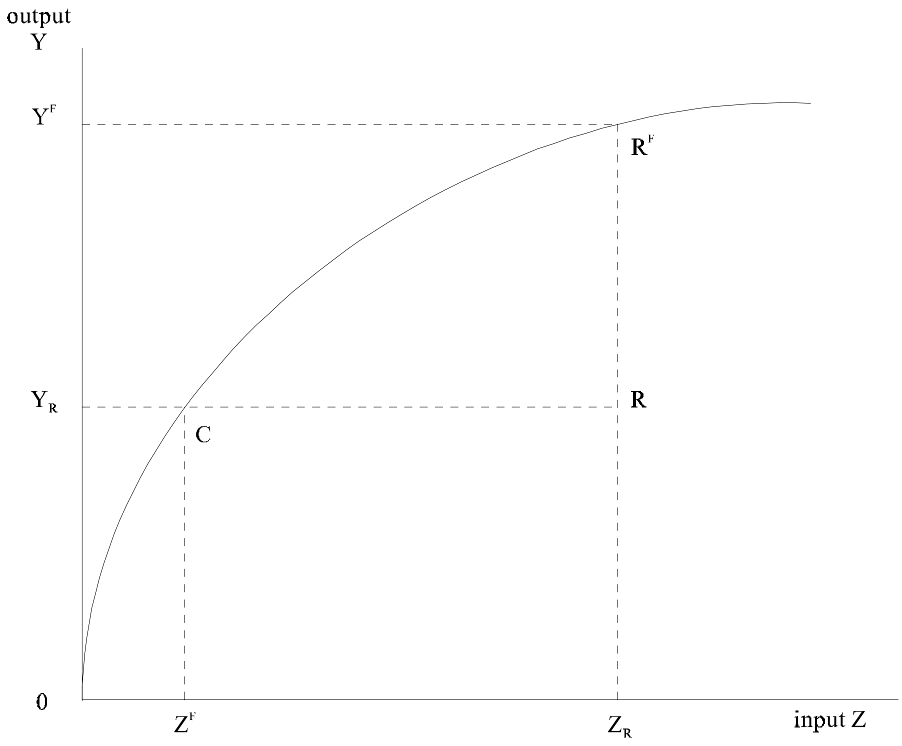

Figure 2.4 Production frontier in output, Y, environmentally detrimental input, Z, space

2.4 The estimation of technical and environmental efficiency

In the agricultural economics literature output is treated frequently as a stochastic variable because of weather conditions, diseases and other exogenous random forces. We assume that the decision variables are fixed in the short run, and that the production level follows, a common and reasonable assumption when estimating production relationships in agriculture (Coelli, 1995b). We therefore specify the following general stochastic production frontier [7]:

$$Y_{it} = F(\mathbf{X_{it}}, Z_{it}; \beta) * \exp\{V_{it} - U_i\}, i = 1, \ldots, I, t = 1, \ldots, T, \tag{2.3}$$

where for all farms indexed with a subscript i and for all years indexed with a subscript t,

Y_{it} denotes the production level;

$\mathbf{X}_{it}$ is a vector of conventional inputs (with x_{it1} = labour, x_{it2} = capital, x_{it3} = variable inputs, x_{it4} = time trend reflecting technological and regulatory developments);

Z_{it} is the environmentally detrimental input (nitrogen surplus);

β is a technology parameter vector to be estimated;

V_{it} is a random error term, independently and identically distributed as $N(0,\sigma_v^2)$, intended to capture events beyond the control of farmers;

U_i is a non-negative random error term, independently and identically distributed as $N^+(\mu,\sigma_u^2)$, intended to capture time-invariant technical inefficiency in production, measured with an output orientation as the ratio of observed to maximum feasible output.

The stochastic version of the output-oriented technical efficiency measure (2.2) is given by the expression

$$TE_i = Y_{it} / [F(X_{it}, Z_{it}; \beta) \bullet \exp\{V_{it}\}] = \exp\{-U_i\}. \tag{2.4}$$

Since $U_i \geq 0$, $0 \leq \exp\{-U_i\} \leq 1$. Technical inefficiency must be separated from statistical noise in the composed error term (V_{it} - U_i) to implement (2.4). Battese and Coelli (1988, 1992) have proposed the technical efficiency estimator

$$TE_i = E[\exp\{-U_i\} | (V_{it} - U_i)]. \tag{2.5}$$

[7] The stochastic production frontier was introduced by Aigner et al. (1977) and Meeusen and Van den Broeck (1977), and later extended to panel data by Pitt and Lee (1981) and Battese and Coelli (1988, 1992).

We did not discuss the issue of data noise in environmental efficiency, captured by the disturbance term V in the exposition on the measurement of environmental efficiency. Figure 2.5 depicts the role of this disturbance term in the estimation of environmental efficiency. In Figure 2.5 the farm uses Z_R and obtains output Y_R which has corresponding stochastic frontier output Y^{FS}, which is less than the value on the deterministic production frontier Y^{FD}, because its productive activity is associated with unfavorable conditions for which the random error V is negative. The stochastic frontier output, Y^{FS}, is equal to $Y^{FD} \bullet \exp\{V\}$. The output corrected for these unfavorable conditions, Y^D_R, results from $Y_R = Y^D_R \bullet \exp\{V\}$. The minimal feasible environmentally detrimental input use conditional on X and Y^D_R is equal to Z^{FS}. Z^{FS} is larger than the minimum feasible environmentally detrimental input use in the deterministic case, Z^{FD}, because under 'normal' conditions output would be larger. If V is positive, everything is reversed. The stochastic measure of environmental efficiency is preferred over the deterministic version because in the former case the farm is compared with an efficient farm encountering identical stochastic conditions. In the latter case the farm is compared with an efficient farm without any noise. Thus a farm with bad weather conditions (a negative V), has an output-oriented efficiency score that is larger than in the deterministic case and an environmental efficiency score that is also larger than in the deterministic case.

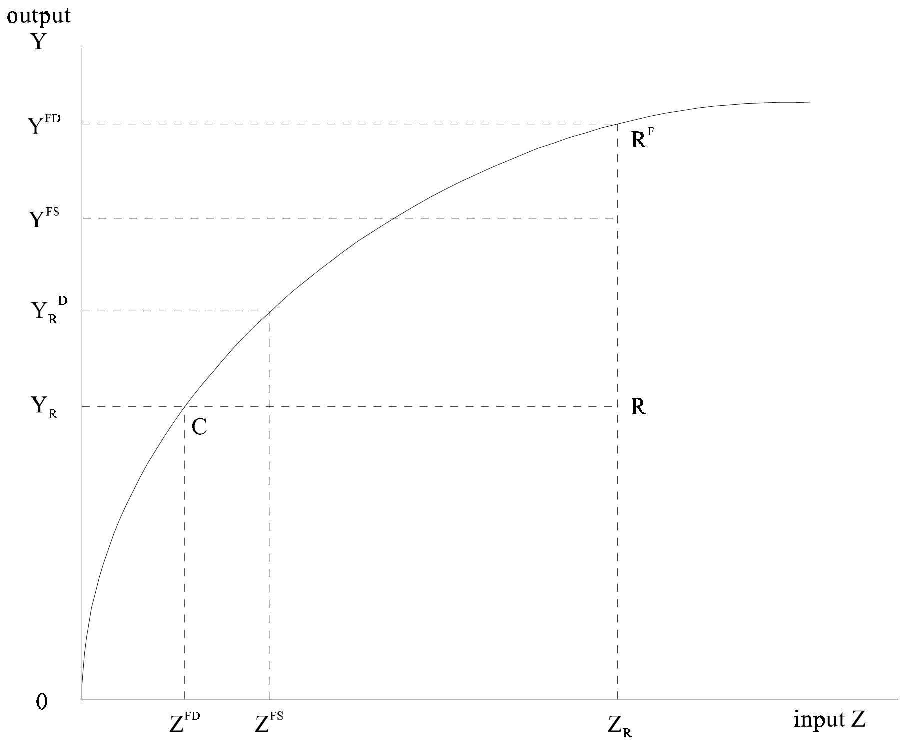

Figure 2.5 Stochastic and deterministic production frontier in output, Y, environmentally detrimental input, Z, space

To derive a stochastic version of the environmental efficiency measure in equation (2.1) we need to specify a functional form for the deterministic kernel of the stochastic production frontier. Writing (2.3) in translog form gives:

$$\begin{aligned}\ln Y_{it} &= \beta_0 + \Sigma_j \beta_j \ln X_{itj} + \beta_z \ln Z_{it} + \tfrac{1}{2}\Sigma_j \Sigma_k \beta_{jk} \ln X_{itj} \ln X_{itk} \\ &+ \Sigma_j \beta_{jz} \ln X_{itj} \ln Z_{it} + \tfrac{1}{2}\beta_{zz} (\ln Z_{it})^2 + V_{it} - U_i . \end{aligned} \tag{2.6}$$

where $\beta_{jk}=\beta_{kj}$.

The logarithm of the output of a technically efficient producer (using X_{it} and Z_{it} to produce Y_{it}^F) is obtained by setting $U_i = 0$ in (2.6). The logarithm of the output of an environmentally efficient producer (using X_{it} and Z_{it}^F to produce Y_{it}) is obtained by replacing Z_{it} with Z_{it}^F and setting $U_i = 0$ in (2.6) to obtain

$$\begin{aligned}\ln Y_{it} &= \beta_0 + \Sigma_j \beta_j \ln X_{itj} + \beta_z \ln Z_{it}^F + \tfrac{1}{2}\Sigma_j \Sigma_k \beta_{jk} \ln X_{itj} \ln X_{itk} \\ &+ \Sigma_j \beta_{jz} \ln X_{itj} \ln Z_{it}^F + \tfrac{1}{2}\beta_{zz} (\ln Z_{it}^F)^2 + V_{it} . \end{aligned} \tag{2.7}$$

The logarithm of the stochastic environmental efficiency measure ($\ln EE_{it} = \ln Z_{it}^F - \ln Z_{it}$), can now be isolated. Setting (2.6) and (2.7) equal yields

$$\begin{aligned}&\tfrac{1}{2}\beta_{zz}[(\ln Z_{it}^F)^2 - (\ln Z_{it})^2] + \Sigma_j \beta_{jz} \ln X_{itj}[\ln Z_{it}^F - \ln Z_{it}] + \\ &\beta_z[\ln Z_{it}^F - \ln Z_{it}] + U_i = 0,\end{aligned} \tag{2.8}$$

which can be rewritten as

$$\tfrac{1}{2}\beta_{zz}[\ln Z_{it}^F - \ln Z_{it}]^2 + [\beta_z + \Sigma_j \beta_{jz} \ln X_{itj} + \beta_{zz} \ln Z_{it}](\ln Z_{it}^F - \ln Z_{it}) + U_i = 0, \tag{2.9}$$

which can be solved for $\ln EE_i = \ln Z_{it}^F - \ln Z_{it}$ to obtain

$$\begin{aligned}\ln EE_{it} &= [-(\beta_z + \Sigma_j \beta_{jz} \ln X_{itj} + \beta_{zz} \ln Z_{it}) \pm \\ &\{(\beta_z + \Sigma_j \beta_{jz} \ln X_{itj} + \beta_{zz} \ln Z_{it})^2 - 2\beta_{zz} U_i\}^{.5}] / \beta_{zz} .\end{aligned} \tag{2.10}$$

Environmental efficiency is calculated using the '+√ formula' in (2.10). This is because a technically efficient farm is necessarily environmentally efficient, and $U_i = 0 \Rightarrow \ln EE_{it} = 0$ only if the '+√ formula' is used. Conditional on (X_{itj},Z_{it}), EE_{it} and U_i are inversely related.

Conditional on (X_{itj}, U_i), or equivalently conditional on (X_{itj}, Y_{it}), EE_{it} and Z_{it} are inversely related. Both relationships hold irrespective of the sign of β_{zz} [8].

An alternative environmental performance index is provided by a radial input-oriented efficiency measure which can be obtained in a similar manner as we calculated the nonradial environmental efficiency index. A radial input-oriented efficiency measure treats the conventional inputs in the same way as the environmentally detrimental input, and scales all inputs by a factor $b_i \leq 1$ to the stochastic production frontier. In Figure 2.3 this generates the radial technical efficiency measure $|0B|/|0R|$. To simplify the derivation we treat the environmentally detrimental input as the fourth conventional input (X_{it5} instead of Z_{it}, the time trend variable is not incorporated in the calculation of input-oriented efficiency). The disturbance term is employed in the same way as it is used in the computation of environmental efficiency. The formulation of input-oriented technical efficiency in a stochastic translog production frontier is (Atkinson and Cornwell, 1994b):

$$\begin{aligned} \ln Y_{it} &= \beta_0 + \Sigma_m \beta_m \ln(b_i \bullet X_{itm}) + \tfrac{1}{2}\Sigma_m \Sigma_p \beta_{mp} \ln(b_i \bullet X_{itm}) \ln(b_i \bullet X_{itp}) \qquad (2.11) \\ &+ \beta_t \ln X_{it4} + \tfrac{1}{2}\beta_{tt} (\ln X_{it4})^2 + \Sigma_m \beta_{mt} \ln(b_i \bullet X_{itm}) \ln X_{it4} + V_{it} \\ &= \beta_0 + \Sigma_j \beta_j \ln X_{itj} + \tfrac{1}{2}\Sigma_j \Sigma_k \beta_{jk} \ln X_{itj} \ln X_{itk} + V_{it} \\ &+ (\ln b_i)^2 [\tfrac{1}{2}\Sigma_m \Sigma_p \beta_{mp}] + \ln b_i [\Sigma_m \beta_m + \tfrac{1}{2}\Sigma_m \Sigma_p \beta_{mp} (\ln X_{itm} + \ln X_{itp}) + \Sigma_m \beta_{mt} (\ln X_{it4})] \end{aligned}$$

where j=1,…,5; k=1,…,5; m=1,2,3,5; p=1,2,3,5; $\beta_{jk}=\beta_{kj}$; $\beta_{mp}=\beta_{pm}$.

Setting the output-oriented specification in (2.6) equal to the input-oriented specification in (2.11) yields

$$\tfrac{1}{2}\Sigma_m \Sigma_p \beta_{mp} (\ln b_i)^2 + c_{it} \bullet \ln b_i + U_i = 0, \qquad (2.12)$$

where $\quad c_{it} = \Sigma_m \beta_m + \tfrac{1}{2}\Sigma_m \Sigma_p \beta_{mp} (\ln X_{itm} + \ln X_{itp})] + \Sigma_m \beta_{mt} \ln X_{it4}$

[8] Note that under a Cobb-Douglas representation of technology all output elasticities are constant and equation (2.10) collapses to $EE_{it} = \exp\{-U_i/\beta_z\}$. In this case a ranking of farms by environmental efficiency scores would be identical to a ranking by technical efficiency scores, and the environmental efficiency measure would add no information to the technical efficiency measure. The two rankings can differ, and the environmental efficiency measure can add independent information of its own, only if output elasticities are variable, in which case EE_{it} depends on (X_{itj}, Z_{it}) as well as on U_i. This property is satisfied by a host of functional forms, including but not restricted to the translog form we use. Note also that with the translog form the discriminant in (2.10) is not guaranteed to be nonnegative. However since the first component is the elasticity of output with respect to Z, the nonnegativity requirement becomes $(\varepsilon_{YZ})^2 \geq 2\beta_{zz}U$. Since $U \geq 0$, the inequality holds if $\beta_{zz} = \partial^2 \ln Y/\partial \ln Z^2 \leq 0$, or if $\beta_{zz} > 0$ and $|\varepsilon_{YZ}|$ is sufficiently large.

which can be solved for $\ln b_i$ to obtain

$$\ln b_i = [-c_{it} \pm (c_{it}^2 - 2\Sigma_m \Sigma_p \beta_{mp} U_i)^{.5}]/\Sigma_m \Sigma_p \beta_{mp}. \qquad (2.13)$$

Again assuming strict monotonicity, a farm which is technically efficient from an output-oriented perspective [$U_i = 0$ in (2.7)] must also be technically efficient from an input-oriented perspective [$b_i = 1$ in (2.13)]. This again requires that the '+√ formula' be used in (2.13). It follows from (2.12) that linear homogeneity in the four inputs is necessary and sufficient for output-oriented technical efficiency to equal input-oriented technical efficiency. It is important to note that although output-oriented efficiency (2.5) is estimated econometrically, environmental efficiency (2.10) and input-oriented efficiency (2.13) are calculated from parameter estimates and the estimated error component.

2.5 Data

In this study we utilise data describing the production activities of 613 highly specialised dairy farms that were in the Dutch Farm Accountancy Data Network (FADN) for part or all of the 1991-1994 period. The FADN is a stratified random sample. Stratification is based on economic farm size, age of the farmer, region, and type of farming. The FADN represents 99% of the milk production and no systematic errors due to non-response are found (Dijk, 1990). We have a total of 1,545 observations in this unbalanced panel, and so each farm appears 2.5 times on average. The period 1991-1994 is chosen because detailed information describing the nitrogen flows at each farm is available from 1991 onwards. The inputs and the output we specify are based upon the production process of dairy farms, including the nitrogen flows, which is depicted in Figure 2.1.

We must address the tradeoff 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. In the translog production frontier specification we have chosen, the conventional inputs are aggregated into three categories (labour, capital and variable inputs), and the desired outputs are aggregated into a single index of dairy farm output. Ball et al. (1994) used these variables also, although they distinguished separate output indices for animal and roughage production. If prices at the farm level are available in the FADN, they are used to calculate price indices. If prices are not present in the FADN, price indices are borrowed from CBS/LEI-DLO (1996). The FADN contains information on the quantity of milk produced and the value of the sales to the milk factory and to other customers. The price that farmers receive from the factory depends on the protein and fat content of the milk, thus milk prices reflect differences in qualities. Part of the farmers sell homemade cheese and butter, or sell milk directly to customers. If we should use an index of the quantity of milk produced, the differences in prices between farmers result from differences in the quality of outputs and from differences in the composition of the components. Therefore we preferred an implicit quantity index. Implicit quantity indices are obtained as the ratio of value to the price index and therefore output is in prices of a specific year, 1991 is the base year. The price index used in this study is the average of the multilateral Törnqvist price index over the farms for every year (Higgins, 1986; Caves et al., 1982). This price index varies over the years but not over the farms, implying that differences in the composition of a netput or quality are reflected in the quantity (Cox and Wohlgenant, 1986). The same method is applied for the aggregation of capital stock and variable input. The output quantity index contains milk, meat, livestock, and roughage sold. These all contain nitrogen flows, and are depicted in Figure 2.1. Labour input consists of family labour, measured in hours. The price index of capital stock is calculated as the multilateral Törnqvist index of the revaluations of the capital stock. The value of many components of capital stock (buildings, equipment and livestock for breeding and utilisation) is known at the start-balance and end-balance of each year. The difference between the start-balance of year t and the end-balance of year t-1 is due to revaluation of capital stock. The price of land is computed as the multilateral Tornqvist price index of the land price for the distinguished soil types. A multilateral Tornqvist price index is used to aggregate the price indices of the components of capital stock (buildings, equipment, livestock and land). Labour and capital are not represented in Figure 2.1, because these inputs do not contain nitrogen flows in the production process (apart from the livestock component of capital stock). The variable input quantity index contains hired labour, concentrates, roughage, fertiliser and other variable inputs. Fertiliser, concentrates and roughage purchased are depicted in Figure 2.1. The environmentally detrimental input quantity index is the nitrogen surplus, the difference between N input and N contained in desirable outputs, measured in kilograms. The nitrogen surplus is represented in Figure 2.1 as the sum of 'nitrogen exchange with soil, ammonia from land, ammonia from stable and manure sold.' The characteristics of the data are summarised in Table 2.1. One feature of the sample is its size dispersion; a farm one standard deviation above the mean is between three and four times as large as a farm one standard deviation below the mean [9].

[9] All variables have been normalised by their sample means. Our findings are not sensitive to alternative normalisations; detailed results based on unnormalised data and data normalised by the sample mean, the sample median and the sample mode are available on request.

Table 2.1 Characteristics of the Sample Variables

Variables	Unit	Mean	Min.	Max.	Std. dev.
Output	1,000 '91 NLG	392	56	1,436	228
Labour	hours	4,101	1,100	11,050	1,533
Capital	1,000 '91 NLG	2,245	430	8,126	1,136
Variable input	1,000 '91 NLG	141	15	642	91
Nitrogen surplus	kg N	14,585	1,884	63,779	8,762

2.6 Empirical results

The output-oriented technical efficiency of each farm is assumed to be constant during the research period and is allowed to follow a two-parameter truncated normal distribution. The time-invariant specification is not unreasonable, since at most four observations per farm, and on average 2.5 observations per farm, are available in the data set. A likelihood-ratio test of the hypothesis that inefficiency is absent is rejected, with a test statistic of 1,111.1. The point estimate of (σ_u/σ_v) suggests that 58% of the residual is due to inefficiency. A likelihood-ratio test of the hypothesis that the one-sided error component follows a one-

Table 2.2 Parameter Estimates a)

Parameter	Coefficient Estimate	Standard Error	Parameter	Coefficient Estimate	Standard Error
β_0	0.148	0.023	β_{lc}	0.237	0.047
β_1	0.149	0.030	β_{lv}	-0.046	0.029
β_c	0.311	0.036	β_{lt}	-0.034	0.028
β_v	0.536	0.022	β_{cv}	-0.196	0.036
β_t	-0.143	0.050	β_{ct}	0.034	0.032
β_z	0.092	0.033	β_{vt}	-0.014	0.022
β_{ll}	-0.122	0.055	β_{lz}	-0.071	0.047
β_{cc}	0.106	0.061	β_{cz}	0.028	0.046
β_{vv}	0.198	0.039	β_{vz}	-0.051	0.038
β_{tt}	0.159	0.050	β_{tz}	0.013	0.029
β_{zz}	-0.004	0.056	μ/σ_u	0.516	0.0003
			σ_u^2/σ_v^2	1.869	0.193
			σ_v^2	0.010	0.0006

a) The subscripts l, c, v, t, z refer to labour, capital, variable input, time trend and nitrogen surplus respectively.

parameter half normal distribution is rejected, with a test statistic of 103.62. Parameter estimates are reported in Table 2.2.

Before turning to an investigation of technical and environmental efficiency, we first consider the structure of the estimated production technology. Table 2.3 reports elasticities of output with respect to each input (including time), evaluated at output deciles. The elasticity of output with respect to time presumably captures the impact of regulatory tightening as well as the effects of whatever technical change may have occurred during this brief period and is nonnegative for 54% of the observations, but it is small at all output deciles. The elasticities of output with respect to the four inputs (excluding time, but including the nitrogen surplus) are positive for 100% of the observations. The sum of the elasticities of output with respect to these four inputs generates an estimated scale elasticity which indicates the presence of increasing returns to scale at all output deciles [10]. The estimated scale elasticity declines with increases in output, and has a value of 1.10 at the sample mean. Likelihood ratio tests led to rejections of homotheticity in all four inputs (χ^2_4 = 29.74 with a critical value of 9.49) and linear homogeneity (χ^2_6 > 1,000 with a critical value of 12.59) [11].

The estimated elasticities of output with respect to the nitrogen surplus are of particular interest. They have a mean value of 0.117, with a standard deviation of 0.04, suggesting that, holding other inputs constant, a one percent reduction in nitrogen surplus requires a sacrifice of a little more than 1/10 of one percent of marketable output. Using mean values reported in Table 2.1, this estimated abatement cost elasticity implies that a reduction of 146 kilograms of nitrogen surplus would 'cost' approximately 460 guilders of 1991. This in turn suggests a 'shadow price' of nitrogen surplus of approximately 3.14 guilders per kilogram. The corresponding 'shadow price' calculations for farms one standard deviation above and below mean size are 2.12 guilders per kilogram and 4.51 guilders per kilogram, respectively. The calculated 'shadow price' of nitrogen surplus decreases with farm size because the estimated elasticity of output with respect to nitrogen surplus decreases with farm size. These 'shadow prices' are upper bounds to true shadow prices and are only valid for a very small change in nitrogen surplus. This is because the elasticities on which they are based, are calculated holding conventional inputs constant at their observed values. Consequently farmers are not allowed to reduce the cost of abatement by substituting conventional inputs for nitrogen surplus. To obtain the actual shadow price that incorporates substitution of inputs and a quantity change of the output, we should have estimated a profit system. Such a framework would allow one to estimate the reduction of profits when the farmer is requested to reduce

[10] An alternative measure of returns to scale is the summation of the output elasticities of the conventional inputs. This measure is slightly less than 1 at all deciles.

[11] Homotheticity requires $\Sigma_k\beta_{jk}=0$; j=l,c,v,t,z; k=l,c,v,z. Linear homogeneity requires $\beta_l+\beta_c+\beta_v+\beta_z=1$ and $\Sigma_k \beta_{jk}=0$; j=l,c,v,t,z; k=l,c,v,z.

nitrogen surplus by 1%. Estimation of such a system goes beyond the focus of this article. To place these figures in perspective, as of 1998 a levy of 1.5 guilders per kilogram must be paid for the nitrogen surplus that exceeds a levy-free surplus. This levy has been guided more by the income of dairy farms than by their environmental damage.

The estimated technical and environmental efficiencies are summarised in Table 2.4. Output-oriented technical efficiency is estimated using (2.5) and input-oriented technical efficiency is estimated using (2.13). Due to the presence of globally increasing returns to scale, input-oriented technical efficiency is higher than output-oriented technical efficiency at all observations. Nonetheless, estimates of output-oriented technical efficiency are impressively high, ranging from 0.55 to 0.99 with a mean of 0.894. Since technical

Table 2.3 Elasticities of output with respect to each input, including time, by output decile

Output Decile	Time	Labour	Capital	Variable input	N surplus	Returns to scale
1.	-0.01	0.09	0.37	0.53	0.18	1.17
2.	0.01	0.09	0.36	0.53	0.16	1.14
3.	0.00	0.09	0.34	0.54	0.14	1.11
4.	0.01	0.11	0.34	0.53	0.13	1.12
5.	0.01	0.11	0.34	0.53	0.12	1.10
6.	0.01	0.12	0.33	0.53	0.11	1.09
7.	0.02	0.13	0.35	0.51	0.10	1.09
8.	0.02	0.14	0.36	0.50	0.10	1.09
9.	0.03	0.12	0.35	0.51	0.08	1.06
10.	0.02	0.13	0.36	0.51	0.06	1.05

Table 2.4 Estimates of technical efficiency and environmental efficiency

	Output-oriented technical efficiency	Input-oriented technical efficiency	Environmental efficiency
1991 mean	0.894	0.904	0.428
1992 mean	0.892	0.902	0.431
1993 mean	0.894	0.903	0.448
1994 mean	0.894	0.903	0.455
overall mean	0.894	0.903	0.441
overall minimum	0.55	0.57	0.00^{+}
overall maximum	0.99	0.99	0.96

efficiency is modelled as being time-invariant, the slight variation in annual means is due to changes in the composition of annual samples as farms enter and exit the sample. These high degrees of technical efficiency suggest that very little marketable output is sacrificed to resource waste.

Environmental efficiency is estimated using (2.10). Environmental efficiency is much lower on average, and exhibits much greater variability, than output-oriented technical efficiency, with a range of from 0.00^{+} to 0.96 and a mean of 0.441 [12]. However, it is noteworthy that environmental efficiency increased steadily during the period, as NEPP began to exert an influence on the behaviour of dairy farm operators. These results suggest that, by 1994, marketable output could have been maintained using observed values of other inputs, while generating 54% less nitrogen surplus [13]. This in turn suggests a dilemma. Achieving output-oriented technical efficiency with given resource use would have led to an 11% increase in marketable output in 1994, and thus to increases in revenue and profit. On the other hand, achieving environmental efficiency would have led to a 54% reduction in emissions-generating nitrogen surplus in 1994, but would have neither increased revenue nor reduced operating costs.

We now consider the compatibility of technical efficiency and environmental efficiency. Although technical efficiency is both necessary and sufficient for environmental efficiency, as demonstrated in Figures 2.2-2.4, no farm in the sample is technically efficient. And a high degree of technical efficiency is neither necessary nor sufficient for a high degree of environmental efficiency. Figure 2.3 demonstrates that a relatively high degree of technical efficiency is compatible with a relatively low degree of environmental efficiency at input mixes with relatively large nitrogen surplus. Also, a relatively low degree of technical efficiency is compatible with a relatively high degree of environmental efficiency at input mixes with relatively small nitrogen surplus. The concordance between the two efficiency measures thus depends on the degree of substitution involving the nitrogen surplus allowed by the production technology.

The ranking according to input-oriented technical efficiency and environmental efficiency of the most and the least output-oriented technically efficient farms is presented in Table 2.5. The concordance between the two technical efficiency rankings is very high, with the only differences in the two rankings being small and due to the presence of scale economies. The concordance between the output-oriented technical efficiency ranking and the environmental efficiency ranking is positive but not as strong. The Spearman rank correlation coefficient between the two measures is 0.873. Farms with the highest and lowest

[12] Two thirds of the predicted rations of observed output to environmentally efficient nitrogen lie within the bounds of the sample data. Although this is a potential problem for all stochastic frontier analysis, the discrepancy between some of the predicted rations and the ratios is a point for further research.

[13] The low average environmental efficiency can be partly explained by the large differences in nitrogen surplus between farms with identical production per ha (Baltussen et al., 1992).

environmental efficiency scores also tend to achieve relatively high and relatively low technical efficiency scores, although there are many exceptions. The largest drop in ranking between output-oriented technical efficiency and environmental efficiency is 1,474 places, while the largest increase is 446 places (both not present in Table 2.5).

Table 2.6 presents the distribution of farms by efficiency measures and indicates that about half (47%) of the least environmentally efficient farms are also among the least technically efficient farms, while the vast majority (98%) of the most environmentally efficient farms are also among the most technically efficient farms. Exceptions are not common, but 13% of the two groups of least environmentally efficient farms are among the two groups of most technically efficient farms, and less than 1% of the two groups of most environmentally efficient farms are among the two groups of least technically efficient farms.

Table 2.5 Ranking of dairy farms according to technical and environmental efficiency

Output-oriented technical efficiency	Input-oriented technical efficiency	Environmental efficiency
1	4	6
2	2	5
3	1	3
4	3	1
5	11	10
6	10	7
7	6	4
8	9	2
9	8	11
10	5	8
1,536	1,534	1,489
1,537	1,533	1,477
1,538	1,540	1,528
1,539	1,538	1,512
1,540	1,539	1,515
1,541	1,541	1,509
1,542	1,543	1,500
1,543	1,542	1,484
1,544	1,544	1,485
1,545	1,545	1,486

Table 2.6 Distribution of farms by output-oriented technical efficiency and environmental efficiency

Technical Efficiency	Environmental efficiency					
	0.0-0.15	0.15-0.35	0.35-0.55	0.55-0.75	0.75-1.0	total
0.45-0.80	47%	20%	--	--	--	26%
0.80-0.90	46%	62%	32%	1%	--	18%
0.90-0.95	4%	16%	63%	53%	2%	32%
0.95-1.00	3%	2%	5%	46%	98%	24%
Total	100%	100%	100%	100%	100%	100%
# Farms	243	350	379	376	197	1,545

Table 2.7 Distribution of dairy farms by environmental efficiency and intensity of production measured as real output (1,000 1991 NLG) per ha

Intensity	Environmental Efficiency						
	0.0-0.15	0.15-0.35	0.35-0.55	0.55-0.75	0.75-1.0	total	# farms
0-7.5	21%	41%	14%	15%	9%	100%	208
7.5-10	16%	24%	24%	23%	13%	100%	433
10-12.5	20%	15%	25%	25%	15%	100%	433
12.5-15	9%	18%	30%	32%	11%	100%	218
15-40	10%	24%	29%	25%	12%	100%	253
% Farms	16%	23%	24%	24%	13%	100%	1,545

Finally we consider the relationship between environmental efficiency and the intensity of farming. There has been an ongoing public debate for several years in the Netherlands concerning whether extensive or intensive farms are more environmentally efficient (Zoebl, 1996). We therefore relate environmental efficiency to the intensity of farming, which we measure as real output (1,000 1991 NLG) per ha. We find a tendency for intensive farms to be more environmentally efficient than extensive farms with respect to their generation of nitrogen surplus, although this tendency is not pronounced. The Spearman rank correlation coefficient between intensity and environmental efficiency is 0.126. Table 2.7 reports more detailed results. The intuition behind this positive relationship between environmental efficiency and intensity of farming is that the total nitrogen surplus is smaller for farmers who use less land and buy more feed. When farmers produce roughage they generate relatively large nitrogen losses because the amount of nitrogen applied in the form of fertiliser and manure is larger than the nitrogen content of the roughage.

2.7 Conclusions and discussion

We have developed an analytical framework within which to calculate environmental efficiency as a single-factor measure of input-oriented technical efficiency. Such a measure of environmental efficiency can identify farms with the smallest and the largest environmentally detrimental emissions to the environment, given their output and their use of conventional inputs. We also showed how this environmental efficiency measure can be estimated within a stochastic translog production frontier context. We have demonstrated the workability of this framework by estimating environmental efficiency (nitrogen surplus efficiency) for each observation in a panel of 613 Dutch dairy farms during the 1991-1994 period.

We have found Dutch dairy farms to have achieved generally high levels of technical efficiency (89 or 90% on average, depending on orientation). However we have also found Dutch dairy farms to have achieved generally low levels of environmental efficiency (44% on average and steadily increasing through the sample period). Although there is a positive relationship between technical efficiency and environmental efficiency, there are many exceptions. The finding that environmental efficiency varies widely is in line with related literature on the Dutch manure surplus; Baltussen et al. (1992) found large variability in the mineral surpluses generated on farms having comparable milk production per ha. We have also estimated 'shadow prices' of the nitrogen surplus. These 'shadow prices' provide a measure of the cost to farms, in terms of foregone real output, of achieving reductions in their nitrogen surplus. These 'shadow prices' are upper bounds to true shadow prices. We estimate these 'shadow prices' as being in the neighbourhood of 3.1 1991 guilders per kilogram of nitrogen surplus. This estimate can provide the Dutch government with guidance when they consider appropriate fees to levy on surpluses. Finally, we have found a weak positive relationship between environmental efficiency and intensity of farming.

3. Environmental efficiency with multiple environmentally detrimental variables; estimated with SFA and DEA [1]

Abstract

The objective of this paper is to estimate comprehensive environmental efficiency measures for Dutch dairy farms. The environmental efficiency scores are based on the nitrogen surplus, phosphate surplus and the total (direct and indirect) energy use of an unbalanced panel of dairy farms. We define environmental efficiency as the ratio of minimum feasible to observed use of multiple environmentally detrimental inputs, conditional on observed levels of output and the conventional inputs. We compare two methods for the calculation of efficiency; namely Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). This paper reveals the strengths and weaknesses for estimating environmental efficiency of the methods applied. Both SFA and DEA can estimate environmental efficiency scores. The mean technical efficiency scores (output-oriented, SFA 89%, DEA 78%) and the mean comprehensive environmental efficiency scores (SFA 80%, DEA 52%) differ between the two methods. SFA allows hypothesis testing, and the monotonicity hypothesis is rejected for the specification including phosphate surplus. DEA can calculate environmental efficiency scores for all specifications, because regularity is imposed in this method.

3.1 Introduction

Increasing agricultural productivity has been a long time policy objective in most Western European countries. Agricultural productivity has been increased by technological developments and by the substitution of fertiliser, concentrates and energy for labour and land. However since this increased use of these variable inputs is the source of the current environmental problems caused by agriculture, sustainable development of a competitive agriculture has become the major objective of the Dutch agricultural policy. To achieve a competitive agriculture, farms have to apply marketable inputs as efficiently as possible, and to create environment-friendly agriculture they have to deal efficiently with the environment. This raises the aggregate questions of how productively efficient and environmentally efficient Dutch dairy farming is with respect to the major environmentally detrimental variables, and whether each type of efficiency has improved or deteriorated since the first regulations

---

[1] Article by Stijn Reinhard, C. A. Knox Lovell, Geert Thijssen; forthcoming in the *European Journal of Operational Research.* Reprinted with permission of Elsevier Science B.V.

became effective. To answer these questions a comprehensive environmental efficiency measure must be developed and computed appropriately.

A variety of environmental performance indices have been proposed in the past, based on adjustments of conventional measures of productive efficiency. The indices can be categorised as those which are calculated using deterministic techniques, which can be either parametric or nonparametric, and those which are estimated using stochastic techniques, which are exclusively parametric. The indices can also be categorised on the basis of whether they treat the environmental effects as inputs or outputs.

Färe et al. (1989) treated environmental effects as undesirable outputs, and they developed a hyperbolic efficiency measure that evaluates producer performance in terms of the ability to obtain an equiproportionate increase in desirable outputs and reduction in undesirable outputs. They developed their measure on a strongly disposable technology (applicable if undesirable outputs are freely disposable) and on a weakly disposable technology (applicable when it is costly to dispose of undesirable outputs, due perhaps to regulatory action). They proposed a nonparametric mathematical programming technique known as Data Envelopment Analysis (DEA) to construct strong-disposal and weak-disposal best-practice production frontiers, and to calculate their hyperbolic efficiency measure. Färe et al. (1993) also treated environmental effects as undesirable outputs, and used a parametric mathematical programming technique similar to goal programming to calculate the parameters of a deterministic translog output distance function. This enabled them to calculate a hyperbolic efficiency measure, and also to calculate shadow prices of the undesirable outputs. Ball et al. (1994) and Tyteca (1997) provided empirical applications of the DEA model proposed by Färe et al. (1989). Hetemäki (1996) also treated environmental effects as undesirable outputs, and used econometric techniques to estimate deterministic and stochastic variants of a translog output distance function, and to obtain estimates of productive efficiency and the shadow prices of undesirable outputs, in the Finnish pulp and paper industry. Reinhard et al. (1999) estimated a stochastic translog production frontier, using a panel of Dutch dairy farms, in which nitrogen surplus was treated as an environmentally detrimental input. They calculated technical efficiency and environmental efficiency, the latter being defined as the ratio of minimum feasible to observed use of nitrogen surplus, conditional on observed levels of the desirable output and the remaining inputs.

This paper is along two lines an extension of the approach developed by Reinhard et al. (1999). First, we extend their approach to multiple environmentally detrimental inputs. Second, we implement this approach using both SFA and DEA, and we compare the two sets of findings.

We define environmental efficiency as the ratio of minimum feasible to observed use of environmentally detrimental inputs, conditional on observed levels of the desirable output and conventional inputs. This measure allows for a radial reduction of the environmentally detrimental inputs applied. Our measure distinguishes from the above mentioned environmental efficiency indices (except Reinhard et al., 1999) in the sense that we treat the environmentally detrimental variables as inputs. Cropper and Oates (1992) and Boggs (1997) also followed this approach. They specified a production function to include a vector of conventional inputs and the quantity of waste discharges. Waste emissions are treated simply as another factor of production. Reductions in these emissions result in reduced output. Pittman (1981) also modelled pollution as an input in the production function because the relation between an environmentally detrimental variable and output behaves like the relation between a conventional input and output.

We are able to measure the environmentally detrimental input usage (excess nitrogen and excess phosphate application and total energy use), and we know that they have undesirable environmental repercussions, but we are unable to measure the repercussions, and so we cannot incorporate undesirable outputs into our analysis. The advantage of this comprehensive environmental efficiency measure compared to the traditional single input - single output measures, like excess nitrogen per ha or energy use per kilogram of milk, becomes apparent when more than one environmentally detrimental input is involved.

There are two essential differences between the econometric approach and mathematical programming methods to the construction of a production frontier and the calculation of efficiency relative to the frontier. The econometric approach has the virtue of being stochastic, and so attempts to distinguish the effects of statistical noise from those of productive inefficiency. However the econometric approach is parametric, and so can confound the effects of misspecification of (even flexible) functional forms (of both technology and inefficiency) with inefficiency. In addition, a flexible form is susceptible to multicollinearity, and theoretical restrictions may be violated. A main attraction of the econometric approach is the possibility it offers for a specification in the case of panel data. It also allows for a formal statistical testing of hypotheses and the construction of confidence intervals (Hjalmarsson et al., 1996). Coelli (1995b) concludes that the stochastic frontier method is recommended for use in agricultural applications, because measurement error, missing variables and weather, etc. are likely to play a significant role in agriculture. The mathematical programming approach is nonstochastic and lumps noise and inefficiency together and calls the combination inefficiency. The DEA version of the mathematical programming approach is nonparametric, and less prone than SFA to specification error. It also imposes regularity conditions a priori rather than testing them ex post. DEA has the additional advantage of being able to accommodate many inputs and many outputs, although it generates more efficient firms when the number of variables increases. We will analyse the strengths and weaknesses of the two methods in computing the comprehensive environmental efficiency scores.

The paper is organised as follows. In section 3.2 the production process of dairy farms, including the environmentally detrimental inputs, is described to provide the variables that have to be modelled. The concepts of technical and environmental efficiency are elaborated in section 3.3. In section 3.4 the environmental efficiency of each farm is modelled within the context of a stochastic translog production frontier. The corresponding DEA model is given in section 3.5. The data are described in section 3.6; they summarise the production activities of an unbalanced panel of 613 Dutch dairy farms over the period 1991-1994. Farm-level technical and environmental efficiencies of the two models are calculated, evaluated and compared in section 3.7. Strengths and weaknesses of the two models are treated in section 3.8. Conclusions are formulated in section 3.9.

3.2 Dutch dairy sector and the environment problem

Milk production takes place on about 37,400 farms in the Netherlands. The majority (80%) of these farms specialise in dairy farming. The dairy sector has a rather intensive character, although the total number of cows has decreased since the implementation of a milk quota system in 1984. In 1994 1.7 million dairy cows were kept, and the average specialised dairy farm maintained about 49 cows on 28 ha.

Nitrogen and phosphate surplus and energy use are the three main environmental problems caused by dairy farms. Nitrogen and phosphate surplus is induced by excess application of manure and chemical fertiliser. Part of these nutrients are taken up by plants, but a large part is emitted to the environment. Nitrogen pollution leads to nitrate contamination of the groundwater aquifers, the most important source of drinking water. Nitrogen also evaporates as ammonia and causes acid rain. Phosphate pollution causes eutrophication of surface water, which endangers plant and fish life. The dairy sector is the second largest energy using sector in Dutch agriculture. Fossil energy use contributes to global warming, due to the emission of carbon dioxide.

To deal with these problems the Dutch have implemented a three-phase National Environmental Policy Plan (NEPP). One of the objectives of this plan is to achieve manuring that is balanced with the extraction of nutrients. Among other things, it has established increasingly restrictive farm manure quotas. These quotas are first based on the phosphate content of manure, because phosphate does not evaporate, and is therefore more easily controlled. Fees are levied on phosphate surpluses, and restrictions are imposed on the spreading of manure. To implement the manure policy with respect to nitrogen, nitrogen inputs and outputs are monitored by means of nutrient balance sheets. These in turn permit an accurate calculation of farm-level nitrogen surplus, the difference between the quantity of nitrogen applied and the quantity of nitrogen in the desirable output. These balance sheets also provide accurate computation of the phosphate surplus. A surplus measures the emission of minerals into the environment. While the environmental effects themselves are difficult to quantify, the mineral surpluses which create these effects can be quantified.

A goal of the Dutch government is an energy productivity increase of 26% by 2000 compared with 1989. To this end the direct energy use of dairy farms (and other small scale users) is taxed with an environment levy. To design and evaluate this energy policy the energy use of farms is monitored. Dairy farms use fossil energy directly as diesel and gas for heating, and they use electricity for milking machines and refrigeration of milk. Dairy farms also apply inputs that contain fossil energy at an earlier stage in the product chain. This energy use is referred to as indirect energy. For instance a lot of energy is used to produce nitrogen fertiliser. Also concentrates contain an implicit amount of fossil energy. We take the direct and indirect use of energy into account, to prevent intensive dairy farms (which

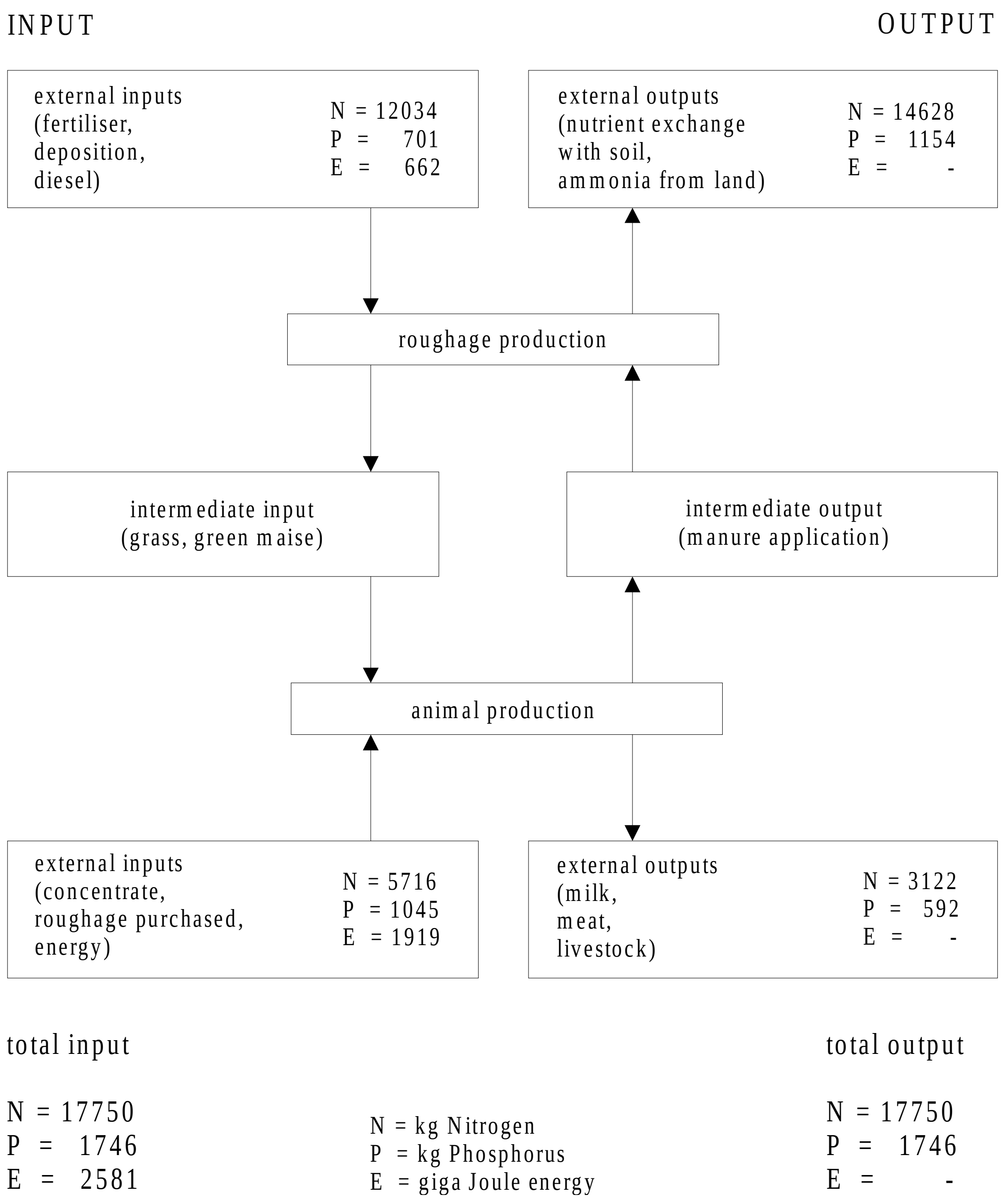

Figure 3.1 Specification of the average nitrogen, phosphate and energy flows of dairy farms in the data set

buy concentrates) from unfairly appearing more energy efficient than extensive farms (which grow roughage). Total energy use measures the application of energy, and is a proxy for the emission of CO_2, which contributes to global warming.

A schematic representation of the main flows of the environmentally detrimental variables is given in Figure 3.1. Variables that affect the nitrogen and phosphorus cycle directly, and variables that contain energy, are presented with the average quantity of the corresponding environmentally detrimental input between brackets. The production process on a dairy farm consists of two parts: (i) roughage production that provides intermediate input (grass and green maize) for the livestock and (ii) animal production that produces marketable outputs and manure. The latter is an intermediate output of the animal production process that is used in the roughage production. Both processes are depicted in Figure 3.1. The inputs (including the intermediate input) are located left and the outputs (including the intermediate output) are on the right.

The average nutrient input per farm in the data set is 17,750 kg N and 1,746 kg P (excluding intermediate input). The average nutrient output per farm contains 17,750 kg N and 1,746 kg P (including the nitrogen and phosphate surplus). The marketable output (milk, meat, livestock and roughage) contains 3,122 kg N and 592 kg P on average. Thus the average nutrient surplus (nutrient exchange with the soil and evaporation of ammonia from land) consists of 82.4% of the N input and 66.1% of the P input. The total energy use contains 2,581 gigajoule, with the indirect energy use being far more important (88%) than direct energy use.

3.3 Environmental efficiency in the multiple environmentally detrimental input case

Environmental efficiency is defined as the ratio of minimum feasible to observed use of environmentally detrimental inputs, conditional on observed levels of output and the conventional inputs. So defined, environmental efficiency is a nonradial input-oriented measure of technical efficiency that allows for a radial reduction of the environmentally detrimental inputs. Details are provided by Kopp (1981) and Banker and Morey (1986). Figure 3.2 portrays a production frontier in conventional input X and environmentally detrimental input Z space, holding output constant at its observed value Y_R. The environmental efficiency in this one bad input case is equal to $|0Z^G|/|0Z_R|$.

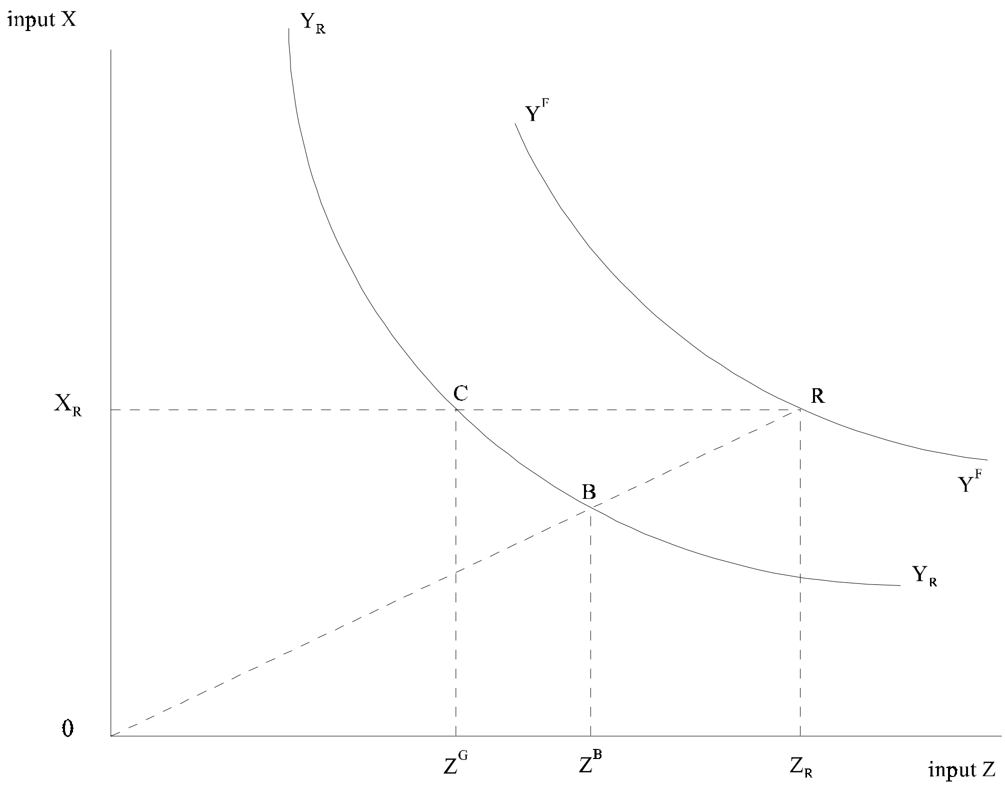

Figure 3.2 Production frontier in bad input Z, conventional input X space

In Figure 3.3 the definition of environmental efficiency is extended to two environmentally detrimental inputs. This method can also be applied to more than two environmentally detrimental inputs. The relation between the two bad inputs is assumed to be similar to the relation between a conventional input and a bad input as drawn in Figure 3.2. Figure 3.3 portrays a production frontier with environmentally detrimental inputs Z_K and Z_M, conditional on observed values of output Y and conventional input X, and $Y \leq F(X,Z_K,Z_M)$. The comprehensive environmental efficiency measure is calculated as a radial contraction of the two environmentally detrimental inputs to the frontier. The comprehensive environmental efficiency index EE_R is defined as

$$EE_R = \frac{|0Z_K^F|}{|0Z_{KR}|} = \frac{|0Z_M^F|}{|0Z_{MR}|} = \min\{\theta : F(X_R, \theta Z_{KR}, \theta Z_{MR}) \geq Y_R\}, \tag{3.1}$$

where $Z_K^F = \theta Z_{KR}$, $Z_M^F = \theta Z_{MR}$ is the minimum feasible environmentally detrimental input use, given $F(\bullet)$ and the observed conventional inputs X_R and output Y_R. Färe and Lovell (1978) show that the radial efficiency measure is greater than or equal to the corresponding nonradial measure. This is also depicted in Figure 3.3; the environmental efficiency based solely on Z_K is equal to $|0Z_K^G|/|0Z_{KR}|$. This is smaller than the comprehensive environmental efficiency measure, which equals $|0Z_K^F|/|0Z_{KR}|$.

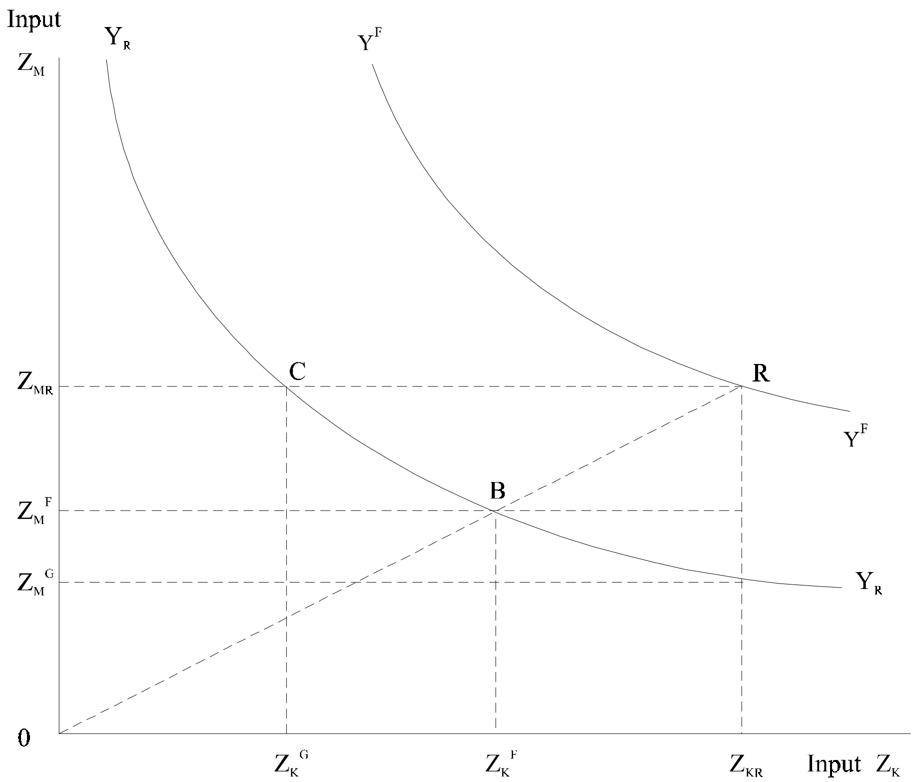

Figure 3.3 Production frontier in bad input Z_K, bad input Z_M space

In Figure 3.2 the observed output is technically inefficient, since *R* lies above the best practice production frontier *F(•)*. It is possible to measure technical efficiency using an input-conserving orientation, as the ratio of minimum feasible input use to observed input use, conditional on technology and observed output production. It is also possible to measure technical efficiency using an output-expanding orientation, as the ratio of observed to maximum feasible output, conditional on technology and observed input usage. As Färe and Lovell (1978) have noted, only under constant returns to scale do the two measures coincide for a technically inefficient producer. Not wishing to impose constant returns to scale on the structure of production technology, we need to select an orientation. We think an output orientation is more appropriate in the current context, and so our measure of technical efficiency TE_R is given by

$$TE_R = [\max\{\phi : \phi Y_R \le F(X_R, Z_R\}]^{-1} = |0Y_R| / |0Y^F|, \tag{3.2}$$

where Y^F is maximum feasible output.

3.4 Stochastic Frontier Analysis

In Stochastic Frontier Analysis (SFA) (Aigner et al., 1977; Meeusen and Van den Broeck, 1977) inefficiency is modelled by an additional error term with a two-parameter (truncated normal) distribution introduced by Stevenson (1980). A stochastic production frontier is defined by:

$$Y_{it} = f(X_{it}, Z_{it}, \beta, \gamma, \zeta)\exp(V_{it} - U_i), \tag{3.3}$$

where for all farms indexed with a subscript i and for all years indexed with a subscript t,

Y_{it} denotes the production level;

$\mathbf{X_{it}}$ is a vector of normal inputs (with X_{it1} = labour, X_{it2} = capital, X_{it3} = variable inputs, X_{it4} = a vector of year dummies reflecting technological and regulatory developments);

$\mathbf{Z_{it}}$ is a vector of environmentally detrimental inputs (with Z_{it1} = nitrogen surplus, Z_{it2} = phosphorus surplus, Z_{it3} = total energy input);

β, γ and ζ are parameters to be estimated;

V_{it} is a symmetric random error term, independently and identically distributed as $N(0,\sigma_v^2)$, intended to capture the influence of exogenous events beyond the control of farmers;

U_i is a non-negative random error term, independently and identically distributed as $N^+(\mu,\sigma_u^2)$.

The stochastic version of the output-oriented technical efficiency measure (3.2) is given by the expression

$$TE_{it} = \frac{Y_{it}}{f(X_{it}, Z_{it}, \beta, \gamma, \zeta)\exp(V_{it})} = \exp(-U_i) \tag{3.4}$$

Since $U_i \geq 0$, $0 \leq \exp\{-U_i\} \leq 1$. In order to implement (3.4), technical inefficiency must be separated from statistical noise in the composed error term (V_{it} - U_i). Battese and Coelli (1988, 1992) have proposed the technical efficiency estimator

$$TE_{it} = E[\exp\{-U_i\} | (V_{it} - U_i)], \tag{3.5}$$

To derive a stochastic version of the environmental efficiency measure (3.1) we need to specify a functional form for the deterministic kernel of the stochastic production frontier. To avoid excessive misspecification we use a flexible translog functional form to model the production technology. (For convenience the farm and time subscripts on the inputs X and Z are suppressed.) Writing (3.3) in translog form gives

$$\ln Y_{it} = \beta_0 + \Sigma_j \beta_j \ln X_j + \Sigma_k \gamma_k \ln Z_k + \tfrac{1}{2}\Sigma_j \Sigma_l \beta_{jl} \ln X_j \ln X_l$$

$$+ \tfrac{1}{2}\Sigma_k \Sigma_m \gamma_{km} \ln Z_k \ln Z_m + \Sigma_j \Sigma_k \zeta_{jk} \ln X_j \ln Z_k + V_{it} - U_i\,, \tag{3.6}$$

where $\beta_{jl} = \beta_{lj}$; $\gamma_{km} = \gamma_{mk}$. The logarithm of the output of a technically efficient producer (using X and Z to produce Y^F, apart from the statistical noise captured by the error component V_{it}) is obtained by setting $U_i = 0$ in (3.6). The logarithm of the output of an environmentally efficient producer (using X and Z^F to produce Y_{it}, apart from statistical noise) is obtained by replacing Z with $EE_{it} \bullet Z_{it}$ (since $Z_K^F/Z_{Kit}= Z_M^F/Z_{Mit}=EE_{it}$) and setting $U_i = 0$ in (3.6) (since, under strict monotonicity, environmental efficiency implies output-oriented technical efficiency) to obtain

$$\ln Y_{it} = \beta_0 + \Sigma_j \beta_j \ln X_j + \Sigma_k \gamma_k \ln(EE_{it} \bullet Z_k) + \Sigma_j \Sigma_k \zeta_{jk} \ln X_j \ln(EE_{it} \bullet Z_k)$$

$$+ \tfrac{1}{2}\Sigma_j \Sigma_l \beta_{km} \ln X_j \ln X_l + \tfrac{1}{2}\Sigma_k \Sigma_m \gamma_{km} \ln(EE_{it} \bullet Z_k)\ln(EE_{it} \bullet Z_m) + V_{it}\,. \tag{3.7}$$

The output of the farm under consideration is defined in (3.6) to be equal to the output of the environmentally efficient farm defined in (3.7). Setting (3.6) and (3.7) equal permits the isolation of the logarithm of the stochastic environmental efficiency measure

$$\begin{aligned} &\Sigma\gamma_k \ln EE_{it} + \Sigma_j \Sigma_k \zeta_{jk} \ln X_j \ln EE_{it} + \\ &\tfrac{1}{2}\Sigma_k \Sigma_m \gamma_{km}[(\ln EE_{it})^2 + \ln EE_{it} \bullet (\ln Z_k + \ln Z_m)] + U_i = 0, \end{aligned} \tag{3.8}$$

resulting in

$$\tfrac{1}{2}\Sigma_k \Sigma_m \gamma_{km}(\ln EE_{it})^2 + b_{it}(\ln EE_{it}) + U_i = 0\,, \tag{3.9}$$

Where $b_{it} = \Sigma_k \gamma_k + \Sigma_j \Sigma_k \zeta_{jk} \ln X_j + \tfrac{1}{2}\Sigma_k \Sigma_m \gamma_{km}(\ln Z_k + \ln Z_m)$.

The b_{it} term is equal to $\Sigma_k(\partial \ln Y/\partial \ln Z_k)$, the sum of the output elasticities with respect to the environmentally detrimental inputs. The b_{it} term is positive if the monotonicity conditions are fulfilled. Application of the root-formula give the solution for $\ln EE_{it}$:

$$\ln EE_{it} = [-b_{it} \pm (b_{it}^2 - 2U_i \Sigma_k \Sigma_m \gamma_{km})^{\frac{1}{2}}] / \Sigma_k \Sigma_m \gamma_{km} \tag{3.10}$$

Environmental efficiency is calculated with the '+√' formula in (3.10). This is because a technically efficient farm is necessarily environmentally efficient, and $U_i = 0 \Rightarrow \ln EE_{it} = 0$ only if the '+√' formula is used. Values of $U_i > 0$ lead to environmental inefficiency ($\ln EE_{it} < 0$), irrespective of the sign of $\Sigma_k \Sigma_m \gamma_{km}$ if the monotonicity conditions are fulfilled.

In SFA we have to deal with a 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. The full translog model with three conventional inputs (excluding a time trend) and three bad inputs is likely to suffer from multicollinearity. To explore the nature of this multicollinearity we calculated the condition index and the variance proportion. The condition indices were by far larger than the yardsticks provided by Belsley et al. (1980) and Judge et al. (1982). One solution for multicollinearity is deletion of variables (Maddala, 1988). We used a consistent and pragmatic method to select candidates for deletion. We did not want to eliminate too many variables from (3.10). We investigated two options, neither of which restricts substitution elasticities to be equal to one, as in a Cobb-Douglas model:

Model 1: $\beta_{jl}=0, \forall_j \forall_l, j \neq l$
Model 2: $\beta_{jl}=0, \forall_j \forall_l, j \neq l; \zeta_{jk}=0, \forall_j \forall_k$

3.5 Data Envelopment Analysis

Different DEA models are computed to reflect the various SFA efficiency scores. A separate production set is calculated for each year, and every observation is compared with the frontier of the production set of the same year. We prefer the calculation of annual production sets to window analysis (Charnes et al., 1985) because we have a large number of observations in each year. We also prefer the calculation of annual production sets to the calculation of Malmquist productivity indices (Färe et al., 1992) because our focus is on environmental and technical efficiency rather than on productivity change. The annual production sets S^t can be defined, following Banker et al. (1984), as

$$S^t = \{(y^t, x^t) : \sum_{i=1}^{I} \lambda_i^{\ t} x_{ij}^t \leq x_j^{\ t}, \quad j = 1,..J$$

$$\sum_{i=1}^{I} \lambda_i^{\ t} y_i^{\ t} \geq y^t,$$

$$\sum_{i=1}^{I} \lambda_i^{\ t} z_{ik}^t \leq z_k^{\ t}, \quad k = 1,..., K$$

$$\lambda_i^{\ t} \geq 0, \sum_{i=1}^{I} \lambda_i^{\ t} = 1\}, \tag{3.11}$$

where farms are indexed with subscript i, conventional inputs are indexed with subscript j, environmentally detrimental inputs are indexed with subscript k, and all variables are indexed with a year superscript t. This production set is convex and allows for variable returns to scale. Environmental efficiency as defined in section 3.3 can be computed with a linear program which measures performance in terms of the ability of a producer to contract its environmentally detrimental inputs, given its output and its conventional inputs. The linear program is similar to the fourth model of Ball et al. (1994), and is expressed as

$$\max_{\theta,\lambda} \theta: \qquad s.t. \ y^{ot} \leq \sum_{i=1}^{I} \lambda_i^{\ t} y_i^{\ t},$$

$$x_j^{ot} \geq \sum_{i=1}^{I} \lambda_i^{\ t} x_{ij}^t, \quad j = 1,..., J$$

$$\theta^{-1} z_k^{ot} \geq \sum_{i=1}^{I} \lambda_i^{\ t} z_{ik}^{\ t}, \quad k = 1,..., K$$

$$\lambda_i^{\ t} \geq 0, \sum_{i=1}^{I} \lambda_i^{\ t} = 1 \tag{3.12}$$

Output-oriented technical efficiency is computed with a model in which efficiency is reflected as the ability of a producer to expand output, given conventional inputs and environmentally detrimental inputs. This model is comparable to the second model of Ball et al. (1994) and can be represented as

$$\max_{\theta,\lambda} \theta: \qquad s.t.\,\theta y^{ot} \le \sum_{i=1}^{I} \lambda_i^{\,t} y_i^{\,t},$$
$$x_j^{ot} \ge \sum_{i=1}^{I} \lambda_i^{\,t} x_{ij}^{t}, \quad j = 1,\ldots,J$$
$$z_k^{ot} \ge \sum_{i=1}^{I} \lambda_i^{\,t} z_{ik}^{t}, \quad k = 1,\ldots,K$$
$$\lambda_i^{\,t} \ge 0, \sum_{i=1}^{I} \lambda_i^{\,t} = 1 \tag{3.13}$$

Input-oriented technical efficiency is computed as the ability of a producer to contract both conventional and environmentally detrimental inputs equiproportionately, conditional on output, and it is expressed as

$$\max_{\theta,\lambda} \theta: \qquad s.t.\, y^{ot} \le \sum_{i=1}^{I} \lambda_i^{\,t} y_i^{\,t},$$
$$\theta^{-1} x_j^{ot} \ge \sum_{i=1}^{I} \lambda_i^{\,t} x_{ij}^{t}, \quad j = 1,\ldots,J$$
$$\theta^{-1} z_k^{ot} \ge \sum_{i=1}^{I} \lambda_i^{\,t} z_{ik}^{t}, \quad k = 1,\ldots,K$$
$$\lambda_i^{\,t} \ge 0, \sum_{i=1}^{I} \lambda_i^{\,t} = 1 \tag{3.14}$$

These models, (3.13) and (3.14), are the original DEA formulations of Banker et al. (1984).

3.6 Data

In this study we utilise data describing the production activities of 613 strongly specialised dairy farms that were in the Dutch Farm Accountancy Data Network (FADN) for part or all of the 1991-1994 period. The FADN is a stratified random sample. Stratification is based on farm size, age of the farmer, region and type of farm. The FADN represents 99% of the milk production, and no systematic errors due to non-response are found (Dijk, 1990). In a few observations the phosphate surplus is negative. These observations cause both theoretical and technical problems. These observations cannot readily be used in either SFA or DEA, because the natural log of negative values is not defined, and because input-oriented DEA is not translation-invariant. In the optimal situation the phosphorus input equals the phosphorus output. Hence negative values are not optimal and the soil will loose its fertility. Because only a very small percentage of the observations (less than 1%) suffers from a phosphate deficit we have decided to omit these observations.

We have a total of 1,535 observations in this unbalanced panel, and so each farm appears on average 2.5 times. The period 1991-1994 is chosen, because detailed information describing the nitrogen flows at each farm is available from 1991 onwards. The inputs and the output we specify are based upon the production process of dairy farms. The production process, including the nitrogen flows, is depicted in Figure 3.1.

In the specification we have chosen the conventional inputs are aggregated into three categories (labour, capital and variable inputs), and the outputs are aggregated into a single index of dairy farm output. Ball et al. (1994) used these variables also, although they distinguished separate output indices for animal and roughage production. If prices at the farm level are available in the FADN, they are used to calculate price indices. If prices are not present in the FADN, price indices are borrowed from CBS/LEI-DLO (1996). The FADN contains information on the quantity of milk produced and the value of sales to the milk factory and to other customers. The price that farmers receive from the factory depends on the protein and fat content of the milk, and so milk prices reflect differences in quality. Some farmers sell home-made cheese and butter, or sell milk directly to customers. If we should use an index of the quantity of milk produced, the differences in prices between farms result from differences in the quality of outputs and from differences in the composition of the components. Then this price index becomes an endogenous variable. Therefore we prefer an implicit quantity index. Implicit quantity indices are obtained as the ratio of value to the price index and therefore output is in prices of a specific year, 1991 being the base year. The price index used in this study is the average of a multilateral Törnqvist price index across farms for each year (Higgins, 1986; Caves et al., 1982). This price index varies over years but not across farms, implying that differences in the composition of a netput or quality are reflected in quantity (Cox and Wohlgenant, 1986). The same method is used to aggregate capital and the variable inputs. The output quantity index contains milk, meat, livestock and roughage sold. These all contain nutrients, which are depicted in Figure 3.1. Labour input consists of family labour, measured in hours. Buildings, equipment, livestock (for breeding and utilisation) and land are the components of capital stock. The capital price index is calculated from the revaluations of the capital stock. The value of many components of capital stock (buildings, equipment and livestock) is known at the start-balance and end-balance of each year. The difference between the start-balance of year t and the end-balance of year t-1 is due to revaluation of capital stock. The price of land is computed as a price index of land for the distinguished soil types. Labour and capital are not represented in Figure 3.1, because these inputs do not contain nutrients or energy (apart from the livestock component of capital stock). The variable input quantity index contains hired labour, concentrates, roughage, fertiliser and other variable inputs. Fertiliser, concentrates and roughage purchased are depicted in Figure 3.1. The nitrogen surplus is represented in Figure 3.1 as the sum of 'nutrient exchange with the soil and ammonia from land'. The nitrogen surplus, the difference between nitrogen input and nitrogen contained in desirable outputs, is measured in kilograms. The phosphate surplus is calculated accordingly. Total energy is the summation of the (implicit) energy content of all inputs in the production process. The characteristics of the data set are summarised in Table 3.1.

Table 3.1 Characteristics of the data set (1,535 observations)

Variables	Unit	Mean	Min.	Max.	Std. dev.
Output	1,000 '91 NLG	400	56	1,456	232
Labour	hours	4,107	1,100	11,050	1,535
Capital	1,000 '91 NLG	2,259	431	8,166	1,143
Variable input	1,000 '91 NLG	147	16	665	92
Nitrogen surplus	kg N	14,628	1,927	63,779	8,764
Phosphorus surplus	kg P	1,154	2	8934	942
Energy	gigajoule	2,581	321	24,213	1,628

3.7 SFA and DEA results

3.7.1 Stochastic Frontier Analysis (SFA)

First the full translog stochastic production frontier with all three environmentally detrimental inputs and a normal - truncated normal error distribution was estimated. This model was tested against simplified models. The production elasticities with respect to phosphate range from -0.040 to 0.095 with a mean of -0.003. The monotonicity assumption for phosphate surplus was violated in more than half of the observations. Because these parameter estimates also generated environmental efficiency scores, which could not be interpreted we tested also a model without phosphate surplus. The full translog frontier without phosphate surplus could not be rejected. Thus we decided to delete the phosphate surplus variables in the stochastic frontier approach. The remaining full translog nitrogen surplus - total energy model was tested against simplified models. The tests were performed nested, so if a simplified model was not rejected the next tests were performed against the simplified model. On basis of these tests, presented in Table 3.2, we select the model 2 specification. (We also explored the option of including a time trend instead of year dummies. The time trend turned out to be negative for more than 40% of all observations. We cannot find an economic explanation for this result. The time trend variable seems to capture something other than technological change, for instance regulation.) The selected model contains a truncated nor-

Table 3.2 *Specification tests of the nitrogen surplus and total energy model for alternative stochastic frontier specifications*

Specification	Null hypothesis	Tested against	Loglike-lihood	Likelihood ratio	χ^2 critical value	Decision
1 Full translog			1633,063			
2 Model 1	$\beta_{jl}=0;\ \forall_j \forall_l,\ j \neq l$	1	1633,063	0	7.82	accepted a)
3 Model 2	$\zeta_{jk}=0, \forall_j \forall_k$	2	1629,517	7.09	16.92	accepted a)
4 Half-normal	$\mu=0$	3	1149,898	959.24	3.84	rejected

a) This model is the new basis (null) model.

Table 3.3 *Parameter estimates a)*

Parameter	Coefficient estimate	Standard error	Parameter	Coefficient estimate	Standard error
β_0	-4.500	1.903	γ_{NN}	-0.068	0.037
β_1	0.342	0.325	γ_{EE}	-0.201	0.017
β_c	1.073	0.318	γ_{NE}	0.094	0.029
β_v	-0.267	0.267	β_{D92}	-0.014	0.009
γ_N	-0.067	0.174	β_{D93}	-0.019	0.009
γ_E	1.124	0.223	β_{D94}	0.004	0.009
β_{ll}	-0.032	0.039	μ/σ_u	0.468	0.0002
β_{cc}	-0.052	0.022	σ_u^2/σ_v^2	2.452	0.255
β_{vv}	0.041	0.023	σ_v^2	0.081	0.0004

a) The subscripts l,c,v,N and E refer to labour, capital, variable input, and nitrogen surplus and energy respectively. D92, D93 and D94 refer to the year dummies.

mal distribution of the non-negative random term *U*. The parameter estimates of the translog frontier are presented in Table 3.3. This model is used to generate the technical efficiency scores and the parameter estimates required to compute environmental efficiency scores.

Before turning to an investigation of technical and environmental efficiency, we first consider the structure of the estimated production technology. Table 3.4 reports elasticities of output with respect to each input. The sum of the elasticities of output with respect to the five inputs generates an estimated scale elasticity which indicates the presence of increasing returns to scale, a finding that is qualitatively comparable to, but somewhat smaller than, that of Reinhard et al. (1999). The elasticities of output with respect to each of the conventional inputs are positive for 100% of the observations and are also in line with the findings of

Reinhard et al. (1999). The mean elasticity with respect to nitrogen surplus is small, and the monotonicity assumption is violated for nitrogen surplus in 21% of the observations. The mean output elasticity of energy is very large, even larger than the mean output elasticity of variable inputs, possibly due to multicollinearity with these variable inputs. The means of the elasticities hardly change through time.

We now turn to the estimated technical and environmental efficiencies, which are summarised in Table 3.5. Output-oriented technical efficiency is estimated using (3.5). Input-oriented technical efficiency is estimated as the maximum radial contraction of all inputs (conventional and environmentally detrimental); in the same way as in Reinhard et al. (1999). Due to the presence of increasing returns to scale, input-oriented technical efficiency scores are higher than output-oriented technical efficiency scores at almost all observations.

Table 3.4 Elasticities of Output in SFA

		Labour	Capital	Variable inputs	Nitrogen	Energy	Total
Overall Mean		0.079	0.314	0.212	0.021	0.464	1.090
Lower quartile		0.072	0.292	0.194	0.003	0.415	1.051
Median		0.080	0.312	0.215	0.020	0.462	1.088
Upper quartile		0.087	0.333	0.231	0.037	0.512	1.131
Mean	1991	0.079	0.313	0.211	0.019	0.470	1.093
	1992	0.079	0.313	0.212	0.021	0.464	1.090
	1993	0.079	0.314	0.213	0.021	0.462	1.089
	1994	0.079	0.314	0.214	0.023	0.459	1.090

Table 3.5 SFA technical and environmental efficiency scores

		Technical (%)		Environmental (%)		
		output	input	all bads	nitrogen	energy
Overall Mean		88.94	89.88	79.54	27.20	79.32
Lower quartile		84.57	85.78	70.76	13.91	70.71
Median		90.73	91.55	81.85	23.78	81.27
Upper quartile		94.85	95.29	89.68	36.50	89.39
Mean	1991	89.01	89.96	79.80	26.83	79.66
	1992	88.77	89.72	79.31	27.13	79.11
	1993	88.97	89.89	79.51	27.26	79.27
	1994	89.03	89.95	79.55	27.57	79.27

The output-oriented and input-oriented technical efficiency scores seem very plausible. As expected, the environmental efficiency scores are smaller, although not dramatically so. Also as expected, the nonradial environmental efficiency scores are smaller than the radial input-oriented technical efficiency scores. To analyse the environmental efficiency scores more closely, the environmental efficiency with respect to the two bad inputs separately is also presented. The nitrogen efficiency scores are very low. Nitrogen is applied inefficiently because in dairy farming the nitrogen surplus is hardly sanctioned yet. The energy efficiency scores are marginally lower than the comprehensive environmental efficiency scores. Thus energy efficiency determines to a very large extent the value of the environmental efficiency score.

Output-oriented technical efficiency is assumed to be constant through time during the research period. The time-invariant specification is not unreasonable, since at most four observations per farm, and on average 2.5 observations per farm, are available in the data set. However due to the unbalanced nature of the panel, the output-oriented technical efficiency scores differ slightly from year to year. Input-oriented technical efficiency, comprehensive environmental efficiency and energy efficiency also show no trend. Nitrogen efficiency increases slightly through time, suggesting that the regulatory impact has been small but positive.

3.7.2 Data Envelopment Analysis (DEA)

The DEA results are based on all three environmentally detrimental inputs, since unlike SFA, phosphate causes no difficulties in DEA. The output elasticities calculated from the dual to the DEA program (3.12) are reported in Table 3.6, and are generally in line with the corresponding SFA results. The mean nitrogen elasticity is again positive and small, as is the mean phosphate elasticity. The mean energy elasticity is again larger than the mean variable input elasticity. The mean returns to scale is marginally larger than the SFA estimate. All in all, there is a high degree of concordance between the SFA and DEA characterisations of production technology.

The DEA models described in section 3.5 are used to compute the efficiency scores presented in Table 3.7. The output-oriented and input-oriented efficiency scores are on average somewhat lower than the corresponding SFA efficiency scores, presumably because SFA incorporates the effects of random noise. The comprehensive environmental efficiency scores (based on the three environmentally detrimental inputs) and energy efficiency scores are also smaller than the corresponding SFA efficiency scores, presumably for the same reason. However in DEA the mean energy efficiency score is larger than the mean environmental efficiency score. The mean nitrogen efficiency score is larger than the corresponding SFA score. The absence of meaningful trends in the DEA technical and environmental efficiency scores has no implication for trends in absolute performance, since separate production sets have been constructed for each year. The only implication which can be drawn from the absence of trends in technical and environmental efficiency scores, is that dispersion within each annual sample has remained virtually unchanged.

Table 3.6 Elasticities of output in DEA

		Labour	Capital	Variable inputs	Nitrogen	Phosphate	Energy	Total
Overall Mean		0.159	0.295	0.204	0.072	0.022	0.359	1.112
Lower quartile		0.000	0.126	0.055	0.000	0.000	0.254	0.963
Median		0.093	0.315	0.148	0.000	0.006	0.369	1.058
Upper quartile		0.236	0.439	0.322	0.109	0.027	0.484	1.178
Mean	1991	0.154	0.274	0.208	0.063	0.021	0.380	1.099
	1992	0.158	0.285	0.215	0.079	0.022	0.359	1.118
	1993	0.164	0.302	0.208	0.075	0.025	0.344	1.119
	1994	0.159	0.319	0.187	0.067	0.019	0.358	1.110

Table 3.7 DEA technical and environmental efficiency scores

		Technical (%)		Environmental (%)			
		output	input	all bads	nitrogen	phosphate	energy
Overall Mean		78.37	81.10	51.95	40.82	18.98	53.30
Lower quartile		70.10	73.74	33.84	24.07	2.87	37.71
Median		77.54	80.00	50.73	35.09	6.57	52.67
Upper quartile		86.35	88.15	65.49	50.53	19.63	64.53
Mean	1991	78.54	81.27	52.57	42.17	20.50	54.63
	1992	78.21	80.91	51.85	40.54	18.67	53.05
	1993	77.64	80.44	50.74	39.25	17.60	51.67
	1994	79.12	81.84	52.77	41.53	19.34	54.05

Table 3.8 reports rank corelations between the SFA scores and the corresponding DEA scores. All rank corelations are positive, ranging from 0.76 for output-oriented technical efficiency to 0.46 for nitrogen efficiency. The rank correlation coefficient for the comprehensive environmental efficiency scores is 0.49. The rank corelations between the SFA output-oriented technical efficiency scores and the other SFA efficiency scores are quite high,

ranging from 1.0 for input-oriented technical efficiency to 0.88 for nitrogen efficiency. The rank correlation between the DEA output-oriented technical efficiency scores and the other DEA efficiency scores is smaller, ranging from 0.90 for input-oriented technical efficiency to 0.70 for nitrogen efficiency.

Table 3.8 Rank correlation coefficients of the efficiency measures a)

	TE-O		TE-I		EE-total		EE-N		EE-E	
	SFA	DEA	SFA	DEA	SFA	DEA	SFA	DEA	SFA	DEA
TE-O-SFA	1.0	0.76	1.0	0.69	0.99	0.50	0.88	0.43	0.98	0.52
TE-O-DEA		1.0	0.76	0.90	0.74	0.72	0.74	0.70	0.71	0.71
TE-I-SFA			1.0	0.70	1.0	0.50	0.86	0.43	0.99	0.52
TE-I- DEA				1.0	0.70	0.72	0.61	0.72	0.68	0.71
EE-SFA					1.0	0.49	0.82	0.42	0.99	0.51
EE- DEA						1.0	0.50	0.79	0.47	0.92
EE-N- SFA							1.0	0.46	0.78	0.53
EE-N- DEA								1.0	0.40	0.76
EE-E- SFA									1.0	0.49
EE-E- DEA										1.0

a) O=output, I=input, N=nitrogen surplus and E=energy.

3.8 Strengths and weaknesses of SFA and DEA with respect to environmental efficiency

SFA and DEA have constructed remarkably similar production frontiers from the data. A comparison of Table 3.4 and Table 3.6 confirms this concordance. Both techniques suggest the presence of scale economies on the order of 1.10. Both techniques provide the same ranking of output elasticities, ranging from energy, capital, variable inputs and labour down to nitrogen, although the magnitudes vary in some cases. This concordance is reassuring.

However a comparison of Table 3.5 and Table 3.7 suggests that SFA and DEA generate somewhat less similar technical and environmental efficiencies relative to their similar production frontiers. SFA technical efficiency scores are higher (by about 10%) than DEA efficiency scores, and exhibit less variability. SFA comprehensive environmental efficiency scores and energy efficiency scores are also higher (by nearly 30%) than comparable DEA scores, while SFA nitrogen efficiency scores are considerably lower than comparable DEA scores. Although SFA and DEA generate somewhat different mean efficiency score magnitudes, an inspection of Table 3.8 confirms that the two techniques generate similar rankings of individual farms on the basis of the various efficiency criteria. This is also reassuring.

We now consider strengths and weaknesses of the two techniques. In contrast to other studies in which SFA and DEA have been compared (e.g., Ferrier and Lovell, 1990; Hjalmarsson et al., 1996), we consider evaluation criteria which are specific to our objective, the measurement of technical and environmental efficiency.

The Ability to Account for Exogenous Influences
SFA is a stochastic technique which contains a random error term, while DEA is a deterministic technique which does not. Statistical noise accounts for nearly 30% of the SFA regression residuals (appendix A). This accounts for the fact that SFA efficiency scores are generally higher than DEA efficiency scores, despite the fact that the characteristics of the two production frontiers are so similar. While efforts are underway to make DEA stochastic (e.g., Land et al., 1993; Olesen and Petersen, 1995), these efforts are in their infancy.

The Ability to Impose or Test Theoretical Restrictions
DEA satisfies monotonicity and curvature restrictions by construction, so the absence of a testing procedure is inconsequential. However these restrictions cannot be imposed in SFA when a flexible translog functional form is specified, which makes the ability to test for the satisfaction of the theoretical restrictions a strength of SFA. The SFA model with all three environmentally detrimental inputs included did not make sense. We encountered occasional violations of monotonicity in the SFA model with two of three environmentally detrimental inputs included. When we tested for monotonicity (but not for curvature), the test uncovered failure for 21% of the observations for the nitrogen surplus input.

3.9 Conclusions

In this paper we have developed an analytical framework within which to calculate environmental efficiency in the presence of multiple environmentally detrimental inputs. This comprehensive environmental efficiency measure can identify farms with the smallest and the largest environmentally detrimental emissions to the environment, in relation to their use of conventional inputs and the output they produce. Our measure enables the aggregation of environmentally detrimental inputs, and it allows the calculation of the environmental efficiency of the distinguished environmentally detrimental inputs. It also indicates which environmentally detrimental input is used most inefficiently, both on individual farms and in the aggregate.

We have found Dutch dairy farms to have respectable levels of technical efficiency (78-89% on average, depending on the empirical technique). We have also found the comprehensive environmental efficiency score to be somewhat smaller on average (52-80% on average, depending on the empirical technique). We have found energy to be utilised more efficiently than nitrogen, with mean nitrogen efficiency scores ranging from 27 to 41%, depending on the empirical technique). Energy efficiency determines to a very large extent the value of the environmental efficiency score.

We have tested this framework extensively with two methods, SFA and DEA. We have evaluated these methods on the basis of their ability to incorporate the effects of statistical noise, their fulfilment of theoretical restrictions, and the possibility to test these restrictions. Both SFA and DEA can estimate environmental efficiency scores, although only SFA incorporates noise. However SFA allows the estimation of environmental efficiency scores only in the two environmentally detrimental input case. The three bad input case (including phosphate surplus) did not fulfil all theoretical restrictions, and monotonicity was violated for phosphate surplus in the three environmentally detrimental input model. The appropriate monotonicity and curvature restrictions are imposed in DEA, and so DEA is able to calculate environmental efficiency for every environmentally detrimental input model. However DEA is deterministic, and is unable to identify whether the environmentally detrimental variables suit the model.

4. Resource use efficiency of Dutch dairy farms; a parametric distance function approach [1]

Abstract

The objective of this paper is to define and to estimate econometrically a resource use efficiency measure using a panel of Dutch dairy farms. Resource use efficiency reflects observed to maximum revenue, including the non-positive revenue of bad outputs. It can be decomposed into technical and environmental efficiency. The characteristics of non-point source pollution influence the output distance function model. The materials balance definition of nitrogen surplus suggests that desirable output and pollution are substitutes. Shadow prices of the undesirable output (nitrogen surplus) are found to be positive for all observations. Intensive farms are more resource use efficient than extensive farms.

4.1 Introduction

The agricultural policy objective of the Dutch government, as in most Western European countries, has changed due to the pollution caused by agriculture. It has evolved from one of concentrating on increasing agricultural productivity into one of enhancing the sustainable development of a competitive agriculture. In the Netherlands the focus is mainly on the environmental pollution due to excess application of nutrients by the livestock sector. Increasing attention has been directed towards the excess application of nitrogen. Nitrogen pollution comes from two sources, and it has three adverse environmental consequences. It arises from the application of chemical fertilisers and from the application of manure produced by cows and pigs, well in excess of amounts needed by plants for their growing process. Manure has evolved from what was once a valuable (and virtually free) input into what has become a waste product whose disposal is costly. The environmental problems created by nitrogen pollution include the eutrophication of surface water, which endangers plant and fish life; the leaching of nitrates into the groundwater aquifers, which contaminates the major source of Dutch drinking water; and the evaporation as ammonia, which contributes to acid rain. The odour of manure is a public nuisance.

To deal with these problems, the Netherlands has implemented a National Environmental Policy Plan (NEPP). Among other things, the government established increasingly

[1] Paper by Stijn Reinhard and Geert Thijssen. Earlier versions of this paper were presented at the annual AAEA meeting, Salt Lake City, August 1998 and the Georgia Productivity Workshop III, Athens (GA), October 1998.

restrictive farm manure quotas. They levied fees on manure surpluses, and imposed restrictions on the spreading of manure. To control the manure policy with respect to nitrogen, nutrient inputs and outputs have to be monitored on farms with more than 2.5 cows (or equivalent livestock) per ha by means of nutrient balance sheets, since January 1st 1998. These balance sheets in turn permit an accurate calculation of farm-level nutrient surplus, the difference between the quantity of nutrients applied and the quantity of nutrients in the desirable output. The value of having a measure of nitrogen surplus is that it provides a reasonably accurate measure of nitrogen discharge into the environment, while the environmental effects themselves are difficult to quantify.

To achieve a competitive agriculture, farms have to apply marketable inputs (conventional resources) as efficiently as possible, and to create the environment-friendly agriculture decreed by NEPP they have to deal efficiently with the environment (natural resources). This raises the question how efficiently conventional resources and natural resources are used in Dutch dairy farming. It also raises the disaggregate questions of which farms are relatively technically efficient and relatively environmentally efficient, and whether or not the two types of efficiency are compatible. To answer these questions a resource use efficiency measure must be developed.

If all that is required is a measure of efficiency, some people may ask: 'Why bother with complex models and estimation techniques?' For example, what is wrong with using nitrogen surplus per ha as a measure of efficiency? Measures such as nitrogen surplus per ha have a serious deficiency in that they only consider environmentally detrimental output and do not incorporate desirable outputs. The use of this measure in the formulation of management and policy advice is likely to result in excessive use of those inputs (the conventional inputs, except for land) which are not included in the efficiency measure (Coelli, 1995b).

To account for more inputs and outputs, an environmental performance measure has been developed by Färe et al. (1989). They evaluate producer performance in terms of the ability to obtain an equiproportionate increase in desirable output and reduction in undesirable output. They use a nonparametric mathematical programming technique known as Data Envelopment Analysis (DEA) to construct their best-practice frontier (see also Ball et al., 1994; Tyteca, 1997). Färe et al. (1996) use DEA to compute a distance function with and without bad outputs. The ratio of the efficiency scores from both models determines the environmental performance indicator. Mathematical programming techniques can also be used to calculate the parameters of an output distance function (see Färe et al., 1993; Coggins and Swinton, 1996). In these two studies shadow prices of the undesirable outputs are calculated, but are imposed to be negative if the firm is technically efficient. This is a reasonable assumption for a point source pollution problem. For example in an industry the production of a good output, such as paper or electricity, typically is accompanied by the joint production of undesirable by-products such as suspended solids or SO_2. Goods and bads that are jointly produced means that reduction of bad output will be 'costly': either resources must be diverted to install equipment that e.g. catches the pollutants in the exhaust pipe, or production of the desirable output has to be cut back or fines must be paid.

By definition, non-point source pollution does not enter the environment at a defined point. As a result it cannot be measured (easily) directly. For example for a dairy farm, the nitrogen emitted from manure or fertiliser cannot be easily caught by a scrubber and extracted from the nitrogen cycle in an environmentally friendly manner. In the case of non-point source pollution the bad output has to be measured indirectly. We use nitrogen surplus (nitrogen in inputs minus nitrogen in desirable outputs) per ha as a proxy for the emission of nitrogen to the environment. This undesirable output is the result of a materials balance definition; nitrogen in inputs has to be divided between good output and bad output. In this context the good output and the bad output are more likely to be substitutes, corresponding to the standard relation between desirable outputs. As a result; the shadow price of bad output will be positive for technically efficient farms [2].

This paper makes a contribution to the applied literature on three fronts. First, we investigate the relation between good and bad outputs using econometric techniques to estimate an output distance function with a panel of Dutch dairy farms. Nitrogen surplus per ha is treated as an environmentally detrimental output. This distinguishes our approach from all of those mentioned above [3]. Second, our approach allows for the characteristics of non-point source pollution. We do not impose restrictions on the curvature of the output distance function. The shadow price of the undesirable output turns out to be positive. Third, we define an environmental efficiency measure and a resource use efficiency measure using the definitions of allocative efficiency, and overall efficiency of the output mix, respectively.

This chapter is organised as follows. In section 4.2, the production process of dairy farms, including the environmentally detrimental nitrogen surplus, is described to provide the variables that have to be modelled. The relation between the good and the bad output and the concepts of environmental efficiency and resource use efficiency are investigated in section 4.3. The translog output distance function is elaborated in section 4.4. The data are described in section 4.5; they summarise the production activities of an unbalanced panel of 662 Dutch dairy farms over the period 1991-1995. Farm-level estimates of technical, environmental and resource use efficiency are calculated, evaluated and compared in section 4.6. Conclusions are formulated in section 4.7.

---

[2] Piot-Lepetit and Vermersch (1998) use DEA to derive a shadow price of organic nitrogen. They find negative shadow prices for nitrogen in manure if it is modeled as a weakly disposable output. They focus only on nitrogen in manure and do not use the materials balance condition.

[3] Only Hetemäki (1996) used also an econometric approach to incorporate pollution in a distance function.

4.2 Dutch dairy sector and the environment problem

The Dutch dairy sector has a rather intensive character, although the total number of cows has decreased since the implementation of a milk quota system in 1984. The relatively large number of cows per ha implies a large production of manure per ha. Together with a high level of fertiliser use, this leads to a large nitrogen surplus, and to correspondingly large flows of nitrogen into the soil and into the air. Part of the nitrogen is taken up by crops, but a large portion of these nutrients is emitted to the environment. Although the use of nitrogen-containing inputs has declined lately, the surpluses of nitrogen that are emitted to the environment are still very high. The nitrogen surplus per ha reflects the environmental degradation better than the total quantity of nitrogen discharged per farm. Therefore, in this paper, we define the bad output as nitrogen surplus per ha. The policy objective with respect to nitrogen emission is translated into a nitrogen loss standard per ha. Emissions above this standard are taxed since January 1st 1998. The levy free surpluses per ha for nitrogen will be reduced step by step.

A schematic representation of the main flows of environmentally detrimental nitrogen is given in Figure 2.1. The production process on a dairy farm consists of two parts: (i) roughage production that provides intermediate input (grass and green maize) for the live-stock and (ii) animal production that produces marketable outputs and manure. The latter is an intermediate output of the animal production process that is used in the roughage production.

Nitrogen evaporates from land as ammonia and leaks into the soil as nitrate, a typical example of non-point source pollution. The total nitrogen input per ha is 513 kg N (excluding intermediate input). Nitrogen incorporated in inputs has to be divided between the good output and the bad output. We expect that therefore the good and the bad output are not complements but substitutes in this context. The desirable output (milk, meat, livestock and roughage) contains 94 kg N per ha. The quantity of the nitrogen surplus is based on a materials balance definition and is equal to 419 kg N per ha [4]. Nitrogen surplus consists of 82% of the N input.

4.3 Resource use efficiency in good and bad output space

Figure 4.1 represents the production possibilities set in the case of point source pollution, without using a materials balance definition (see e.g. Coggins and Swinton, 1996). The outer boundary 0BC depicts the best practice output frontier. According to Färe et al. (1989) the relation between good output and bad output is represented by a technology which is weakly

[4] These numbers are based on our sample and differ slightly from Figure 2.1

disposable in bad output. This means that bad output is not freely (or costlessly) disposable. A reduction in bad outputs is feasible only if desirable outputs are simultaneously reduced, conditional on the inputs.

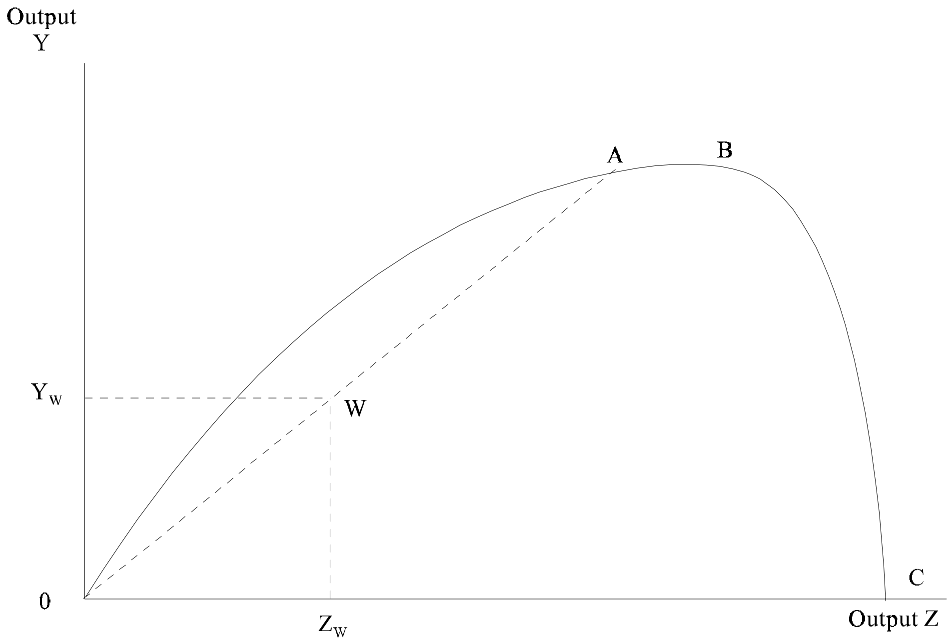

Figure 4.1 Production possibility set in good output, Y, bad output, Z, space

The technology is represented by the output set $P(X)=\{(Y,Z)$: X can produce $(Y,Z)\}$, where X is the input vector, Y is the good output vector and Z is the bad output vector. The technology satisfies weak disposability if $(Y,Z) \in P(X)$ implies that $(\theta Y,\theta Z) \in P(X)$, for every $\theta \in [0,1]$. Further, the desirable outputs are assumed to be strongly disposable (i.e., $(Y,Z) \in P(X)$ and $Y' < Y$ imply $(Y',Z) \in P(X)$) and exhibit nulljointness (i.e., if $(Y,Z) \in P(X)$ and $Z = 0$ then $Y = 0$). For a treatment of the properties that $P(X)$ customarily satisfies, see Färe and Primont (1995).

An alternative representation of the technology, conveying the same information, is the output distance function. The output distance function is defined as

$$D_O(Y,Z,X) = \min\{\theta : (Y/\theta, Z/\theta) \in P(X)\} \tag{4.1}$$

The output distance function is non-decreasing in the output Y, non-increasing in X, linearly homogenous in Y and Z, and convex in Y and Z. The distance function will take a value which is less than or equal to one if the output vector (Y,Z) is an element of the feasible output set $P(X)$. The distance function will take a value of unity if (Y,Z) is located on the outer boundary of the output set. The distance function measure is an output-oriented measure of technical efficiency. In Figure 4.1 the distance value associated with output bundle *W* is $D_O(Y_W, Z_W, X) = |0W|/|0A|$.

The distance function can be used to compute shadow prices of the bad output. The ratio of the good output shadow price and the bad output shadow price is reflected by the slope of the distance function frontier at the observed output mix (Färe and Primont, 1995:59) and therefore

$$r_Z = r_Y * \frac{\partial D_o(X,Y,Z)/\partial Z}{\partial D_o(X,Y,Z)/\partial Y} \tag{4.2}$$

where r_Z is the shadow price of the undesirable output and r_Y is the shadow price of the desirable output. In empirical studies in which the negative shadow prices of the bad output is imposed (e.g. Färe et al., 1993; Coggins and Swinton, 1996), the focus is only on the trajectory 0*B*.

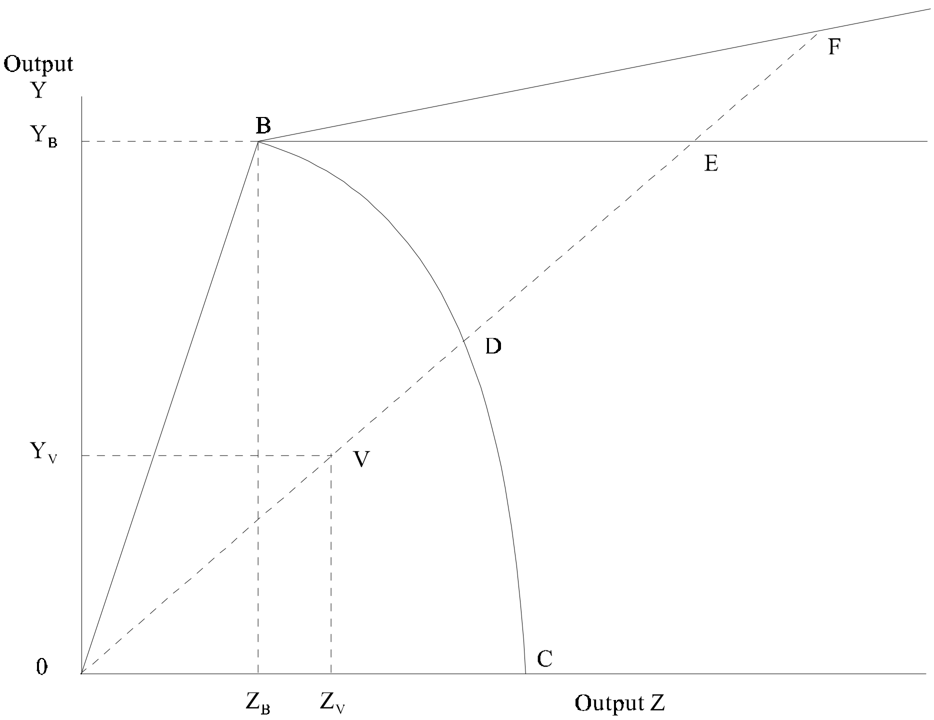

Figure 4.2 Production possibility set in good output, Y, bad output, Z, space

In the case of non-point source pollution, the undesirable output is determined with a materials balance definition. Nutrients in inputs have to be divided between good output and bad output. In this context the relation between good output and bad output is in line with the standard relation between desirable outputs, similar to the trajectory *BC* in Figure 4.2. This relation between good and bad output is characterised by positive shadow prices for the bad output. In this figure it is assumed that there are no points in the production possibility set left to the line 0*B*, due to technical (biological) restrictions.

In point B in Figure 4.2 the resources are optimally used, because (i) point B is on the frontier, so the conventional resources (inputs) are used in a technically efficient manner, and (ii) in point B the natural resources are optimally used, because it is located on the radial with the lowest production of undesirable outputs per unit of desirable output.

Point B in Figure 4.2 can be defined as

$(Y_B, Z_B) \in P(X)$ where $R(X,p) = \max \{p_y Y + p_z Z: (Y_B, Z_B) \in P(X), p_z \leq 0\}$

where p_y and p_z denote vectors of output prices (good output and bad output respectively) and $R(X,p)$ is the revenue function (which is dual to the distance function) described by Färe and Primont (1995). The price of bad output is equal to zero, or negative if a tax is imposed on the undesirable output. When the price of bad output reflects its damage, this definition compares to Perman et al. (1996), who define the net benefit of pollution as the difference between the benefit of desirable output and the damages resulting from bad output.

To obtain a performance measure of the application of conventional resources, the output distance function measure can be used. Conventional resources are used efficiently at the frontier. In Figure 4.2 the technical output-oriented efficiency measure (*TE*) associated with output bundle V is

$$TE_V(Y_V, Z_V, X) = D_O(Y_V, Z_V, X) \tag{4.3}$$

and is equal to $|0V|/|0D|$ in Figure 4.2 (point *D* is equal to $V/D_o(Y_v, Z_v, X)$).

The natural resources, *Z*, are applied efficiently at the lowest production of undesirable outputs per unit of desirable output. The measure for environmental efficiency (*EE*) has to relate the ratio of good and bad output at point *D* (equal to the ratio at *V*) to the maximum ratio, at point *B*. A convenient measure is the definition of allocative output efficiency (Färe and Primont, 1995:64). This measure of environmental efficiency relates the observed output mix projected at the frontier with the optimal output mix, which for the output bundle *V* is equal to

$$EE_V(Y_V, Z_V, X, p_Y, p_Z) = \frac{(p_Y Y_V + p_Z Z_V)/D_O(Y_V, Z_V, X)}{R(X, p)} \tag{4.4}$$

where $R(X,p) = \max \{p_y Y + p_z Z: (Y, Z) \in P(X), p_z \leq 0\}$

where p_y and p_z denote vectors of prices of good output and bad output respectively and $R(X,p)$ is the revenue function. If p_Z is equal to 0, then EE_V is given by $|0D|/|0E|$. If p_Z is negative, because of a tax on the bad output, then EE_V is given by $|0D|/|0F|$. A more negative price of bad outputs (a more damaging bad output) leads to smaller environmental efficiency scores. The price of bad output is assumed to be equal to zero, or negative if a tax is imposed on the undesirable output.

This definition of environmental efficiency differs from the definition used by Tyteca (1997) and Reinhard et al. (1999). They define environmental efficiency as the ratio of minimum feasible to observed use of an environmentally detrimental input, conditional on observed levels of the desirable output and the conventional inputs. Their definition of environmental efficiency implies technical efficiency and not necessarily a small emission of bad output per unit of desirable output. An advantage of our definition of environmental efficiency is that a more environmentally efficient farm will have a smaller emission of bad output per unit of desirable output and that the environmental efficiency score differs for different farms located on the frontier.

We want to have a resource use efficiency measure (*RE*) that combines the *TE* and *EE*. We call point B in Figure 4.2 'resource use efficient', since the conventional resources and the natural resources are used efficiently [5]. For our measure of resource use efficiency we want to compare the observed point *V* with resource use efficient point *B*. A convenient measure for resource use efficiency is the definition of overall output efficiency (Färe and Primont, 1995: 64). *RE* compares the observed revenue with the maximum revenue of the desirable and undesirable outputs given the amount of inputs and the output prices. *RE* for output bundle *V* is equal to

$$RE_V(Y_V, Z_V, X, p_Y, p_Z) = \frac{(p_Y Y_V + p_Z Z_V)}{R(X, p)} \tag{4.5}$$

Maximum revenue is represented in Figure 4.2 by the line BE when the price of a bad output is equal to zero, *RE* is given by $|0V|/|0E|$. If p_Z is negative, *RE* can be represented by $|0V|/|0F|$. The more negative the price of the bad output, the smaller the resource use efficiency score will be.

It follows from the above definitions that resource use efficiency can be decomposed into a technical efficiency and an environmental efficiency component

$$RE_V(Y_V, Z_V, X, p_Y, p_Z) = TE_V(Y_V, Z_V, X) * EE_V(Y_V, Z_V, X, p_Y, p_Z) \tag{4.6}$$

If the relation between good and bad output can be represented by Figure 4.1, identical definitions of the efficiency scores can be used. Then the optimal point will be to the left of

[5] The term 'resource use efficient' was also used by the agronomist De Wit (1992). He defined a farm resource use efficient if the production possibilities of the resources are fully exploited.

point B if a negative price of bad output is assumed. In the optimal point the slope of the distance function is equal to the price ratio of good and bad output.

4.4 Translog output distance function

The curvature of the distance function is not clear beforehand (either Figure 4.1 or Figure 4.2). However, in both cases the distance function should be convex in Y and Z. We use an econometric analysis to investigate the relation between the good and the bad output. In a parametric empirical analysis, the appropriate functional form has to be selected. To model the second-order effect (such as the convexity restriction), a flexible functional form should be used (Greene, 1997). A second desirable property of the functional form for the distance function is that it permits the imposition of homogeneity. A third property is that the inefficiency component can be calculated easily. These criteria result in the choice of the translog functional form by studies on distance functions in the literature (Morrison and Johnston, 1996; Coelli and Perelman, 1996, and Grosskopf et al., 1997). We follow this choice; in contrast to this literature we will test the convexity restriction.

The translog output distance function for two desirable outputs and one undesirable output can be described as [6]:

$$
\begin{aligned}
\ln D_{Oit} &= \alpha_0 + \sum_{j=1}^{2} \alpha_{Yj} \ln Y_{itj} + \alpha_Z \ln Z_{it} + \frac{1}{2}\sum_{j=1}^{2} \sum_{m=1}^{2} \alpha_{YjYm} \ln Y_{itj} \ln Y_{itm} + \frac{1}{2}\alpha_{ZZ} \ln Z_{it}{}^{2} + \\
&\sum_{j=1}^{2} \alpha_{YjZ} \ln Y_{itj} \ln Z_{it} + \sum_{k=1}^{3} \beta_k \ln X_{itk} + \frac{1}{2}\sum_{k=1}^{3}\sum_{l=1}^{3} \beta_{kl} \ln X_{itk} \ln X_{itl} + \sum_{k=1}^{3}\sum_{j=1}^{2} \beta_{kYj} \ln X_{itk} \ln Y_{itj} \\
&+ \sum_{k=1}^{3} \beta_{kZ} \ln X_{itk} \ln Z_{it} + \sum_{t=2}^{5} \beta_t TD_t
\end{aligned}
\tag{4.7}
$$

where for all farms indexed with a subscript i=1,…,I, and for all years indexed with a subscript t=1,…,T,

D_{Oit} denotes the output distance function measure;

$\mathbf{Y_{it}}$ is a vector of desirable outputs per ha (Y_{it1}=milk, Y_{it2}=other desirable output);

Z_{it} is the undesirable output per ha (nitrogen surplus per ha);

$\mathbf{X_{it}}$ is a vector of conventional inputs per ha (X_{it1} = labour, X_{it2} = capital, X_{it3} = variable input);

---

[6] A translog distance function with two outputs was not convex in the outputs. This was one reason to specify two desirable outputs and one undesirable output. Another reason is that it is in line with literature to specify two outputs for the production process of Dutch dairy farms (Helming et al., 1993; Boots et al., 1997).

TD_t is a time dummy variable, reflecting unbiased technological development;
α, β parameters to be estimated.

Theoretically required regularity conditions for this function include homogeneity of degree one in outputs. We imposed symmetry. These conditions require the constraints:

$$\begin{aligned}
&\alpha_{Y1} + \alpha_{Y2} + \alpha_Z = 1, \qquad \alpha_{Y1Y1} + \alpha_{Y1Y2} + \alpha_{Y1Z} = 0, \qquad \alpha_{Y1Y2} + \alpha_{Y2Y2} + \alpha_{Y2Z} = 0,\\
&\alpha_{Y1Z} + \alpha_{Y2Z} + \alpha_{ZZ} = 0; \quad \beta_{kY1} + \beta_{kY2} + \beta_{kZ} = 0, \qquad \forall_k;\\
&\alpha_{Y1Y2} = \alpha_{Y2Y1}; \qquad \beta_{kl} = \beta_{lk} \quad ,\forall_{k,l}
\end{aligned} \tag{4.8}$$

As in Coelli and Perelman (1996) and Morisson and Johnston (1996), we impose these constraints by normalising the output distance function by one of the outputs. The estimation results obtained with an output distance function are not affected by the choice of the normalising output. The major problem with econometric estimation of distance functions is that one does not observe the dependent variable. We solve this problem by the use of the inefficiency component U ($U \geq 0$):

$$\begin{aligned}
&D_O(x, y, z) * \exp(U) = 1\\
&\ln D_O(x, y, z) + U = 0
\end{aligned} \tag{4.9}$$

By using the linear homogeneity restrictions (equation (4.8)), choosing the desirable output Y_1 as the normalising output, adding a random error term, V, and rewriting the distance measure $\ln D_{Oit}$ as $-U_{it}$. We can rewrite the output distance function as:

$$\begin{aligned}
-\ln Y_{it1} = {} & \alpha_0 + \alpha_{Y2} \ln Y^*_{it2} + \alpha_Z \ln Z^*_{it} + \frac{1}{2}\alpha_{Y2Y2} (\ln Y^*_{it2})^2 + \frac{1}{2}\alpha_{ZZ} (\ln Z^*_{it})^2 + \alpha_{Y2Z} \ln Y^*_{it2} \ln Z^*_{it} +\\
& \sum_{k=1}^{3} \beta_k \ln X_{itk} + \frac{1}{2}\sum_{k=1}^{3}\sum_{l=1}^{3} \beta_{kl} \ln X_{itk} \ln X_{itl} + \sum_{k=1}^{3} \beta_{kY2} \ln X_{itk} \ln Y^*_{it2} + \sum_{k=1}^{3} \beta_{kZ} \ln X_{itk} \ln Z^*_{it} +\\
& \sum_{t=2}^{5} \beta_t TD_t + U_{it} + V_{it}
\end{aligned} \tag{4.10}$$

where

Y^*_{it2} = Y_{it2}/Y_{it1}

Z^*_{it} = Z_{it}/Y_{it1}

V_{it} = a random error term, independently and identically distributed as $N(0,\sigma_v^2)$, intended to capture events beyond the control of farmers;

U_{it} = $(U_i * \exp(-\eta(t-T)))$

U_i = a non-negative random error term, independently and identically distributed as $N^+(\mu,\sigma_u^2)$, intended to capture time-invariant technical inefficiency in outputs;
η,μ parameters to be estimated.

This transformed model can be represented by a stochastic cost frontier. The value of the distance function is obtained by

$$D_{Oit} = E[\exp\{-U_{it}\} | (V_{it} - U_{it})]. \tag{4.11}$$

Battese and Coelli (1988) proposed this estimator in case of panel data.

To calculate the environmental and resource use efficiencies, the maximum feasible revenue has to be determined. We calculate the maximum revenue (at the resource use efficient point *B*) for every observation in two steps, because the technically feasible output set restricts the maximum revenue.

(i) The maximum ratio of the predicted Y_1 (using equation (4.10) with V_{it}=0) and observed bad output in the sample is assumed to be the maximum feasible ratio [7]. This maximum ratio is used for all observations.

(ii) The maximum revenue is obtained as the revenue of the technically efficient production at the maximum ratio (using equation (4.10) with U_{it}=0, V_{it}=0 and minimum Z^*_{it}). The observed prices are used for Y_1 and Y_2. A chosen ex post price is used for *Z*.

4.5 Data

In this study we use data describing the production activities of highly specialised dairy farms that participated in the Dutch Farm Accountancy Data Network (FADN). The FADN is a stratified random sample. Stratification is based on farm size, age of the farmer, region and type of farm. The FADN covers 99% of the milk production, and no systematic errors due to non-response are found (Dijk, 1990). Thus the FADN is representative of highly specialised dairy farms.

We have selected farms from this unbalanced panel that had at least one observation in the 1991-1995 period. Our data set contains 1,923 observations of 662 farms, and so each farm appears on average 3.1 times. The period 1991-1995 has been chosen, because detailed information describing the nitrogen flows at each farm is available from 1991 onwards. The

[7] Another possibility to determine the maximum feasible ratio would be to use the ratio of the value of the outputs and observed bad output. However, to make the calculations straightforward we look only at Y_1, which is by far the most important output.

inputs and the outputs we specify are based upon the production process of dairy farms. The production process, including the nitrogen flows, is depicted in Figure 2.1.

For estimation of the translog production frontier we have to deal with a tradeoff 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. In the specification we have chosen the conventional inputs are aggregated into three categories (labour, capital and variable inputs). The labour input consists of total family labour, measured in hours. Capital stock is composed of buildings, equipment, livestock for breeding and utilisation. The variable input contains hired labour, concentrates, roughage, fertiliser and other variable inputs. The desirable outputs are aggregated into two variables: milk and an index of other desirable dairy farm output. The latter output contains meat, livestock and roughage sold. We used an implicit quantity index to aggregate the FADN data into the distinguished variables. Implicit quantity indices are obtained as the ratio of value to the price index, 1991 is the base year. More detailed information on the construction of the price indices can be found in section 2.5. Ball et al. (1994) also used these variables, although they distinguished separate output indices for animal and roughage production.

Table 4.1 Characteristics of the Sample Variables (1,923 observations)

Variables	Unit	Mean	Min.	Max.	Std. dev.
Milk	kg/ha	12,659	3,321	35,380	3,819
Other output	1991 NLG/ha	2,284	190	26,055	2,974
Labour	hours/ha	140	13	644	69
Capital	1991 NLG/ha	21,349	6,607	61,639	7,344
Variable input	1991 NLG/ha	4,306	894	19,149	2,327
Nitrogen surplus	kg N/ha	419	54	1,385	125
Land	hectares	35	5	121	19

The nitrogen surplus, the difference between nitrogen input and nitrogen contained in desirable outputs, is measured in kilograms N. The characteristics of the sample are summarised in Table 4.1. Because we defined the bad output as nitrogen surplus per ha, we transformed all variables into a per ha measure.

4.6 Empirical results

We estimated the transformed output distance function by maximum likelihood using the FRONTIER package developed by Coelli (1994). The parameter estimates and standard errors are presented in Table 4.2. We started with the full translog specification and tested whether some parameters could be deleted. The simplified translog distance function was tested to be the most appropriate specification; see Table 4.3. The hypothesis of time invariant efficiency scores could not be rejected. The hypothesis of a half-normal distribution of the logarithm of the distance function measure was rejected against the truncated normal distribution. A likelihood-ratio test of the hypothesis that inefficiency is absent is rejected.

Table 4.2 Parameters estimates and Standard errors of the normalised translog stochastic output distance function a)

	Parameter estimate	Standard Error
α_0	-4.00	1.944 b)
α_{Y2}	0.268	0.041 b)
α_Z	0.647	0.122 b)
α_{Y2Y2}	0.079	0.007 b)
α_{ZZ}	0.132	0.037 b)
α_{Y2Z}	0.007	0.012
β_l	0.245	0.211
β_c	-0.805	0.414
β_v	0.588	0.237 b)
β_{ll}	0.052	0.020 b)
β_{cc}	0.112	0.055 b)
β_{vv}	-0.370	0.030
β_{lc}	-0.024	0.029
β_{lv}	-0.036	0.019
β_{cv}	-0.051	0.033
β_{92}	-0.007	0.004
β_{93}	-0.023	0.005 b)
β_{94}	-0.058	0.005 b)
β_{95}	-0.048	0.005 b)
$\sigma_v^2+\sigma_u^2$	0.032	0.004 b)
$\gamma=\sigma_u^2/(\sigma_v^2+\sigma_u^2)$	0.907	0.012 b)
μ	0.191	0.025 b)

a) The subscripts Y2,Z,l,c,v refer to desirable output other than milk, undesirable output, labour, capital and variable input respectively; b) Denotes significant parameters (at the 95% confidence interval).

Two thirds of the parameter estimates of the selected functional form appeared to be significant (at the 95% significance level).

A central property of the output distance function is convexity in the good and bad outputs. We tested for every observation whether the principal minors of the Hessian matrix are all positive. The estimated output distance function is found to be convex for 79.9% of the observations. We may conclude that the output distance function is an appropriate model in this respect**.**

Table 4.3 Specification tests for alternative stochastic distance function models

Model	Null hypothesis	Loglikelihood	Likelihood ratio	χ^2 critical value	Decisions
Full translog time-variant efficiency		1938.935			
Full translog time-invariant efficiency	η=0	1938.935	0.000	3.84	not rejected
Simplified translog	β_{kY2}=0; β_{kZ}=0; $\forall_k$	1938.928	0.014	12.59	not rejected
Cobb-Douglas		1847.645	182.57	18.31	rejected
Half-normal	μ=0	1926.692	12.236	3.84	rejected
No inefficiency	γ=0	1189.608	1498.640	7.05	rejected

One of the central elements of the paper is the investigation of the relation between the good and the bad output. The first derivatives of the output distance function with respect to output (either good or bad) are positive for all observations. Therefore, the ratio of the first derivatives with respect to the outputs is positive. A reduction in undesirable output is accompanied by an increase in desirable output. Desirable output and nitrogen surplus behave like substitutes, as depicted in Figure 4.2. To compute the shadow price of bad output using equation (4.2), the market price of desirable output is assumed to reflect the shadow price. The shadow price of nitrogen surplus turns out to be positive for all observations, see Table 4.3. Contrary to other research, in which the shadow price of bad output is restricted to be negative, we find that the projection of the observation on the frontier is to the right of point *B*. To get a better insight into this output distance function we also calculated the elasticities with respect to the conventional inputs, see Table 4.4. As expected, an increase in capital and variable inputs has a negative effect on the output distance for all observations. The elasticity with respect to labour appeared to be positive in 8.6% of the observations.

Table 4.4 Elasticities of the distance function measure with respect to each output and input, and the shadow price of the bad output (in NLG per kg N surplus per ha)

	Mean	Min	Max
Elasticity Z (N surplus)	0.180	0.01	0.34
Elasticity Y_1 (Milk)	0.744	0.37	0.98
Elasticity Y_2 (Other output)	0.075	-0.07	0.30
Elasticity labour	-0.037	-0.17	0.05
Elasticity capital	-0.236	-0.35	-0.12
Elasticity variable input	-0.393	-0.54	-0.27
Shadow price Z	5.36	1.11	8.16

Table 4.5 Technical, environmental and resource use efficiency scores (p_Z=0)

	Technical efficiency	Environmental efficiency	Resource use efficiency
Overall Mean	0.804	0.897	0.723
Minimum	0.42	0.74	0.37
Maximum	0.99	1.00	0.96

We now turn to the estimated technical, environmental and resource use efficiencies. The estimates of output-oriented technical efficiency (the distance function measure) seem reasonable, ranging from 0.42 to 0.99 and a mean of 0.804 (Table 4.5). Because of the dual relationship between the revenue function and the distance function, this result can be interpretted as an increase of the revenue at the average by 24% (= 1 - 1/0.804) due to attaining the efficiency frontier. To calculate the environmental efficiency scores, we have to make an assumption with respect to the price of the bad output. In the research period nitrogen surplus was not restricted for dairy farms, therefore we select p_z equal to zero. This is an upper bound for the true social price of the undesirable output. Environmental efficiency is larger, on average, than output-oriented technical efficiency, with a range from 0.74 to 1.00 and a mean of 0.897. The maximum environmental efficiency score is per definition equal to unity, because the maximum revenue at the frontier is determined by the sample. At the average the social revenue can increase by 11% (= 1- 1/0.901) by going along the frontier to the optimal output mix.

The technical efficiency measure focuses on the utilisation of the conventional resources and the environmental efficiency measure relates the observed output mix to the optimal output mix. Multiplication of technical and environmental efficiency results in resource use efficiency. The resource use efficiency is by definition smaller than the technical and environmental measures, ranging from 0.37 to 0.96 and a mean of 0.723. The total possible increase in revenue in moving from the observed output mix to the efficient utilisation of inputs at the optimal output mix is equal to 38%.

The correlation between the distinguished performance measures is presented in Table 4.6. The rank correlation between the technical efficiency and the environmental efficiency scores is small and positive. Technical efficiency and environmental efficiency are positively correlated to the resource use efficiency measure, due to the definition of resource use efficiency. Nonetheless large differences in the ranking according to the technical, environmental and resource use efficiency measures exist. A farm that is judged efficient according to standard technical measures might not be environmentally efficient at all. For instance the environmentally efficient farm is ranked 1,891 according to its technical efficiency score.

A different p_z will not influence the ranking of farms according to environmental efficiency scores. The magnitude of the environmental efficiency scores will be different, the ranking of resource use efficiency scores is hardly influenced (e.g. rank correlation of the resource use efficiency scores using p_z=0 and p_z=-2.5 is 0.999). The Spearman correlation coefficient with respect to the environmental efficiency measure and the resource use efficiency measure increases if p_z decreases.

Table 4.6 Spearman correlation coefficients of the efficiency measures (technical efficiency, environmental efficiency, resource use efficiency), nitrogen surplus per ha and desirable output per kg N surplus (p_Z=0)

	TE	EE	RE	N surplus per ha	Output per kg N surplus
Technical efficiency	1.000	0.206	0.440	0.365	0.110
Environmental efficiency		1.000	0.962	-0.316	0.934
Resource use efficiency			1.000	0.251	0.340
N surplus per ha				1.000	-0.243
Output per kg N surplus					1.000

We will now investigate the relationship between our developed measures and popular measures for environmental performances in the Netherlands: output per kg of N surplus, N surplus per ha, and cows per ha.

Due to the definition of environmental efficiency the EE scores are highly positively correlated to the output per kg N surplus. The EE scores are negatively correlated with N

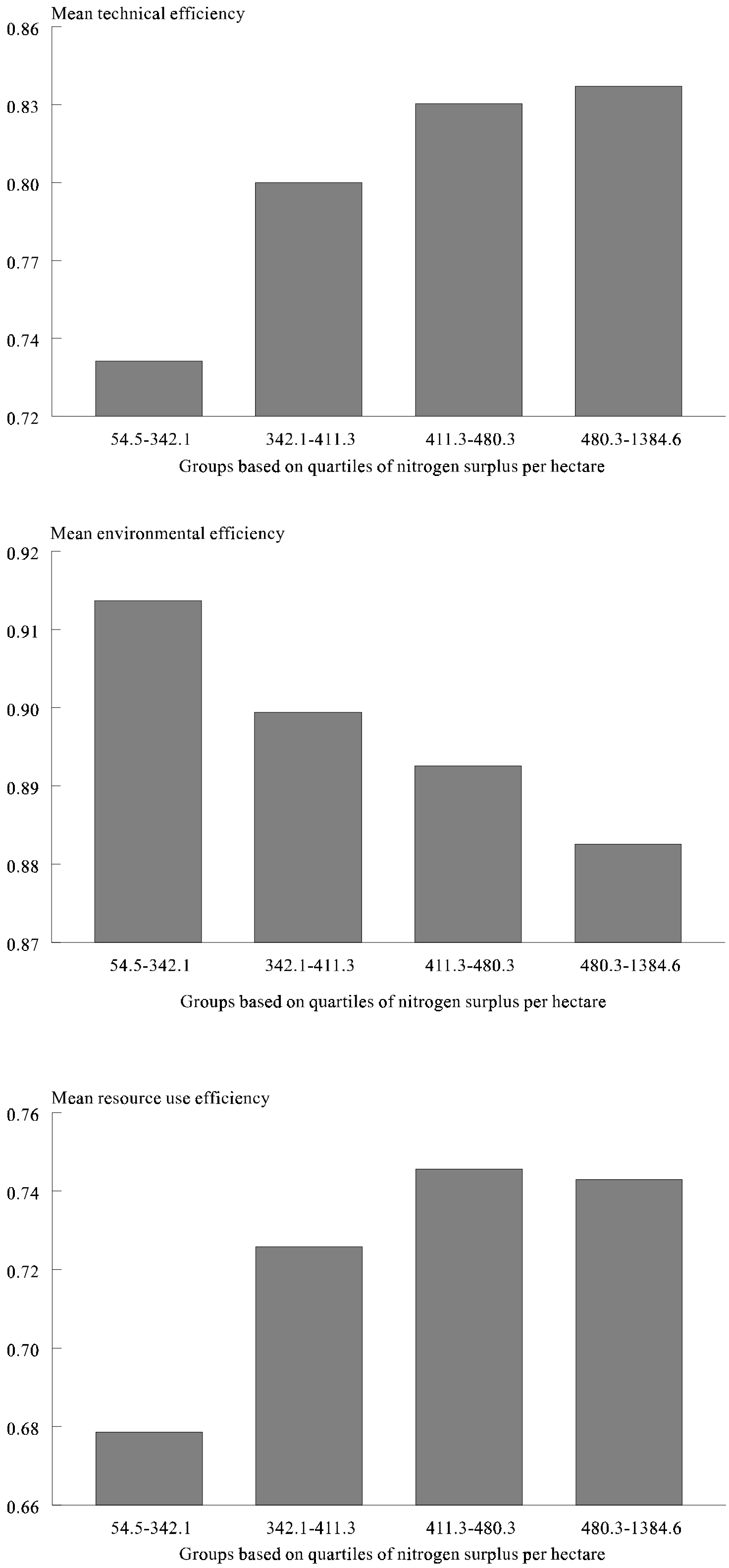

Figure 4.3 Mean technical efficiency, environmental efficiency and resource use efficiency per group based on quartiles of nitrogen surplus per ha

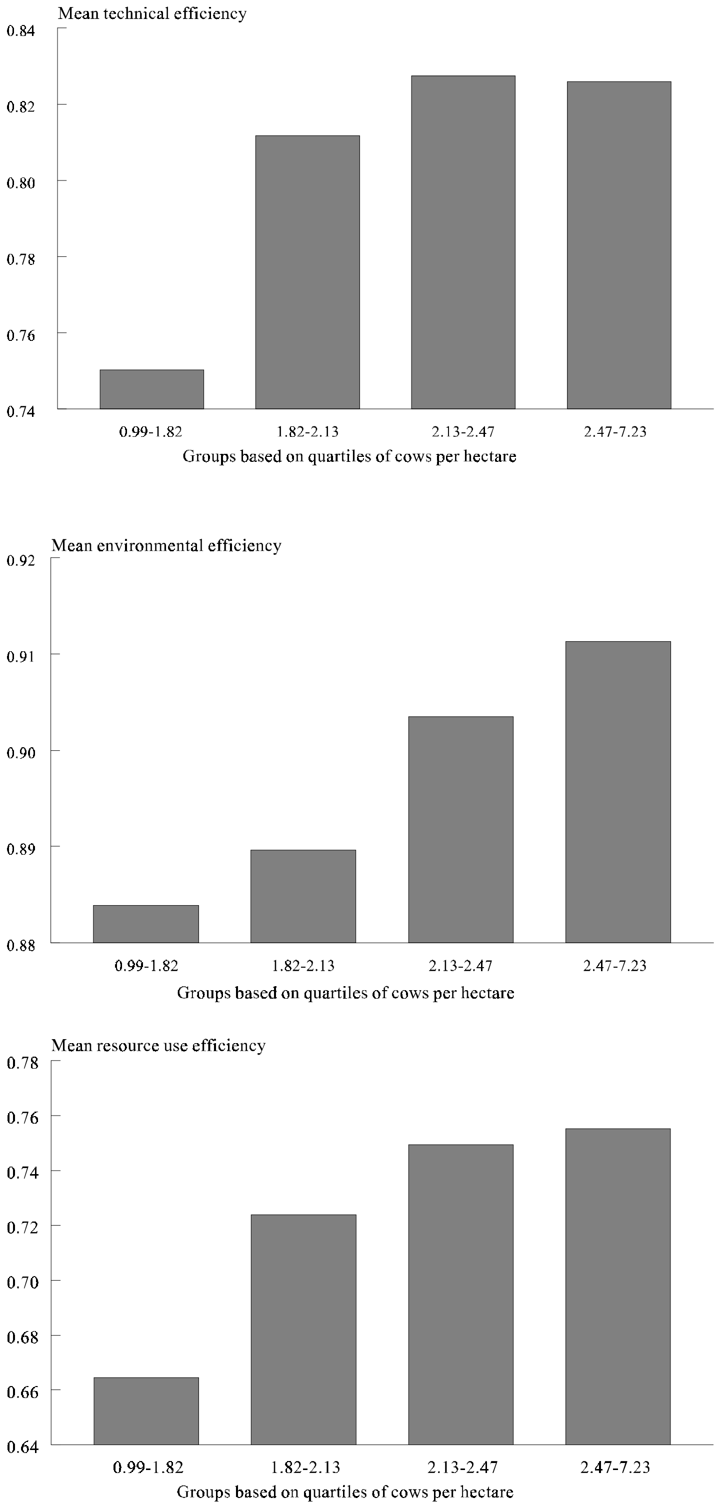

Figure 4.4 *Mean technical efficiency, environmental efficiency and resource use efficiency per group based on quartiles of cows per ha*

surplus per ha. Farms with a small nitrogen surplus are more environmentally efficient, because their ratio of desirable output and undesirable output is more favourable than that of farms with a large nitrogen surplus per ha. Farms with a large nitrogen surplus per ha show up to be more technically efficient, the relation between technical efficiency and output per kg of N surplus is less strong. The resulting resource use efficiency is positively correlated to N surplus per ha and to output per kg of N surplus. (see Table 4.6 and Figure 4.3).

There has been an ongoing debate in the Netherlands whether intensive or extensive farms are more environmentally efficient. We find that the environmental efficiency and the intensity (measured as dairy cows per ha) are positively correlated (Figure 4.4). On intensive farms the output per kg N surplus is higher than on extensive farms. Above the median (2.13 dairy cows per ha) technical efficiency is more or less stable. The resulting resource use efficiency increases with intensity but stabilises in the fourth quartile (more than 2.47 cows per ha).

Currently, 'nitrogen surplus per ha' is used as a measure for the environmental performance of dairy farmers. It is a partial measure and it is likely to result in excessive use of those inputs, which are not included in this measure. Nitrogen surplus per ha also does not take into account the desirable output. A measure that incorporates output is 'desirable output per unit of nitrogen surplus'. This measure suffers from similar drawbacks, because the inputs are not included. The virtue of the developed resource use efficiency measure is that it combines the production of environmentally detrimental output with the use of inputs and the production of desirable outputs into one measure.

4.7 Conclusions

In this chapter, a resource use efficiency measure is defined and estimated using a panel of Dutch dairy farms. Resource use efficiency reflects observed to maximum feasible revenue, including the non-positive revenue of bad outputs. This resource use efficiency measure enables the identification of farms that are characterised by efficient use of conventional resources (technical efficiency) and efficient use of natural resources (environmental efficiency).

The undesirable output of dairy farms investigated in this paper is nitrogen surplus per ha. Nitrogen emission from dairy farming is a typical non-point source pollution, it is measured applying a materials balance. Using the Stochastic Frontier Approach, a translog output distance function model is estimated without restriction on the (sign of the) shadow price of the bad output. Due to the materials balance definition of nitrogen surplus, good output and bad output turn out to be substitutes, in contrast to assumptions on point source pollution in previous research (Färe et al., 1993; Coggins and Swinton, 1996) that imposed negative shadow prices. We found that the shadow price for nitrogen surplus is positive for all observations.

The mean 'upper bound' resource use efficiency for Dutch dairy farms is 0.725, which is the product of the technical efficiency (with a mean of 0.804) and the 'upper bound' environmental efficiency (with a mean of 0.901). These efficiency measures are upper bounds because we used zero revenue of nitrogen surplus. Nitrogen surplus is not taxed in the research period. A negative revenue of the bad output (reflecting social costs of the production of bad output) will result in smaller environmental efficiency scores and resource use efficiency scores. The rank correlation between technical efficiency and environmental efficiency scores is small. Technical efficiency and environmental efficiency are positively correlated to the resource use efficiency measure, due to the definition of resource use efficiency. Nonetheless, large differences in the ranking according to the technical and environmental efficiency measures exist.

Farms with a small nitrogen surplus per ha are relatively environmentally efficient but technically inefficient. The resulting rank correlation of nitrogen surplus per ha and resource use efficiency is positive. The output per kilogram of N surplus is highly correlated with the environmental efficiency score, but hardly correlated with the technical efficiency score. Both popular measures (nitrogen surplus per ha and desirable output per kg nitrogen surplus) to evaluate environment friendly production are partial measures and do not take account of either desirable outputs or conventional inputs, respectively. The developed resource use efficiency measure is preferred because it combines the production of environmentally detrimental output to the inputs and desirable output as well.

5. Nitrogen efficiency of Dutch dairy farms; a shadow cost system approach [1]

Abstract

In this paper we analyse the cost efficiency and nitrogen efficiency of an unbalanced panel of Dutch dairy farms. The Dutch government aims for farms that are both cost-efficient and nitrogen-efficient. Nitrogen efficiency is defined as minimal to observed use of nitrogen (N-containing inputs) conditional on output and quasi-fixed inputs.

Nitrogen efficiency is computed in a shadow cost system framework. The nitrogen-efficient production is found at the optimal mix of variable inputs, determined by the nitrogen content of these inputs. The optimal nitrogen content ratio is imputed as price distortion factors in the estimated cost function. The mean input-oriented technical efficiency is 84%. The mean allocative efficiency is 95%. Both N fertiliser and feed are overused. The nitrogen surplus at the nitrogen efficient point is less than half of the observed surplus, while the production costs increase only with 3%.

5.1 Introduction

Increasing agricultural productivity has been a long-time policy objective in most Western European countries. Agricultural productivity has increased rapidly since World War II; technological development enabled substitution of fertiliser and energy for labour. However, the increased use of these variable inputs is the source of the current environmental problems caused by agriculture. In recent years increasing attention has been directed to the dairy sector, in which nitrogen pollution has been particularly severe, despite a restricted output quantity (milk). Now sustainable development of a competitive agriculture is the major objective of the Dutch agricultural policy. To achieve a competitive agriculture, farms have to apply marketable inputs as efficiently as possible, and to create environment-friendly agriculture, they have to deal efficiently with environmentally detrimental nitrogen. This raises the question of how efficient Dutch dairy farming is with respect to conventional inputs and nitrogen.

The question raised above can be reformulated into the aggregate questions as to how efficiently nitrogen containing inputs are applied in Dutch dairy farming and whether nitrogen efficiency, technical efficiency and allocative efficiency are compatible. The quantity

[1] Paper by Stijn Reinhard and Geert Thijssen.

of nitrogen supplied is likely to differ from the cost minimising level of nitrogen (e.g. Yadav et al. 1997) [2]. Therefore, we prefer a shadow cost system, in which shadow prices can deviate from market prices, over a standard cost system.

Nitrogen pollution emitted by dairy farming is an example of non-point source pollution. By definition it does not enter the environment at a defined point. The materials balance condition is used to measure the nitrogen discharge to the environment. Nitrogen surplus, defined as the difference between nitrogen in inputs and nitrogen in desirable outputs, approximates these emissions. Nitrogen surplus can theoretically be reduced by increasing the nitrogen content of (desirable) output conditional on the conventional inputs, or by reducing the nitrogen content of the inputs, conditional on the output (or by a combination of both). In the Netherlands the output quantity (milk) and the nitrogen content of milk (protein) are restricted by a quota regime. (Biological constraints also limit the nitrogen content of desirable output.) Therefore, we focus on reduction of nitrogen containing input, conditional on the output. Nitrogen efficiency is defined as minimal to observed use of nitrogen in inputs conditional on the output, quasi-fixed inputs and the nitrogen content of inputs.

This chapter is structured as follows. Literature on environmental performance measurement and efficiency measurement in a cost function framework is reviewed in section 5.2. The dairy sector and the environmental problems it causes are described in section 5.3. A cost system that allows estimation of technical efficiency, allocative efficiency and nitrogen efficiency is presented in section 5.4. The translog specification of this shadow cost system is treated in section 5.5. The empirical elaboration of this system is presented in section 5.6. The data utilised for estimation are summarised in section 5.7 and the estimation results are given in section 5.8. The discussion concludes this chapter.

5.2 Literature review

A variety of environmental performance indices have been proposed in the past, based on adjustments of conventional measures of productive efficiency. Most of them treated point source pollution as an undesirable output. An environmental performance index in which the bad output is modelled as a weakly disposable output, has been developed by Färe et al. (1989). Ball et al. (1994) and Tyteca (1997) provided empirical applications of the DEA model proposed by Färe et al. (1989). Färe et al. (1993) and Coggins and Swinton (1996) calculated output distance functions. They derived shadow prices for undesirable outputs for each observation. Pittman (1981) and Cropper and Oates (1992) modelled pollution as an input in the production function because the relation between an environmentally detrimental

[2] Yadav et al. (1997) use a yield response function to compute the profit maximising level of N application.

variable and desirable output looks like the relation between conventional input and output. Reinhard et al. (1999) elaborated on this approach and estimated environmental efficiency based on a stochastic translog production frontier, in which nitrogen surplus was treated as an environmentally detrimental input.

Our approach differs from the aforementioned papers because we do not model the non-point source pollution itself but, based on the materials balance condition, we derive environment performance measures on the basis of the nitrogen inputs. The link between neoclassical production theory and materials balance is rarely touched upon in the literature. Some of the theoretical and conceptual steps taken in this direction, were set out by Anderson (1987), Smith and Weber (1989) and Van den Bergh and Nijkamp (1994). The materials balance condition implies that the nutrients in desirable output and discharge of nitrogen equal the nutrients in input. If the inputs are utilised more efficiently, less input is necessary to produce identical output and consequently nitrogen emission is reduced. We elaborate on this concept of the materials balance condition by applying techniques from efficiency measurement to obtain performance measures.

Attention has been paid in literature to reduction of nitrogen inputs. Chemical fertiliser has been recognised as a major source of agricultural pollution. A number of authors have analysed policy alternatives for limiting fertiliser use, e.g. Burrell (1989), Oude Lansink and Peerlings (1997), Vatn et al. (1997), Yadav et al. (1997). A tax on purchased inorganic fertiliser has been identified as the easiest option to reduce excess nitrogen in agriculture (Vatn et al., 1997). Our approach differs because we analyse the possible reduction of nitrogen emission resulting from increasing efficiency of dairy farms and we focus on the two major sources of Dutch nitrogen pollution.

If output is fixed, cost minimisation of farmers is assumed, and price information of inputs is available, the cost function is the appropriate approach. Cost efficiency can be decomposed into technical and allocative efficiency. Cost efficiency is estimated comparing input use of the observed firm to the economic optimal input use conditional on output. The cost function approach is also most appropriate when an input oriented efficiency measure is estimated parametrically (Greene, 1993; Atkinson and Cornwell, 1994b). A firm is allocatively efficient when the marginal rate of technical substitution between any two inputs is equal to the ratio of corresponding input prices. Deviations from cost-minimising behaviour have been modelled in two different ways: in terms of a component error structure or as a set of parameters that scale prices. The first approach was suggested by Schmidt and Lovell (1979). The firm is assumed to minimise actual costs and its failure to do so is reflected in the disturbances, which prevent the first-order conditions from holding. Error components capturing allocative efficiency enter both the cost and share equations. Estimation within this error components framework depends on arbitrary and restrictive functional form and distributional assumptions (Greene, 1993). Therefore we prefer the second approach, first suggested by Lau and Yotopoulos (1971). The basic idea is that firms minimise shadow costs (or behavioural costs) and not actual costs. Lovell and Sickles (1983) and Atkinson and Halvorsen (1984) elaborated on this approach by assuming that firms minimise actual costs only if the ratio of shadow prices equals the ratio of market price. Panel data permits the identification and consistent estimation of input and firm-specific allocative inefficiency, as well as firm-specific technical inefficiency (Kumbhakar, 1996; Atkinson and Cornwell, 1994a; Balk and Van Leeuwen, 1998).

Our approach differs from these studies. Whereas in the literature the objective is costs minimisation, in this chapter we focus on cost minimisation and nitrogen surplus minimisation. This approach allows the weighing of economics and environment.

5.3 Dutch dairy farming and the environment

In dairy farming nitrogen pollution is induced by the excess application of purchased feed (that is processed by cows into manure) and chemical nitrogen fertiliser. Part of the nutrients is taken up by plants, but a large portion is emitted to the environment. Three major environmentally detrimental flows of nitrogen into the environment are identified. Nitrogen pollution leads to nitrate contamination of the groundwater aquifers, the most important source of drinkingwater, and to eutrophication of surface waters. Nitrogen evaporates as ammonia and causes acid rain, denitrification leads to emission of greenhouse gas (N_2O).

To deal with these problems, the Netherlands has implemented a three-phase National Environmental Policy Plan (NEPP). Among other things, they established increasingly restrictive farm manure quotas. These were first based on the phosphate content of manure, because phosphorus does not evaporate and is therefore more easily controlled. The government levied fees on manure surpluses, and imposed restrictions on the spreading of manure.

Nitrogen emission is non-point source pollution and can hardly be measured directly. The major flows of the nitrogen cycle of dairy farming are presented in Figure 2.1. Nitrogen evaporates from land as ammonia and leaks into the soil as nitrate, a typical example of non-point source pollution. The three aforementioned discharges of nitrogen into the environment are not measured directly on FADN farms, therefore we use nitrogen surplus as a proxy for the environmentally detrimental repercussions and is defined (measured) as nitrogen in inputs minus nitrogen in desirable outputs. Our objective here is not to evaluate the harm caused by excess nitrogen, but rather to attempt to measure the possibilities and costs to the agricultural sector of abatement of excess nitrogen.

5.4 Efficiency measures

We start with a standard cost function, incorporate input technical efficiency and expand this model to a shadow cost system. Thereafter, we will use the materials balance definition to define our nitrogen efficiency measure in this framework.

In the standard approach, farmers are assumed to minimise costs of the variable inputs, restricted by the production function. The cost function is a function of market prices of the variable inputs w, the output volume y and the quantities of the fixed inputs q. According to duality theory, this cost function is increasing and concave in prices, linearly homogenous in prices, increasing and convex in the output, and decreasing in the fixed inputs. To incorporate input-oriented technical efficiency, this model is extended according to Atkinson and Cornwell (1994b) and Kumbhakar (1996)

$$\begin{aligned} &\min_x \mathbf{w}'\mathbf{x} \\ &s.t.\ f(\tau\mathbf{x}, q) = y \end{aligned} \tag{5.1}$$

where $\mathbf{x}$ is a J vector of variable inputs, f is a neoclassical production function, common to all farms, and τ ($0 < \tau \leq 1$) is a parameter which measures the extent to which minimal input usage differs from actual input usage conditional on the output and on the input mix (input-oriented technical efficiency). The first order conditions are

$$\frac{\partial f / \partial(\tau x_j, q)}{\partial f / \partial(\tau x_l, q)} = \frac{w_j}{w_l}, \qquad j, l = 1.....J \tag{5.2}$$

These first order conditions and the production function can be used to solve for the inputs (x^f is the technically efficient quantity of inputs):

$$\tau * x_j \equiv x_j^f(w, y, q) \tag{5.3}$$

These input demand functions can be used to derive the cost frontier defined as

$$C(w, y, q) = \sum_j^J w_j * \tau * x_j \tag{5.4}$$

The actual costs, $\mathbf{w'x}$, are equal to [3],

[3] An example of a study that estimated technical efficiency conditional on (quasi) fixed inputs is offered by Wang et al. (1996).

$$w'x = (1/\tau)C(w, y, q) = C(w/\tau, y, q) = \min_{\tau x}[(w/\tau)(\tau x) \big| f(\tau x, q) = y)] \tag{5.5}$$

The second equality follows from the fact that a cost function is linearly homogeneous in w. To reach the frontier, a farm must lower costs by $[(C/\tau) - C]$. The convex relation between output and costs is presented in Figure 5.1. Farm R is technically inefficient, the same amount of output can be produced at less cost. The input-oriented efficient production is at point B.

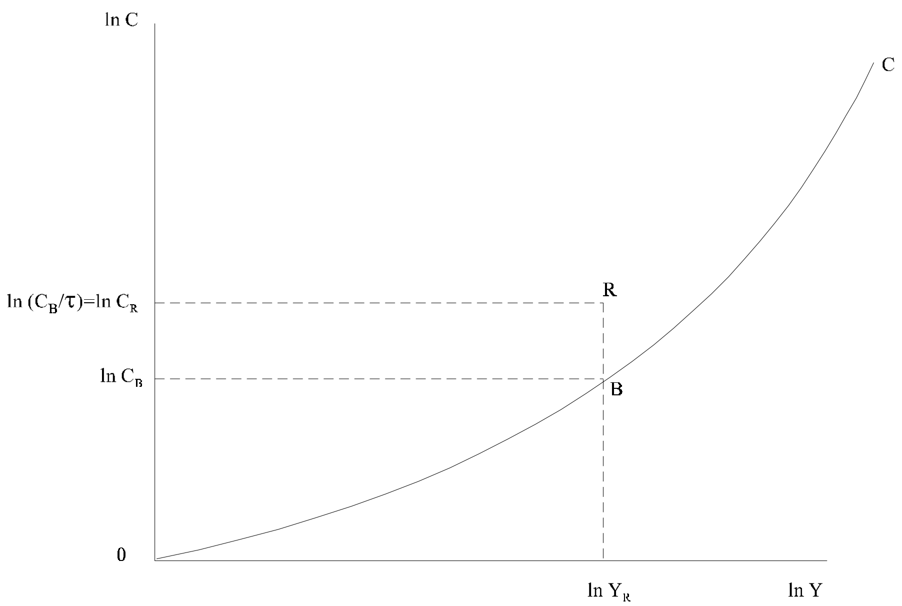

Figure 5.1 Cost function in cost - output space

To obtain a measure for allocative efficiency, farms are assumed to minimise shadow costs and not actual costs. That is, we allow farms to make mistakes in allocating their inputs. These mistakes, labelled as allocative efficiency, are captured by the θ parameters, which are unity only if the input allocation is efficient. The first order conditions are

$$\frac{\partial f / \partial(\tau x_j, q)}{\partial f / \partial(\tau x_l, q)} = \frac{\theta_j w_j}{\theta_l w_l} = \frac{w_j^*}{w_l^*}, \qquad j, l = 1.....J \tag{5.6}$$

where θ_j represents price distortions. Since a particular input can be over- or underused, θ_j can be less or greater than unity. $\mathbf{w}^*$ is a vector of shadow prices, which are assumed to be parametrically related to the market prices [4]. Only the ratios θ_j/θ_l can be identified for each firm. Atkinson and Cornwell (1994a) and Kumbhakar (1996 and 1997) choose arbitrarily one input as numeraire and normalise the relative price distortion coefficients. Generally for materials (in our case intermediate inputs) it is assumed that their shadow price is always equal to their market price over all periods examined. The corresponding θ_j is normalised to 1. These first order conditions and the production function can be used to solve for the inputs:

$$\tau * x_j \equiv x_j^f(w^*, y, q) \tag{5.7}$$

These input demand functions can be used to derive a 'shadow cost function' [5] defined as

$$C(w^*, y, q) = \sum_j^J w_j^* * \tau * x \tag{5.8}$$

Therefore (Atkinson and Cornwell, 1994):

$$(1/\tau)C(w^*, y, q) = C(w^*/\tau, y, q) = \min_{\tau x}[(w^*/\tau)(\tau x) | f(\tau x, q) = y)] \tag{5.9}$$

The two components of cost efficiency (technical and allocative efficiency) are combined in Figure 5.2. Farm R is technically inefficient, the same amount of output can be produced at lower cost with an identical input ratio (farm B). In Figure 5.2 input-oriented technical efficiency is equal to $|0B|/|0R| = wx_B/wx_R = w^*x_B/w^*x_R$ (where x_B, x_R is the quantity of x at point B, R respectively in Figure 5.2). Farm B is technically efficient, but not allocatively efficient, because the ratio of inputs is optimal for the shadow prices (reflected by the line w^*), but not for the actual prices (reflected by the line w). Farm A is cost (technically and allocatively) efficient, the farm is on the isoquant and the input ratio is optimal according to the actual prices. The allocative efficiency of farm B is given by wx_A/wx_B and represented in Figure 5.2 by $|0D|/|0B|$. Cost efficiency is defined as the product of these two measures and is equal to wx_A/wx_R, and represented in Figure 5.2 by $|0D|/|0R|$.

[4] This is an assumption already made by Lau and Youtopoulos (1971) but which is still the standard assumption in literature (see e.g. Atkinson and Cornwell, 1994b).

[5] A shadow cost function is identical to a standard cost function with shadow prices substituted for market prices.

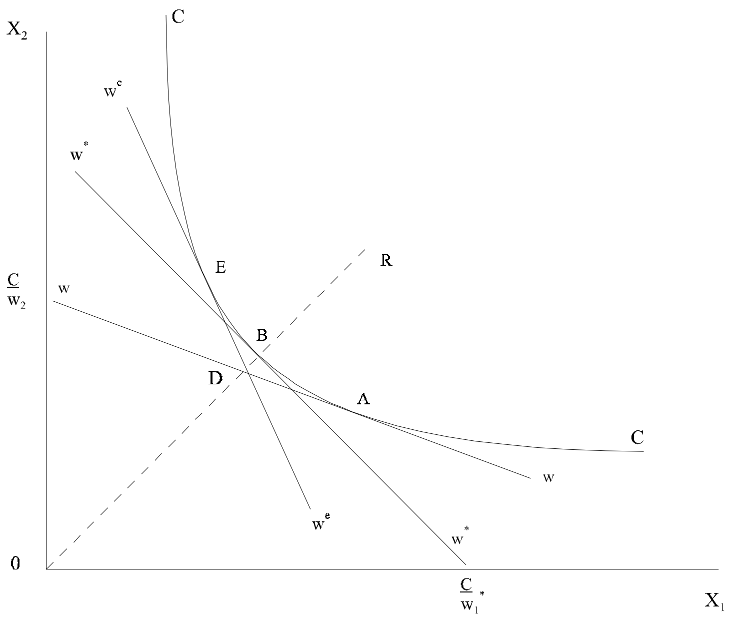

Figure 5.2 Technical efficiency, cost efficiency and nitrogen efficiency

Shephard's Lemma can be used to derive the optimal input demand functions

$$\tau * x_{jit} = x_j^f(w^*, y, q) = \frac{\partial C(w^*, y, q)}{\partial w_j^*} \tag{5.10}$$

where x^f is the shadow cost efficient quantity of inputs. Shadow cost shares are defined as:

$$S_j^* = \frac{\partial \ln C(w^*, y, q)}{\partial \ln w_j^*} = \frac{\theta_j * w_j * x_j^f(w^*, y, q)}{C(w^*, y, q)} \tag{5.11}$$

While the farm is assumed to minimise shadow cost, we observe only actual costs, market prices and input shares. Therefore, we relate actual cost with shadow costs, shadow prices with observed prices and actual cost shares with shadow cost shares. The expression for actual cost, C^R, in terms of shadow costs and shadow cost shares is, using equation (5.10) and (5.11):

$$C^R = \sum_j w_j * x_j = \frac{1}{\tau} \sum_j w_j * \tau * x_j = \frac{1}{\tau} \sum_j w_j * x_j^f(w^*, y, q) = \frac{1}{\tau} C(w^*, y, q) * \sum_j \frac{S_j^*}{\theta_j} \tag{5.12}$$

The expression for actual cost share in terms of shadow cost shares are, using equation (5.11) and (5.12):

$$S_j^R = \frac{w_j * x_j}{C^R} = \frac{\tau^{-1} * w_j^* * x_j^f}{C(w^*, y, q)} * \frac{C(w^*, y, q)}{C^R} * \frac{w_j}{w_j^*} = \frac{\tau^{-1} * C(w^*, y, q)}{C^R} * \frac{S_j^*}{\theta_j} = \frac{S_j^* \theta_j^{-1}}{\Sigma_k S_k^* \theta_k^{-1}} \quad (5.13)$$

In our novel approach farmers minimise nitrogen surplus by minimising the nitrogen input of the variable inputs, restricted by the production function conditional on the output volume *y* and the quantities of the fixed inputs *q*. We assume that the nitrogen content of the distinguished variable inputs is given. We exploit the similarity of cost minimisation and nitrogen minimisation and we adapt the standard shadow cost function approach to compute nitrogen efficiency. Minimising the nitrogen quantity in nitrogen containing inputs (N inputs) subject to the production function can be formulated as

$$\begin{aligned} &\min \Sigma_j \rho_j x_j(y, q) \\ &s.t.\ \ f(x, q) = y \end{aligned} \quad (5.14)$$

where ρ_j = Nitrogen content of input *j*. The Lagrangian expression is

$$L(x, \lambda) = \Sigma_j x_j \rho_j - \lambda(f(x, q) - y) \quad (5.15)$$

Using (5.15)

$$\frac{\partial f(x, q)}{\partial x_i} / \frac{\partial f(x, q)}{\partial x_j} = \frac{\rho_i}{\rho_j} \equiv \frac{w_i * \eta_i}{w_j * \eta_j} \quad (5.16)$$

where η= nitrogen distortion factors are defined such that $w_i * \eta_i = \rho_i$.

We define the environmentally optimal price $w_i^e = w_i * \eta_i$ (see again Figure 5.2). This environmentally optimal price is not known beforehand, but the ratio of these prices is known. Because of the linear homogeneity property of the cost function in prices we can normalise to one of the inputs. The environmentally optimal prices are substituted in the cost function to obtain costs and input use at the environmentally optimal point. Nitrogen efficiency is defined as the minimum to observed application of nitrogen conditional on desirable output, and the quasi fixed inputs

$$NE = \sum_j \rho_j x_j^e / \sum_j \rho_j x_j \tag{5.17}$$

where x^e is the quantity of input x that minimises nitrogen input.

The materials balance condition of the nitrogen cycle ensures that harmful nitrogen emission (nitrogen surplus) of output constrained dairy farming is minimised if a farm is nitrogen efficient in the inputs. Nitrogen surplus is calculated using the materials balance definition:

$$NS = \Sigma \rho_j x_j - \rho_y y \tag{5.18}$$

where
NS = nitrogen surplus;
ρ_y = nitrogen content of output.

The idea of nitrogen efficiency is illustrated in Figure 5.2. The minimal nitrogen surplus is found at the isoquant where the marginal rate of technical substitution of N inputs is equal to the ratio of the nitrogen content of the N inputs. The ratio ρ_1/ρ_2 is depicted in Figure 5.2 by the line w^e. Point E represents the minimum feasible nitrogen surplus [6]. This is the optimal point from an environmental perspective. Nitrogen efficiency consists of a technical efficiency component and an allocative efficiency component, similar to cost efficiency. If input-oriented technical efficiency is increased, the costs and nitrogen input are reduced in the same rate. The technical efficiency component of nitrogen efficiency is identical to the standard input-oriented technical efficiency measure. The allocative component of nitrogen efficiency resembles the ratio of the nitrogen content of the observed input mix and the nitrogen content of the optimal input mix from environmental perspective. The relation between (cost) allocative efficiency and nitrogen allocative efficiency is not clear beforehand. Thus an optimal ratio of inputs with respect to costs does not have to be the optimal ratio for the environment (as shown in Figure 5.2).

5.5 Translog shadow cost system

By specifying an appropriate functional form for the shadow cost function we can derive an estimable expression for actual cost and actual cost shares from equations (5.12) and (5.13).

[6] The minimal nitrogen input is restricted from below by the nonnegative nitrogen surplus. A negative nitrogen surplus will lead to a nitrogen deficit (in the long run) and is not desired.

We employ the translog, and add firm subscripts, *i*, and time subscripts, *t* (Kumbhakar, 1996:232).

$$\begin{aligned}&\ln C^*_{it} = \alpha_0 + \Sigma_j \alpha_j \ln w^*_{jit} + \tfrac{1}{2}\Sigma_j \Sigma_l \alpha_{jl} \ln w^*_{jit} \ln w^*_{lit} + \beta_y \ln y_{it} + \\ &\tfrac{1}{2}\beta_{yy}(\ln y_{it})^2 + \Sigma_j \alpha_{yj} \ln y_{it} \ln w^*_{jit} + \Sigma_n \zeta_n \ln q_{nit} + \tfrac{1}{2}\Sigma_n \Sigma_m \zeta_{nm} \ln q_{nit} \ln q_{mit} + \\ &\Sigma_n \Sigma_j \alpha_{nj} \ln q_{nit} \ln w^*_{jit} + \Sigma_n \beta_{ny} \ln q_{nit} \ln y_{it}\end{aligned} \tag{5.19}$$

where α_{jl} = α_{lj} $\forall j,l,j \neq l$; $\varsigma_{nm} = \varsigma_{mn}$ $\forall n,m,n \neq m$

$\mathbf{w}^*_{it}$ = vector of shadow prices of the variable inputs (with w^*_{1it} = N fertiliser, w^*_{2it} = feed, w^*_{3it} = intermediate inputs (non N input));

y_{it} = output quantity;

q_{it} = vector of (quasi) fixed inputs (with q_{1it} = labour, q_{2it} = capital);

α,β,ζ = parameters to be estimated.

The corresponding shadow cost share equations are

$$S^*_{jit} = \alpha_j + \Sigma_l \alpha_{jl} \ln w^*_{lit} + \alpha_{yj} \ln y_{it} + \Sigma_n \alpha_{nj} \ln q_{nit} \tag{5.20}$$

The translog actual cost system can be represented by the logarithm of eq (5.12):

$$\ln C^R_{it} = \ln C^*_{it}(w^*, y, q) + \ln(\Sigma_j S^*_{jit} \theta^{-1}_{jit}) + \ln(\tau^{-1}_{it}) = \ln C^A_{it} + \ln C^\theta_{it} + \ln(\tau^{-1}_{it}) \tag{5.21}$$

C^A = cost efficient costs (obtained by restricting θ_j =1; $\forall j$; τ =1) (point A in Figure 5.2);
C^θ = increase in cost due to allocative inefficiency (reciprocal of allocative efficiency);
τ_{it} = input-oriented technical efficiency.

The cost efficient cost function:

$$\begin{aligned}&\ln C^A_{it} = \alpha_0 + \Sigma_j \alpha_j \ln w_{jit} + \tfrac{1}{2}\Sigma_j \Sigma_l \alpha_{jl} \ln w_{jit} \ln w_{lit} + \beta_y \ln y_{it} + \\ &\tfrac{1}{2}\beta_{yy}(\ln y_{it})^2 + \Sigma_j \alpha_{yj} \ln y_{it} \ln w_{jit} + \Sigma_n \zeta_n \ln q_{nit} + \tfrac{1}{2}\Sigma_n \Sigma_m \zeta_{nm} \ln q_{nit} \ln q_{mit} + \\ &\Sigma_n \Sigma_j \alpha_{nj} \ln q_{nit} \ln w_{jit} + \Sigma_n \beta_{ny} \ln q_{nit} \ln y_{it}\end{aligned} \tag{5.22}$$

where $\mathbf{w}_{it}$ is a vector of market prices of variable inputs

The logarithm of the reciprocal of the allocative efficiency score is:

$$\begin{aligned}\ln C_{it}^{\theta} &= \Sigma_j \alpha_j \ln\theta_{jit} + \tfrac{1}{2}\Sigma_j \Sigma_l \alpha_{jl} \ln\theta_{jit} \ln\theta_{lit} + \Sigma_j \Sigma_l \alpha_{jl} \ln w_{jit} \ln\theta_{lit} + \\ &\Sigma_j \alpha_{yj} \ln y_{it} \ln\theta_{jit} + \Sigma_n \Sigma_j \alpha_{nj} \ln q_{nit} \ln\theta_{jit} + \\ &\ln\{\Sigma_j \theta_{jit}^{-1}[\alpha_j + \Sigma_l \alpha_{jl} \ln(w_{lit} * \theta_{lit}) + \alpha_{jy} \ln y_{it} + \Sigma_n \alpha_{nj} \ln q_{nit}]\}\end{aligned} \tag{5.23}$$

where θ_{it} is vector of price distortion coefficients, which will be estimated.
The cost share equation is, using equation (5.13):

$$S_{jit}^{R} = \frac{[\alpha_j + \Sigma_l \alpha_{jl} \ln(w_{lit} * \theta_{lit}) + \alpha_{jy} \ln y_{it} + \Sigma_n \alpha_{nj} \ln q_{nit}]\theta_{jit}^{-1}}{\Sigma_j [\alpha_j + \Sigma_l \alpha_{jl} \ln(w_{lit} * \theta_{lit}) + \alpha_{jy} \ln y_{it} + \Sigma_n \alpha_{nj} \ln q_{nit}]\theta_{jit}^{-1}} \tag{5.24}$$

The shares at the cost efficient point, A, (S_j^A) can be calculated from equation (5.24) and taking θ equal to unity. The quantity of the inputs at this point, x^A, can be computed as (Atkinson and Halvorsen, 1984):

$$x_{jit}^{A} = \frac{S_{jit}^{A} * C_{it}^{A}}{w_{jit}} \tag{5.25}$$

The nitrogen distortion factors η_{jit} are used to compute the nitrogen input at the nitrogen efficient point E (Figure 5.2). We normalise on feed input (η_2=1). The production costs and shares at the nitrogen efficient point, E, can be obtained from equation (5.21) and (5.24) by substitution of η_{jit} for θ_{jit} and restricting τ to unity. The quantities of the N inputs are computed similar to equation (5.25).

5.6 Empirical elaboration

We added a time trend and a quadratic time trend to the cost system specification to capture disembodied technological change and added time-input and time-output interaction terms to allow for embodied technological change of inputs and output. We also added an error term. The shadow cost system is highly parameterised. Therefore, we use a sequential approach to estimate the cost system and use the parameter estimates of the preceding step as starting values. First the standard cost system is estimated (equation (5.21) and (5.24)), technical and allocative efficiency are both restricted to be equal to unity (model 1).

Second, time-invariant technical efficiency is modelled by adding I-1 firm-dummies (DUM_i) to equation (5.21), allocative efficiency is restricted to be equal to one (model 2).

The firm-dummy of the technically efficient farm is omitted. Technical efficiency in this model is computed as

$$\tau_i = \exp(-u_i); \tag{5.26}$$

where u_i = firm specific effect (parameter estimate of firm-dummy DUM_i).

The time-invariant specification of technical efficiency in model 2 might be too restrictive. Farms are replaced after participating 7 years in the Dutch FADN. Therefore we were not able to estimate a firm-specific path of technical efficiency as in Cornwell et al. (1990) and Balk and Van Leeuwen (1998). The firm specific effect in model 2 also combines the effect of technical efficiency and a site-specific component.

These two drawbacks are solved in model 3, in which we model time-varying technical efficiency by explanatory variables (Kumbhakar et al., 1991) [7]. The allocative efficiency is still restricted to be unity. We distinguish time-varying technical efficiency (Wang et al., 1996) and a site (farm) specific component (Heshmati and Kumbhakar, 1994).

Technical efficiency is modelled by variables that can describe the ability of the manager, a variable that describes management characteristics, the intensity and the number of dairy cows; see equation (5.27). Age, education and experience describe the ability of the manager (Rougoor et al., 1998; Kumbhakar et al., 1991). The milk production per cow is a function of the feeding and breeding program of the farm (Weersink et al., 1990). Hallam and Machado (1996) found a relation between intensity and technical efficiency. The number of cows captures the relation between technical efficiency and herd size (e.g. Weersink et al., 1990; Ahmad and Bravo-Ureta, 1995).

$$v_{it} = \exp(\chi_1 AGE_{it} + \chi_2 EXPER_{it} + \chi_3 ED_{it} + \chi_4 MILK_{it} + \chi_5 INT_{it} + \chi_6 \#COWS_{it}) \tag{5.27}$$

where

AGE	= age of the manager;
EXPER	= number of years he (or she) is manager;
ED	= education (=1 if secondary or higher agricultural education, otherwise =0);
MILK	= milk production per dairy cow;
INT	= dairy cows per ha;

[7] One other possibility for identifying a time-path for technical inefficiency is to divide the sample into homogenous groups of firms and to impose the restriction that the level and the development of technical efficiency is identical for within groups but varies across groups. However, there is no obvious basis for dividing the data set into homogeneous groups.

#COWS = number of dairy cows (dairy cow equivalents);
$\chi_1,\ldots,\chi_6$ = parameters to be estimated.

The technical efficiency score, is computed as τ_{it}=min(v_{it})/ v_{it};

Site-specific effects, ψ, are modelled by variables that reflect site-specific conditions (soil type and region)[8] and are computed as

$$\psi_{it} = \exp(\Sigma_{k=1}^{3} \varphi_k SOIL_{ki} + \Sigma_{l=4}^{7} \varphi_l REGION_{li}) \tag{5.28}$$

where
SOIL = 3 dummy variables for soil type[9];
REGION = 4 dummy variables to cover the five distinguished regions.
φ = parameters to be estimated.

Fourth we added in comparison to model 3 a time invariant allocative efficiency similar to Atkinson and Halvorsen (1984). We restricted θ_j to be time invariant and equal across firms in model 4.

Finally the complete model with individualised technical and allocative efficiency scores is estimated (model 5). We were not able to estimate firm-specific allocative efficiencies because this model contains too many parameters. The large number of farms and the short time period were not sufficient to estimate this model. Examples of firm-specific (and time-varying) allocative efficiency estimated in the literature are based on balanced long panels (15 years or more) for instance Atkinson and Cornwell (1994a), Oum and Zhang (1995) and Balk and Van Leeuwen (1998). We follow amongst others Stefanou and Saxena (1988) and Kumbhakar and Bhattacharyya (1992) and model firm specific allocative efficiency by varying the price distortion factor with explanatory variables. Stefanou and Saxena (1988) used years of education and years of management experience. Kumbhakar and Bhattacharyya (1992) used years of education and farm size. The quantity of inputs (feed) purchased depends highly on the intensity of the farm. We assume that allocative efficiency is a function of intensity; measured as the number of dairy cows per ha. The individualised allocative efficiency specification of equation (5.29) guarantees non-negative values of the price distortion factors[10].

[8] We omitted explaining variables that were not significant at the 95% interval in eq (5.28) and (5.29).
[9] $SOIL_1$=(1=seasediment clay, 0=elsewhere); $SOIL_2$=(1=peat, 0=elsewhere); $SOIL_3$=(1=clay on peat, 0=elsewhere).
[10] Stefanou and Saxena (1988) used a squared expression instead of the exponential expression of (5.29).

$$\theta_{jit} = \exp(\xi_{j0} + \xi_{j1} AGE_{it} + \xi_{j2} ED_{it} + \xi_{j3} INT_{it}) \tag{5.29}$$

where

AGE	=	age of the manager;
ED	=	education (=1 if higher agricultural education, otherwise = 0);
INT	=	intensity; measured as dairy cows per ha;
ξ	=	parameters to be estimated;
j	=	1 = N fertiliser, 2 = feed, 3 = intermediate inputs. (θ_{3it} is assumed to be 1).

5.7 Data

In this paper we use data describing the production activities of highly specialised dairy farms that were in the Dutch Farm Accountancy Data Network (FADN). The FADN is a stratified random sample. Stratification is based on economic farm size, age of the farmer, region and type of farming. The FADN represents 99% of the milk production and no systematic errors due to non-response are found (Dijk, 1990). The sample used for the estimation consists of all farms that are at least five years in the panel in the period 1985-1995. Milk quotas were effective in this entire research period. This sample has 2,589 observations of 434 farms, thus these farms are on average 6 years in the panel. We use three variable inputs: purchased feed (concentrates, roughage), N fertiliser and remaining intermediate inputs (P, K fertiliser, farm contracting, hired labour, energy etc.). Labour and capital are treated as fixed inputs. The outputs (mainly milk and beef) are aggregated into a single index of dairy farm output. Our sample contains specialised dairy farms, therefore sales of beef are only a small part of the total turnover. Helming et al. (1993) used comparable groups of inputs but distinguished less variable inputs (they combined N fertiliser and intermediate inputs) and more quasi fixed inputs in their profit system for Dutch dairy farms. We used an implicit quantity index for aggregation of FADN data into the distinguished inputs and output. Implicit quantity indices are obtained as the ratio of value to the price index and therefore output is in prices of a specific year; 1991 is the base year. Labour input consists of total family labour, measured in hours. Capital stock is composed of land, buildings, equipment and livestock for breeding and utilisation. More detailed information on the aggregation of the underlying data can be found in section 2.5 The nitrogen content of the N inputs and output (ρ) is observed per farm.

Table 5.1 Characteristics of the sample variables; 2,589 observations

Variables	Unit	Mean	Min.	Max.	Std. dev.
Purchased feed	1,000 '91 NLG	80.0	5.0	452.9	57.0
Nitrogen fertiliser	1,000 '91 NLG	13.0	0.0	50.2	7.6
Intermediate input	1,000 '91 NLG	46.2	2.5	235.8	32.8
Output	1,000 '91 NLG	377.7	57.1	1,391.2	209.0
Labour	Hours	4,110	899	11,050	1,467
Capital	1,000 '91 NLG	2,202	398	6,016	1,033
Nitrogen surplus	kg N	11,813	-2,016 a)	70,344	7,115

a) Only one observation has a negative nitrogen surplus.

5.8 Estimation results

The estimations are done in SAS with ITSUR (iterative seemingly unrelated regression). We imposed linear homogeneity [11] and dropped the intermediate input share equation to avoid singularity. The estimation results of this model and the following models are summarised in Table 5.2. model 1 (standard cost system) fulfils the theoretical assumptions well (see Table 5.2). The (mean) own price elasticities of the variable inputs are negative. The second derivatives with respect to variable input are almost all negative (N fertiliser for 95% of the observations). The cost elasticity with respect to the quasi-fixed inputs are negative (and small). The returns to scale (Caves et al., 1981) is slightly larger than 1, implying that the firms exhibit economies of size.

In model 2 (fixed effects model) the theoretical assumptions are a little less fulfilled [12]. The sign of the cost elasticity with respect to the quasi-fixed inputs (labour and capital) was as assumed negative in the mean. The returns to scale are extremely large (1.41) in this model, indicating enormous economies of size. The technical efficiency turned out to be very small, with a mean of 0.42. It seems that the included dummies pick up more than only the technical efficiency.

Model 3 with time-varying technical efficiency (modelled by explaining variables) provides comparable estimates as model 1. The adjusted R^2 of the cost function is larger than that of model 1, due to the explanatory variables. The mean technical efficiency score is larger than in the second model, because the firm-specific elements are separated from the technical efficiency score in contrast to model 2.

[11] $\Sigma_j\alpha_j=0$, $\Sigma_j\alpha_{jl}=0$, $\Sigma_j\alpha_{nj}=0$, $\Sigma_j\alpha_{yj}=0$.

[12] A smaller number of observations satisfy the assumption that the second derivative with respect to input prices is negative.

The fourth model, with time-invariant allocative efficiency, seems too restrictive. The price distortion factors are incredibly large for variable inputs and the parameter estimates of the price distortion factors are not significant at the 5% level. We also found allocative efficiency scores larger than unity. The allocative efficiency is calculated as the reciprocal of C^{θ}; see equation (5.23). A Wald-test did not reject model 3 in favour of model 4 at the 90% confidence level. We prefer model 3 over model 4.

The final model 5 with time and firm varying allocative efficiency performs better than model 4. The mean allocative efficiency score is large (0.953), this is not surprising because we calculated the allocative efficiency of variable inputs (contrary to research in which allocative efficiency of quasi fixed inputs is calculated). The mean price distortion factors of feed and nitrogen fertiliser are smaller than 1, implying that both inputs are over-utilised

Table 5.2 Estimations results (means) of the five models: 'standard' cost system (model 1), fixed effects model (model 2), 'explained' technical efficiency model (model 3), fixed allocative efficiency (model 4) and 'explained' variable allocative efficiency model (model 5)

	Model 1 Cost system	Model 2 FE-model	Model 3 explain-TE	Model 4 fixed Allocative Efficiency	Model 5 explain- Allocative Efficiency
Technical efficiency	1	0.418	0.838	0.854	0.845
Allocative efficiency	1	1	1	0.876	0.953
θ N fertiliser	1	1	1	12.06	0.85
θ feed	1	1	1	9.08	0.50
θ intermediate input	1	1	1	1	1
Price elasticity N ferti.	-0.17	-0.13	-0.31	-0.33	-0.06
Price elasticity feed	-0.30	-0.06	-0.31	-0.12	-0.56
Price elas interm input	-0.30	-0.08	-0.34	-0.05	-0.16
Elasticity labour	-0.07	-0.03	-0.11	+0.05	-0.10
Elasticity capital	-0.02	-0.13	+0.07	-0.17	+0.10
Elasticity output	1.02	0.82	1.08	1.24	0.95
Returns to scale	1.01	1.41	0.97	0.93	1.05
% 2nd deriv. neg N fert	95	93	95	96	75
% 2nd deriv. neg feed	100	97	100	98	100
% 2nd deriv. neg int. inp.	100	96	100	72	100
Adjusted R^2 cost function	0.8965	0.9392	0.9107	0.9108	0.9128
Adjusted R^2 N fertiliser	0.3305	0.3293	0.3305	0.3315	0.4126
Adjusted R^2 feed	0.4078	0.4052	0.4078	0.4123	0.4669
Technological change %	2.01	1.26	1.55	1.81	1.66

compared with intermediate inputs. Feed is more overused than N fertiliser. We assumed that intermediate outputs are applied allocatively efficient. The price distortion factors range for θ_F (=θ_2) from 0.11 to 0.74 and for θ_N (=θ_1) from 0.38 to 1.31. The mean technical efficiency score is 0.845. The nitrogen input at the cost efficient point is in all observations larger than the nitrogen input at the technically efficient point. The concavity assumptions with respect to N fertiliser are less fulfilled than in model 3. The Wald-statistic did not reject model 3 in favour of model 5 at the 90% confidence level. In model 3, 4 and 5 we find positive mean elasticities with respect to one of the quasi-fixed inputs. These counterintuitive results may be caused by the fact that the research period starts right after the implementation of milk quota (Elhorst, 1990:141).

To compute the nitrogen efficiency, the nitrogen distortion factors η_{jit} have to be added to the cost system. These η_{jit} raise the environmental price of fertiliser relative to intermediate inputs and feed. For a correct estimation of nitrogen efficiency, the cost function has to be concave as theoretically required (see section 5.4). The model with explained allocative efficiency (model 5) does not suit the concavity conditions well (see Table 5.2). We found that for 572 observations the nitrogen efficiency scores at the technical efficient point were larger than one, which does not correspond with the theory. Therefore we used model 3 (with technical efficiency only) to impute the nitrogen distortion factor. For ten observations we found nitrogen efficiency scores that did not fulfil the theoretical requirements, they were larger than 1 at the technical efficient point. These ten farms were atypical (e.g. largest nitro-

Table 5.3 *Development of technical efficiency, allocative efficiency, price distortion factors in model 5 and the development of technical efficiency, nitrogen efficiency and nitrogen distortion factors in model 3*

Year	# Obs.	Model 5				Model 3		
		TE	AE	θ feed	θ N fert	TE	N efficiency	η_1
1985	115	0.811	0.940	0.448	0.794	0.807	0.556	11.548
1986	195	0.824	0.944	0.472	0.819	0.819	0.574	11.730
1987	253	0.838	0.953	0.503	0.843	0.831	0.570	12.318
1988	277	0.843	0.955	0.516	0.860	0.836	0.575	13.378
1989	327	0.842	0.954	0.514	0.861	0.835	0.570	13.706
1990	327	0.845	0.954	0.511	0.849	0.839	0.584	12.043
1991	318	0.848	0.955	0.515	0.854	0.842	0.592	11.666
1992	280	0.855	0.957	0.525	0.864	0.848	0.591	12.541
1993	214	0.856	0.956	0.518	0.848	0.850	0.590	13.789
1994	157	0.863	0.955	0.514	0.855	0.857	0.612	13.760
1995	126	0.863	0.955	0.512	0.838	0.858	0.617	10.647

gen surplus, negative nitrogen surplus when nitrogen efficient, did not apply N fertiliser). We disregarded these ten farms in our further analysis of nitrogen efficiency. From the remaining 2,579 observations (99,6%) the mean nitrogen efficiency score is 0.561. The minimal score was 0.33 and the maximum 0.88. The nitrogen efficiency increases if all farms achieve technical efficiency. The nitrogen allocative efficiency score is only 0.67 (minimum 0.40, maximum 0.999).

Table 5.4 Parameter estimates

	Model 3		Model 5			Model 3		Model 5	
α_0	1.901		0.437		γ_{ti}	0.008	a)	0.005	a)
α_I	-0.213	a)	-0.0004		γ_{tf}	-0.007	a)	-0.005	a)
α_f	1.407	a)	1.3034	a)	γ_{tN}	-0.001	a)	-0.0003	
α_N	-0.193	a)	-0.033		γ_{ty}	0.010	a)	0.008	
α_{ii}	0.103	a)	0.169	a)	γ_{tl}	0.010	a)	0.007	
α_{ff}	0.069		0.015		γ_{tc}	-0.026	a)	-0.021	a)
α_{NN}	0.054	a)	0.088	a)	χ_1	0.0011	a)	0.0010	a)
α_{if}	-0.0588		-0.048	a)	χ_2	-0.0008		-0.0009	
α_{In}	-0.044	a)	-0.121	a)	χ_3	-0.0326	a)	-0.0384	a)
α_{fN}	-0.010		0.033	a)	χ_4	-0.00003	a)	-0.00003	a)
α_{yi}	-0.126	a)	-0.086	a)	χ_5	0.0673	a)	0.070	a)
α_{yf}	0.205	a)	0.138	a)	χ_6	-0.001	a)	-0.0009	a)
α_{yN}	-0.079	a)	-0.052	a)	φ_1	0.029	a)	0.027	a)
β_y	0.569		0.379		φ_2	-0.036	a)	-0.033	a)
β_{yy}	0.178	a)	0.173	a)	φ_3	-0.048	a)	-0.049	a)
ζl	0.309		0.318		φ_4	0.175	a)	0.179	a)
ζ_c	-0.242		0.111		φ_5	-0.052	a)	-0.056	a)
ζ_{ll}	0.203	a)	0.211	a)	φ_6	-0.049	a)	-0.050	a)
ζ_{cc}	0.147		0.092		φ_7	-0.110	a)	-0.112	a)
ξ_{lc}	-0.089		-0.074		ξ_{10}	-		-	
α_{li}	-0.112	a)	-0.109	a)	ξ_{11}	-		0.0061	a)
α_{lf}	0.111	a)	0.0922	a)	ξ_{12}	-		-0.2892	a)
α_{lN}	0.0008		0.017	a)	ξ_{13}	-		-0.153	a)
α_{ci}	0.209	a)	0.164	a)	ξ_{20}	-		-	
α_{cf}	-0.298	a)	-0.214	a)	ξ_{21}	-		-	
α_{cN}	0.0891	a)	0.050	a)	ξ_{22}	-		-	
β_{ly}	-0.063		-0.086		ξ_{23}	-		-0.3034	a)
β_{cy}	-0.085		-0.057						
γ_t	0.085	a)	0.079						
γ_{tt}	0.010	a)	0.009	a)					

a) The estimate differs significantly from zero at the 5% level.

Due to the use of explaining variables the technical efficiency, allocative efficiency and nitrogen efficiency scores show variation in time. Also the unbalancedness of the panel contributes to this variation. The development of the technical efficiency scores is increasing in time and is similar in model 3 and model 5. The mean allocative efficiency hardly shows any variation in time. Nitrogen efficiency is steadily increasing in time, see table 5.3.

The sign of the estimates of the χ parameters in equation (5.27) provides information about the relation between the explaining variables and the technical efficiency scores, (see Table 5.4). The number of years experience as a farm manager, the dummy variable for lower agricultural education and milk yield are positively related with technical efficiency. Age is negatively related with technical efficiency. Weersink et al. (1990) found a comparable result; and attributed it to the fact that elder people have not dealt with modern technology (e.g. computers) in their education.

The Spearman rank correlation of the nitrogen efficiency score and the technical efficiency score is positive (0.181), because technical efficiency is a component of nitrogen efficiency (see section 5.4). We find that the correlation between (nitrogen) technical efficiency score and the nitrogen allocative efficiency score is negative, -0.230 (Table 5.5). Thus the more technically efficient farms have a less optimal ratio of variable inputs from environmental point of view.

Table 5.5 Rank correlation of nitrogen efficiency and its two components, (nitrogen) technical efficiency and nitrogen allocative efficiency, model 3 (2,579 observations) a)

	N efficiency	(Nitrogen) Technical efficiency	Nitrogen allocative efficiency
N efficiency	1.000	0.181	0.892
(Nitrogen) Techncial efficiency		1.000	-0.230
Nitrogen allocative efficiency			1.000

a) All coefficients differ significantly from zero at 95% level.

Nitrogen efficient production comes with costs. At the nitrogen efficient point the costs are on average 17% higher than in the technical efficient situation and 3% higher than the observed costs. The nitrogen surplus at the nitrogen efficient point is less than half the observed nitrogen surplus and 57% of the nitrogen surplus at the technically efficient point (Table 5.6). The nitrogen efficient production can only be reached if the shadow price of N fertiliser (the environmentally optimal price) increases with a factor 12.5 on average (Table 5.2). The market price of N fertiliser does not have to change per se, but this can also be obtained by regulation. A smaller rise of the N fertiliser shadow price reduces the nitrogen surplus a little less but also has less costs. For instance, if the nitrogen shadow price is increased to only a quarter of the environmentally optimal price, the costs at the nitrogen efficient point are 3% higher and the nitrogen surplus is 29% smaller than at the technically efficient point.

There has been an ongoing public debate for several years in the Netherlands concerning whether extensive or intensive farms are more environmentally efficient (Zoebl, 1996). We consider the relationship between the distinguished efficiency measures and intensity of farming. We find that intensity is positively related with nitrogen efficiency scores (Table 5.7). The most intensive farms have the largest N efficiency scores. This result is even more pronounced, if we consider the tendency for intensive farms to be less technically and allocatively efficient than extensive farms.

Table 5.6 The average production costs (in guilders of 1991) and the average nitrogen surplus (in kg N) at the observation R, the technical efficient point B, and the nitrogen efficient point E (Figure 5.2)

	Observed (fitted)	Technical efficient	Nitrogen efficient
Average costs	135,551	117,706	140,130
Nitrogen surplus	13,304	10,892	6,223

Table 5.7 Mean efficiency scores by intensity (cows per ha)

Intensity	%	Model 3		Model 5
		technical efficiency	nitrogen efficiency	allocative efficiency
< 1.85	23.8	0.860	0.527	0.975
1.85-2.25	32.0	0.854	0.558	0.964
2.25-2.65	23.4	0.835	0.573	0.951
> 2.65	20.8	0.796	0.589	0.916

5.9 Conclusions

We defined and estimated the nitrogen efficiency of a panel of Dutch dairy farms. Due to the materials balance condition and the fixed output, farmers who minimise nitrogen containing inputs emit the smallest amount of nitrogen into the environment (conditional on output, quasi fixed inputs and the nitrogen content of inputs). We allow that farmers might deviate from cost minimising behaviour with respect to market prices. We use a shadow cost system in which farmers are assumed to minimise shadow costs. Shadow prices can deviate from market prices due to regulations, risk adverse behaviour or by lack of knowledge. The structure of our panel prohibited the estimation of a very flexible specification of allocative efficiency. Such a specification is namely highly parameterised. Shadow cost models with 'explained' technical efficiency and price distortion factors could be estimated. The mean technical efficiency is 84%. The price distortion factors of the nitrogen containing inputs (nitrogen-fertiliser and feed) are smaller than 1, thus N fertiliser and feed and are overused in comparison with intermediate inputs. We found that the mean allocative efficiency score is large (0.95). This is not surprising because we estimated the allocative efficiency of variable. We could not reject model without allocative efficiency against the model with allocative efficiency. We prefer the former model.

The high level of allocative efficiency suggests that dairy farms adjust the input mix to price changes. Therefore the price mechanism could be used to decrease the nitrogen surplus. Nitrogen efficiency is obtained at minimum nitrogen input. We added environmental price distortion factors to our preferred model and computed the nitrogen efficiency of all observations. The mean nitrogen efficiency score is 0.561. Nitrogen efficiency has alike cost efficiency a technical efficiency (mean 0.84) and a nitrogen allocative efficiency component (mean 0.67). Thus, if all dairy farms would obtain technically efficient production, the mean nitrogen efficiency is only 0.67.

To increase the nitrogen allocative efficiency the shadow price ratio of N-containing inputs has to be increased (especially for N fertiliser). The most simple policy to implement the shadow price is to tax the use of chemical fertiliser, or to restrict the use of chemical fertiliser. At the nitrogen efficient point the costs are on average 17% higher than in the technical efficient situation and 3% higher than the observed costs. A smaller increase in the shadow price of nitrogen fertiliser can already reduce the average nitrogen surplus remarkably. The intensity of farming is negatively related to technical efficiency and positively correlated to nitrogen efficiency.

6. Analysis of environmental efficiency variation [1]

Abstract

In this paper we develop and implement a methodology for explaining variation in environmental efficiency across firms. We formulate a two-stage model. In the first stage we use stochastic frontier analysis to estimate both technical and environmental efficiency. In the second stage we again use stochastic frontier analysis to regress estimated environmental efficiency scores against a variety of technology, physical environment and management variables. We estimate the impacts of each explanatory variable on environmental efficiency. We also derive adjusted estimates of environmental efficiency from the one-sided error component. We illustrate our methodology with an empirical application to a panel of Dutch dairy farms. We find that environmental efficiency can be improved by encouraging a higher milk yield or providing farmers with more insight into the nutrient balance of their farms.

6.1 Introduction

In this chapter we provide a methodology for an empirical analysis of the sources of variation in environmental efficiency in Dutch dairy farming, where environmental degradation has been severe, and where nitrogen emission abatement is a policy objective of the Dutch government. Previous chapters provided environmental efficiency scores that gave insight how technically efficient and environmentally efficient Dutch dairy farming is. To be able to formulate policy that improves the environmental performance of farms, the impact of various characteristics on environmental efficiency has to be identified. Therefore, the objective of this paper is to explain the variation of environmental efficiency scores across farms. This raises two questions: (a) what variables are associated with variation in environmental efficiency, and (b) what methodology is most appropriate to incorporate these explanatory variables into a model of environmental efficiency?

The general idea behind our approach is that if we could include all relevant inputs and outputs in our analysis we would not find any inefficiency. In 1933 Knight noted that if all outputs and inputs are included, all units would achieve the same unitary efficiency score, since neither matter nor energy can be created or destroyed (Lovell, 1993:4). Stigler

[1] Modified version of the paper by Stijn Reinhard, C.A.Knox Lovell and Geert Thijssen, to be presented at the VI European Productivity and Efficiency Workshop, Copenhagen, October 1999.

(1976:215) substantiated that the efficiency differences in agriculture (variation in output conditional on inputs) are all attributed to specific inputs; in this example entrepreneurial capacity. Tyteca (1996) advocated in the same line that a possible explanation for environmental inefficiencies is the fact that the production technology is not completely specified or known. From various efficiency models, we compose a comprehensive model of dairy farming. The explanatory variables are identified in a comparison between the production process modelled in the first stage and the comprehensive dairy farming model presented.

We proceed in two stages. In the first stage we formulate and estimate a composed error stochastic *production* frontier model, in which conventional and environmentally detrimental inputs are combined to produce marketable output. In this framework estimates of output-oriented technical inefficiency are extracted from the one-sided error component, and estimates of environmental inefficiency are derived from estimates of parameters in the model, including both technology parameters and parameters describing the distribution of the one-sided error component; see chapter 2.

In the second stage we formulate and estimate a composed error stochastic *environmental efficiency* frontier model, in which the environmental efficiencies estimated in the first stage are regressed against a set of explanatory variables. Two types of information emerge from the second stage. One is evidence on the directions and magnitudes of the impacts of the explanatory variables on estimated environmental efficiency. This evidence is derived from the estimated coefficients of the deterministic part of the environmental efficiency frontier. The other is evidence on the ability of individual producers to maximise environmental efficiency conditional on their explanatory variables. This evidence is extracted from the one-sided error component of the environmental efficiency frontier. These 'net' environmental efficiency scores are thereby adjusted for variation in the environment in which dairy farming takes place.

This chapter is structured as follows. In section 6.2 we present our methodology. In section 6.3 a comprehensive model of dairy farming is used to identify determinants of environmental efficiency. In section 6.4 we review the agricultural economics literature on potential explanatory variables and we present our data set. Our empirical findings appear in section 6.5. We conclude with a summary and discussion of our findings.

6.2 Modelling and estimating technical and environmental efficiency

We begin by summarising the first stage of our two-stage methodology. The definitions of technical and environmental efficiency are used from chapter 2. We repeat the equations that are used in chapter 2 to compute output-oriented efficiency and environmental efficiency respectively.

The stochastic version of the output-oriented technical efficiency measure is provided by the expression

$$TE_i = Y_{it} / [F(\mathbf{X_{it}}, Z_{it}; \boldsymbol{\beta}) \bullet exp\{V_{it}\}] = exp\{-U_i\},\ i = 1, \ldots, I. \tag{6.1}$$

where $F(\mathbf{X_{it}}, N_{it}; \boldsymbol{\beta})$ is the deterministic kernel of the stochastic production frontier $[F(\mathbf{X_{it}}, N_{it}; \boldsymbol{\beta}) \bullet \exp\{V_{it}\}]$, and for all farms indexed with a subscript i and for all years indexed with a subscript t,

- Y_{it} denotes the production level;
- $\mathbf{X_{it}}$ is a vector of conventional inputs;
- Z_{it} is the environmentally detrimental input (nitrogen surplus);
- $\boldsymbol{\beta}$ is a technology parameter vector to be estimated;
- V_{it} is a random error term, independently and identically distributed as $N(0, \sigma_v^2)$, intended to capture events beyond the control of farmers;
- U_i is a non-negative random error term, independently and identically distributed as $N^+(\mu, \sigma_u^2)$, intended to capture time-invariant technical inefficiency in production.

We used a translog specification for the deterministic kennel *F(•)*. The logarithm of the stochastic environmental efficiency measure can be computed from the parameter estimates and input quantities of a stochastic production frontier as

$$\ln EE_{it} = [-(\beta_z + \Sigma_j \beta_{jz} \ln X_{itj} + \beta_{zz} \ln Z_{it}) \pm \{(\beta_z + \Sigma_j \beta_{jz} \ln X_{itj} + \beta_{zz} \ln Z_{it})^2 - 2\beta_{zz} U_i\}^{.5}] / \beta_{zz}. \tag{6.2}$$

In the second stage environmental efficiency is related to a set of explanatory variables and re-estimated in light of their influece. For the second stage analysis two methods have been developed in literature; for an overview see Greene (1997:109-111) and Kumbhakar and Lovell (1999). (i) The standard approach is to regress efficiency scores against a set of explanatory variables. OLS is frequently used (e.g. Hallam and Machado, 1996), although a limited dependent variable estimation technique such as tobit is preferred (e.g. Weersink et al., 1990). However regardless of the estimation procedure employed, the two-stage approach suffers from a fundamental inconsistency. It is assumed in the first stage that the inefficiencies are identically distributed, but this assumption is contradicted in the second stage regression in which predicted efficiencies are assumed to have a functional relationship with the explanatory variables. (ii) Consequently Battese and Coelli (1995) have developed a single stage procedure for the joint estimation of technical efficiency and the impacts of the explanatory variables.

We employ a two-stage approach to the explanation of variation in environmental efficiency, although it differs from the standard approach in two ways. First, although output-oriented technical efficiency as defined in equation (6.1), is *estimated* econometrically, environmental efficiency as defined in equation (6.2) is *calculated* from parameter estimates describing the structure of production technology and the one-sided error component. This is important because, while the iid assumption on the U_i is inconsistent with the use of estimates of TE_i as dependent variables in a second stage regression, no such assumption is made concerning EE_{it}. Thus it is permissible to use environmental efficiency scores as dependent variables in a second stage regression.

The second departure from the standard approach is that we use a stochastic frontier regression model in the second stage. The basic idea is to construct a best practice environmental efficiency frontier, and to obtain revised estimates of environmental efficiency which account for variation in the explanatory variables. This procedure offers two advantages over the standard approach: (i) it generates adjusted environmental efficiency estimates, which neither OLS nor tobit can provide; and (ii) it generates statistically superior estimates of the impacts of the explanatory variables on environmental efficiency, since it allows for skewness in the regression residuals which would cause OLS and tobit parameter estimates to be biased and inconsistent. Skewness provides an indication that environmental inefficiency remains even after accounting for variation in the explanatory variables (Greene, 1997:99).

The environmental efficiency frontier regression model can be expressed in general form as

$$EE_{it} = G(\mathbf{W_{it}};\delta)\bullet exp\{V^*_{it} - U^*_i\},\ i = 1,\ldots,I,\ t = 1,\ldots,T, \tag{6.3}$$

where $G(\mathbf{W_{it}};\delta)$ is the deterministic kernel of the stochastic environmental efficiency frontier $[G(\mathbf{W_{it}};\delta)\bullet \exp\{V^*_{it}\}]$, $\mathbf{W_{it}}$ is a vector of observed explanatory variables expected to influence environmental efficiency, δ is a vector of parameters to be estimated, $V^*_{it} \sim N(0,\sigma^2_{V^*})$ and $U^*_i \sim N^+(\mu^*,\sigma^2_{U^*})$. In this formulation variation in estimated environmental efficiency is apportioned to three sources: (i) the impacts of the observed explanatory variables captured by $G(\mathbf{W_{it}};\delta)$; (ii) statistical noise reflected in V^*_{it}; and (iii) an unexplained shortfall of environmental efficiency beneath best practice observed in the sample reflected in U^*_i. Estimates of EE_i obtained in the first stage of the analysis do not take variation in explanatory variables into consideration. The impacts of these variables are incorporated into estimates of the adjusted measures of environmental efficiency AEE_i. These adjusted measures are defined as the ratio of environmental efficiency actually achieved to maximum feasible environmental efficiency, conditional on the observed explanatory variables and statistical noise, and so

$$AEE_i = EE_{it}/[G(\mathbf{W_{it}};\delta)\bullet exp\{V^*_{it}\}] = exp\{-U^*_i\},\ i = 1,\ldots,I. \tag{6.4}$$

In order to implement (6.4) U^*_i must be separated from statistical noise in the composed error term (V^*_{it} - U^*_i). Farm-specific estimates of AEE_i are obtained from

$$AEE_i = E[exp\{-U^*_i\} \,/\, (V^*_{it} - U^*_i)],\ i = 1,\ldots,I. \tag{6.5}$$

Although estimates of EE_{it} obtained in the first stage of the analysis do not take variation in explanatory variables into consideration, the impacts of these variables are incorporated into estimates of AEE_i. Since for any farm the net impact can be either positive or negative, AEE_i can be either smaller than or greater than EE_i.

6.3 Identifying the determinants of environmental efficiency

As presented in section 6.1, the main idea of our approach to identify explanatory variables is that if we could use *all the relevant* relations in dairy farming to *compute* the (first stage) efficiency scores, we would not find any inefficiency. Thus differences across efficiency scores are assumed to be caused by omitted variables and measurement errors in the first stage analysis. We compare the various frontier approaches used in agriculture literature to identify omitted variables and measurement error of the first stage analysis, which can be used as explanatory variables in the second stage.

Farrell (1957:255) noted that there are many possibilities to define a frontier. He discussed two methods (i) a theoretical function specified by engineers and (ii) an empirical function based on the best results observed in practice. He elaborates the latter method, because it is very difficult to specify a theoretical frontier for a complex process. Tyteca (1996) distinguishes a thermodynamic, a technological and a best practice frontier [2]. The thermodynamic frontier is based on fundamental principles governing the processes considered. The technological frontier is based on an inventory of best existing, commercially available technologies for the processes under consideration. Uhlin (1985:27) distinguished three different frontiers (i) laboratory; technically feasible but not yet realised; (ii) blueprint; a situation with all resources variable and top management; and (iii) best-practice. Also De Koeijer et al. (1998) describe three frontiers (agronomic, ecological and economic) with corresponding efficiency measures.

We adapt the aforementioned concepts and distinguish among a blueprint frontier [3], an optimal technology frontier, a best practice (technical efficiency) frontier, and a best environmental practice (environmental efficiency) frontier. These frontier models differ with

[2] Tyteca also distinguishes an 'ideal' frontier that can be calculated using 'technological definitions' and 'thermodynamic definitions'. He does not calculate an ideal frontier.
[3] Our blueprint frontier differs from the one defined by Uhlin.

respect to the aggregation level (e.g. crop, field, farm, farm and environmental pressure) and with respect to the scientific area in which these models are developed (agronomy, farm economics, microeconomics and environmental economics respectively). In the agricultural literature frontiers are computed for different levels of aggregation. We use the information contained in these frontier models to construct a compretensive model of dairy farming (Figure 6.2). Finally the environmental efficiency frontier is confronted with this model to identify the omitted variables and measurement errors. Advantages of this approach are (i) knowledge of different scientific background is incorporated in the model; and (ii) different aggregation levels are represented in the model. First we describe the distinguished frontier models, after which we combine these frontier models into one model.

(i) *A blueprint technology* describes the basic biological processes at the plant or animal level accurately (e.g. photosynthesis through solar radiation). These relations are researched in a laboratory (or based on theory). Optimal production is based on optimal growth-limiting (abiotic factors: nutrients and water; these factors are non-substitutable) and growth-reducing factors (biotic factors like diseases and weeds), conditional on growth-defining factors (temperature and solar radiation) (Van Ittersum and Rabbinge, 1997) [4]. The environment of the plant (e.g. fixed inputs) is not modelled (e.g. Vellinga and Van Loo, 1994).

Factors	Frontier models			
	Blue print	Optimal technology	Technical efficiency	Environmental efficiency
Solar radiation				
Temperature				
Water				
Nutrients				
Roughage production				
Diseases and weeds				
Soil				
Variable inputs				
Weather				
Technology				
Milk and beef				
Labour				
Capital				
Institutions				
Environmental pressure				

Figure 6.1 Factors incorporated in the various models describing efficiency of dairy farming

[4] As noticed by Farrell (1957), blueprint technology frontiers ('a theoretical function specified by engineers') are only available for portions of the production process.

(ii) *An optimal technology* considers the processes at the experimental field plot level. The description of the production process is less detailed than blueprint production (e.g. a description of photosynthesis is not included), and it describes relations at a higher aggregation level (e.g. soil and technology are incorporated). Given the physical environment (soil, temperature and weather) the growth limiting and growth-reducing factors are empirically optimised. All resources are considered variable (e.g. Chambers et al., 1998; De Wit, 1992; Chambers and Lichtenberg, 1996 [5]).

(iii) For *technical efficiency* the production frontier is determined by the sample of farms. The production process is described at farm level. Optimal production is based on technical relations that are derived from actual economic behaviour of individual farmers and is also determined by stochastic elements, quasi fixed inputs and the institutional environment (e.g. Färe and Whittaker, 1995; Weersink et al., 1990; Hallam and Machado, 1996).

(iv) Finally if *environmental efficiency* is estimated, the environmental pressure is taken into account as well. In addition to technical efficiency, emissions into the environment due to dairy farming are considered (e.g. Ball et al., 1994; Reinhard et al., 1999).

The lower the aggregation level of the production factors, the higher the accuracy of describing the actual relations of the production process. Comparing these models, we see that there is no single model available that describes in detail all relations in dairy farming, see Figure 6.1. Therefore each model is vulnerable to omitted production factors. Figure 6.2 presents all factors of the aforementioned frontier models.

Figure 6.2 provides a model of dairy farming that summarises all elements of the aforementioned frontier models. It also describes the relations between the distinguished factors as presented in Figure 6.1. Dairy farming consists of *roughage production* [6] and livestock production. The stochastic elements *diseases and weeds* are incorporated into the production process. The inputs can be divided into *variable inputs* (including *nutrients*), *labour* and *capital*. The marketable output is mainly an aggregate of *milk and beef*. The physical environment consists of the exogenous physical factors that are related to land location. These factors cannot easily be manipulated by the farmer (e.g. *soil*, *temperature*, *solar radiation*, *water*). *Weather* is modelled in Figure 6.2 as a stochastic exogenous factor that influences the physical environment. Weather is the variation in *temperature* and precipitation (*water*) across farms and through time. The *institutional* environment influences almost all inputs, outputs and the production process; e.g. regulations on the utilisation of

[5] Chambers and Lichtenberg (1996) determine frontier technology based on two experimental data sets, although they do not compute efficiency scores explictly.

[6] The factors presented in Figure 6.1 are given in italics in the text.

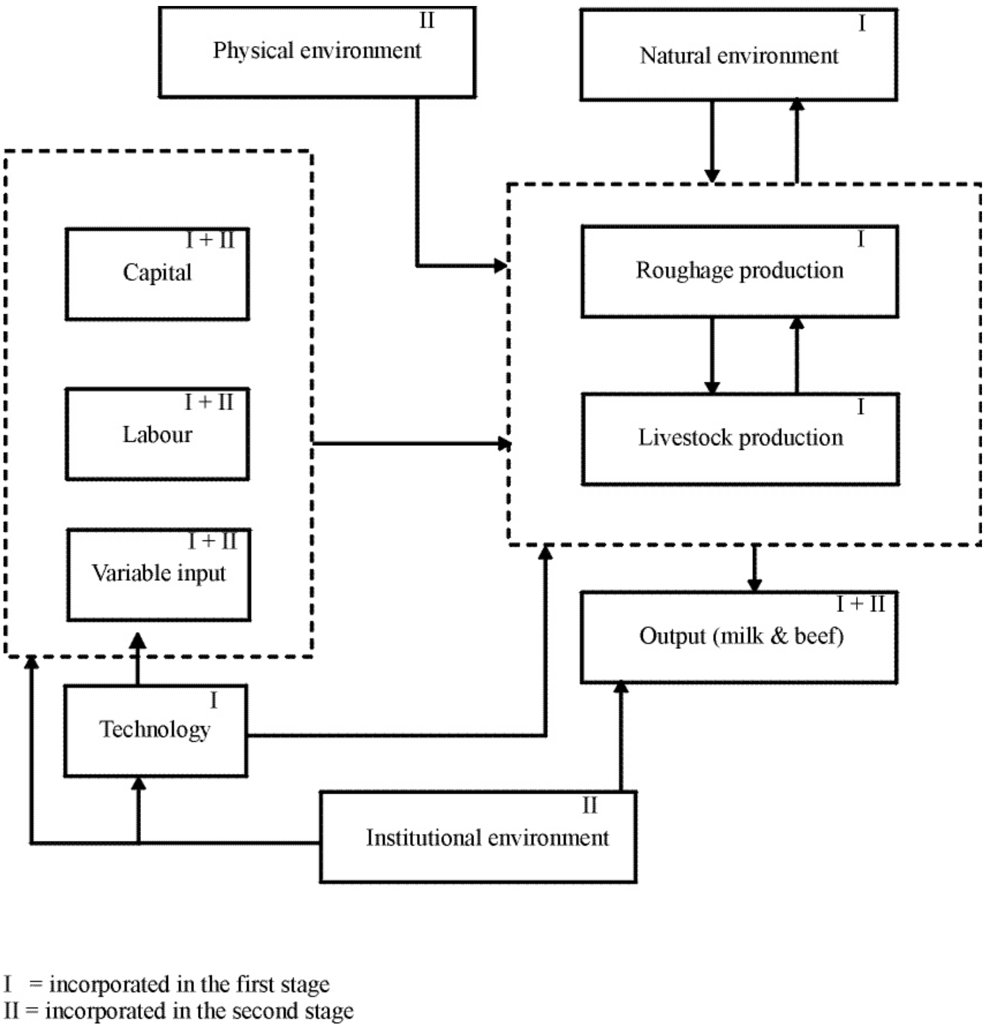

Figure 6.2 A schematic representation of dairy farming

land, production quotas for milk, taxes on excess manure. Technology is disaggregated into embodied and disembodied technological change. Embodied technological change influences the production process through capital and variable inputs. Disembodied technological change influences the production process through labour. The diffusion of technological change (new to the firm) is connected with an entrepreneurial or management factor. The environmental pressure captures the nutrient flows from dairy farming into the environment. For example nitrogen surplus consists amongst others of evaporation of ammonia and leaching of nitrates into groundwater.

We assume that the environmental inefficiency scores are due to omitted variables and measurement error. Thus, the factors depicted in Figure 6.2 that are not modelled appropriately in the first stage have to be incorporated in the second stage. In the first stage we specify a production frontier with a single output (an index of dairy farm output), three conventional inputs (labour and indices of capital and variable inputs), a single environmentally detrimental input (nitrogen surplus), and a time trend. Disembodied technological change is captured by the time trend, and embodied technological change is captured by cross-products of the time trend with the conventional inputs. Environmental efficiency is computed, conditional on stochastic disturbances, as in equation (6.2). We do not know exactly what is incorporated in the stochastic part. We assume that the effect of weather on the production process is captured in this stochastic part. This first stage analysis is described in detail in Chapter 2.

Two elements of the production process are not taken into account in the first stage at all, namely the physical environment and the institutional environment; see Figure 6.2. They are outside the control of the farmer. In the first stage observations are related to optimal performance (defined by the sample) in the same year. Factors that affect all observations in our sample every year in the same way cannot be used as explanatory variables. Most regulations affect farmers identically but their repercussions differ between years.

Another problem is the measurement of the variables that are used in the first stage. Variables whose productive capacities are not accurately measured will cause apparent inefficiencies. The productive capacity of family labour is not correctly measured in the first stage. The variable 'family labour' is expressed in hours; labour quality is not accounted for in this variable (productive capacity depends on quality as well). Variable inputs and outputs are aggregated from a lot of components. The information about quality is relatively well preserved in this aggregation; see chapter 2. However information is lost about the nitrogen content of the inputs and outputs. The quantity of nitrogen in inputs and in outputs defines the nitrogen surplus. To correct for this loss of information about the nitrogen content of inputs and outputs, we use feed per cow, kg of N fertiliser per ha and the percentage dairy farming in total output as explanatory variables**.**

By using the aggregate capital stock variable in the production frontier we implicitly assume that the capital service flow of its components is identical. Capital service flows cannot be measured directly. To correct for information that is lost in the aggregation of capital stock, we specify the number of cows as an explanatory variable. The quality of the herd is not entirely taken care of in the aggregation process of breeding and utilisation of livestock. Therefore we use the milk yield to express the quality of the herd.

In Figure 6.2 factors that are not modelled in the first stage are marked only with II, while factors that are not completely modelled in the first stage are marked with I and II. Six factors in the dairy production process are not adequately captured in the first stage.

- *Labour quality* (*LQ*) captures the management qualities of the farmer. A portion of these characteristics can be affected by the farmer (education). Labour quality includes the farmer's ability and learning by doing.

- *Nitrogen in variable inputs (NI)* reflects differences in nitrogen content of variable inputs that are lost in the aggregation process.

- *Nitrogen in outputs (NO)* reflects differences in nitrogen content of outputs that are lost in the aggregation process.

- C*apital services (CS)* reflects information that is lost in the aggregation process of various capital components. The capital services variable also reflects the quality of capital goods not adequately accounted for in the aggregation of capital.

- *Physical environment* (*PE*) captures differences in solar radiation, soil quality and infrastructure. These exogenous variables can hardly be changed. In the extreme case farms could be moved from a region that is unfavourable with respect to environmental efficiency to a more favourable area.

- The *institutional environment* (*IE*) is determined by government regulatory agencies and is outside the control of the farmer; e.g. the Dutch environmental policy. In the research period the impact of the Dutch environmental policy differs across farms, because it depends on the phosphate surplus.

The technological development is assumed to be captured in the first stage. However, the actual variation in technology employed at the individual farm can differ. Differences between intensive and extensive farming are included in the variable 'nitrogen in variable inputs'. Variation between specialised and mixed farming is captured by nitrogen in outputs.

In a stochastic production frontier setting, the economic behaviour of the farmer is implicitly assumed to be either output or profit maximisation, conditional on the inputs. The pursuit of alternative objectives (or farming styles, Van der Ploeg et al., 1994) can also be a reason that farmers are not on the frontier. Farming styles are not readily observable (Dijk et al., 1998), and so they cannot be used as explanatory variables. We might miss minor relations as well, and also some measurement error is still present in the variables specified in the first stage. Also the proxies we use in the second stage for these six factors do not capture these factors completely. For instance the region and soil type are used to describe the physical environment, but these two variables cannot capture all variation in solar radiation, precipitation, etc. Therefore we also have to deal in the second stage with an omitted variable problem. The variation of these omitted characteristics in the second stage, U^*, is captured by the inefficiency component of the second stage stochastic frontier model.

A log-linear model is chosen for the second stage, so that parameter estimates are identical to elasticities. The model can be given as

$$\ln EE_{it} = \delta_0 + \delta_1 \ln LQ_{it} + \delta_2 \ln NI_{it} + \delta_3 \ln NO_{it} + \delta_4 \ln CS_{it} + \delta_5 \ln PE_{it} + \delta_6 \ln IE_t + V^*_{it} - U^*_{it}, \tag{6.6}$$

where

LQ	=	labour quality;
NI	=	nitrogen in inputs;
NO	=	nitrogen in outputs;
CS	=	capital services;
PE	=	physical environment;
IE	=	institutional environment;
δ	=	vector of parameters to be estimated;
V^*	=	random error component, $V^* \sim$ iid $N(0,\sigma_{V^*}^2)$;
U^*	=	error component describing environmental efficiency, $U^* \sim$ iid $N^+(\mu^*,\sigma_{u^*}^2)$.

6.4 Literature review on explanatory variables and data

In this section we review agricultural economics and environmental economics literature on efficiency measurement to extract possible explanatory variables. Therafter we present the available explanatory variables in our data set.

The literature review is summarised in Table 6.1. The labour quality is to a large extent determined by the management quality. The quality of the management performance is determined by personal characteristics of the farm manager. Rougoor et al. (1998) divide these personal characteristics into (i) drives and motivation; (ii) abilities and capacities and (iii) background and experience. Off-farm income and years of farm management experience are the variables found in the literature to describe motivation and experience, respectively. The abilities and capacities are described by (formal) education, use of extension services and dairy herd improvement association, and choices of the production process made by the farmer. Specification of the inputs refers in most cases to the quantity of feed purchased. Output is specified by the degree of specialisation and by characteristics of the milk produced. Characteristics of the capital stock are used to specify capital in the analysis of efficiency. Milk yield is used as a characteristic of the quality of the livestock component of capital. Often efficiency is related to farm size. However there is no agreement on whether efficiency is positively or negatively related to farm size. Only regional dummies were found as proxies for the physical environment. The institutional environment is modelled by a

Table 6.1 Overview of variables used to explain efficiency variation

Variables	Reference
Labour quality	
(a) drives and motivation	
- off-farm income	Kalirajan, 1990; Kumbhakar, 1993 a)
(b) abilities and capacities	
- years of education	
- dummies for education level	Jamison and Lau, 1982; Stefanou and Saxena, 1988; Weersink et al.,1990; Kalirajan, 1990; Kumbhakar et al., 1991.
- extension services	Bravo-Ureta and Rieger, 1991
- fees paid to Dairy Herd Improvement Association	Müller, 1974
- crop establishment, timing of crop transplant	Kalirajan, 1990
(c) background and experience	
- years of farm management	Müller, 1974 b); Uhlin, 1985;Weersink et al., 1990; Stefanou and Saxena, 1988; Bravo-Ureta and Rieger, 1991
Input specification	
feed per cow, land per cow	Hallam and Machado, 1996
concentrate feed per cow	Ahmad and Bravo-Ureta, 1996
share feed purchased	Weersink et al., 1990
Output specification	
butterfat	Weersink et al., 1990
specialisation	Uhlin, 1985; Hallam and Machado, 1996
Capital specification	
vintage capital stock	Uhlin, 1985.
herd size	Ahmad and Bravo-Ureta,1996; Weersink et al., 1990
milk yield	Weersink et al., 1990
Size specification	
farm size	Bravo-Ureta and Rieger, 1991; Kumbhakar et al., 1991; Lund et al., 1993; Hallam and Machado,1996; Andreakos et al., 1997
Physical environment	
regional dummies	Weersink et al.,1990; Khumbhakar et al., 1991; Hallam and Machado, 1996; Reinhard and van der Zouw,1995
Institutional environment	
dummy for rented farms	Hallam and Machado, 1996; Kalirajan, 1990
dummy for environmental regulation	Hetemäki, 1996

a) The explanatory variables were used in the production function as quasi-fixed inputs; b) M⁵ller (1974) used a management index, based on a performance evaluation of managers. The criteria seemed to be related to their relative production costs.

dummy variable that reflects farm ownership, [7] and a dummy variable for the period of regulation is also used. The literature review shows that the explanatory variables are merely chosen ad hoc.

In Table 6.2 we present the available explanatory variables in the Dutch Farm Accountancy Data Network (FADN) [8]. We use off-farm income as a proxy for the drive and motivation of the farmer. We conjecture that on the one hand a large amount of off-farm income reduces the motivation of the farmer to generate a high income from farming as well. On the other hand a large off-farm income is a sign of high labour quality, because the farmer is also able to earn money off the farm. Therefore we cannot assume anything about the sign of the corresponding parameter estimate. The abilities and capacities of the farmer are captured by education. Education is distinguished in four categories in the data set. The percentage of the manager's labour in total family labour is used to capture the quality of family labour (we assume that the manager is more highly qualified than the other family members). The background and experience is reflected by the age of the manager, the number of years experience as a farm manager and the number of years of participation in FADN. FADN participants receive an extensive balance sheet and nutrient account, they have reduced their nutrient surplus more than farmers without a nutrient account (Poppe et al., 1995:78).

Nitrogen in inputs is captured by the quantity of feed per cow and the quantity of nitrogen fertiliser per ha. The quantity of purchased feed per cow also incorporates information about the presence of intensive livestock. The share of dairy farming in total production is an indicator of the specialisation of the production process and is an indicator for nitrogen in output. Capital specification is obtained by the size of the herd and 'sales and growth of livestock per cow'; the milk yield is an indicator for the quality of the herd. We do not use farm size as a separate variable because it is strongly correlated with herd size.

The physical environment is captured by the soil type and by regional dummies. The regional dummies reflect differences in solar radiation, water availability, infrastructure etc. Changes in the institutional environment are reflected by year dummies. We assume that regulation affects all farmers identically. The year dummy also incorporates annual differences in weather conditions.

All variables except the dummy variables are normalised by their sample means. The normalised variables are independent of units of measurement, and the mean impact of each variable is zero.

As mentioned before, an explicit indicator of farming style does not exist. However, a few of the technology parameters reflect some aspects of farming style. For instance a farmer who is very motivated to take care of cows will have a high milk yield. We do not

[7] Property is an element of the institutional environment (Williamson, 1998).
[8] A brief description of the Dutch FADN can be found in chapter 2.

have a variable available to model the motivation of the farmer towards environmental efficiency as well.

Table 6.2 The Explanatory Variables Used (the share of the observations that is described by a dummy variable is given in Table 6.3)

Variable	Mean	Min	Max	St. Dev
Labour quality				
education	4 categories			
age (years)	47.5	21	78	11.4
years manager	20.2	1	54	11.1
years FADN	2.7	1	9	1.9
labour manager %	85.2	12.5	100	17.0
off farm income (NLG)	28,091	0	365,203	24,579
Nitrogen in Inputs				
feed per cow (NLG/cow)	1,110.8	122.6	6,139.4	627.3
N fertiliser per ha (kg/ha)	256.1	0	569.9	84.7
Nitrogen in Output				
dairy (%)	78.2	66.7	99.9	5.6
Capital Specification				
number of cows	75.7	11	270	41.4
sales and growth (NLG/cow)	743	-641	2,850	258
milk yield (kg/cow)	5,315	2,326	7,673	868
Physical environment				
soil types	7 soil type dummies			
region	5 regional dummies			
Institutional environment				
year dummies	3 year dummies			

6.5 An empirical investigation into the determinants of environmental efficiency

In this section we implement the second stage of our two-stage model. In this stage we quantify the relationships between the explanatory variables and the environmental efficiency (EE) scores we obtained in the first stage. Since it is the environmental efficiencies we wish to explain, we summarise their distribution in Figure 6.3. With an overall sample mean of 0.441 and standard deviation of 0.249, there is a lot of variation in environmental efficiency to be explained in a second stage regresion.

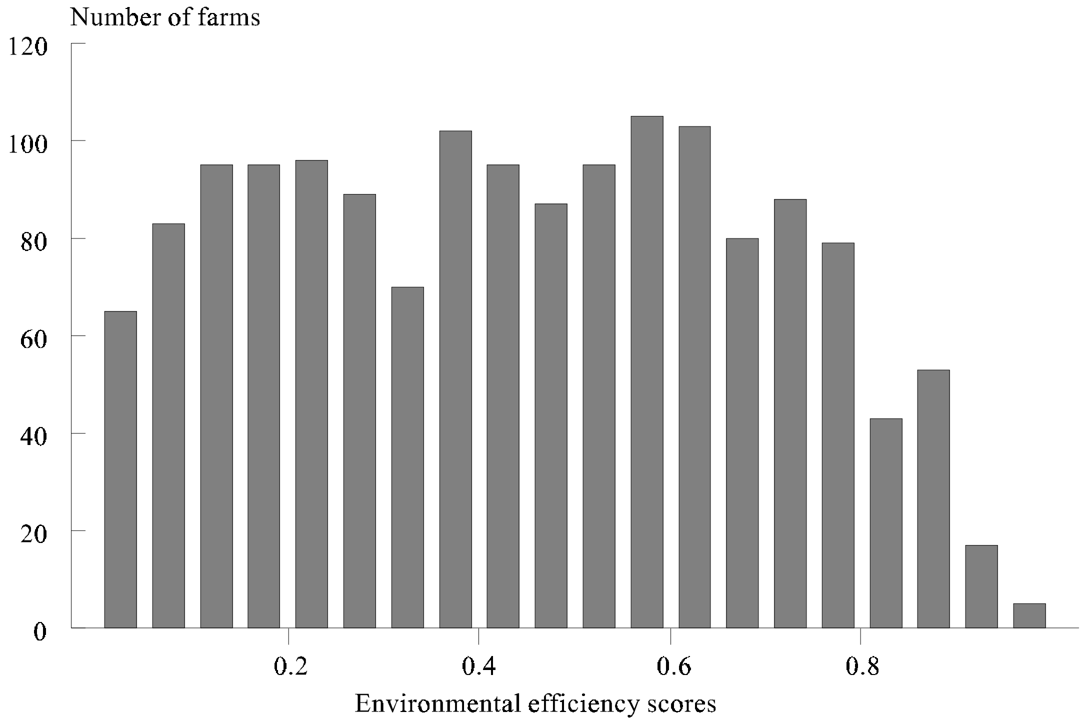

Figure 6.3 Histogram of Environmental Efficiency Scores

We used the software package FRONTIER (Coelli, 1994) to estimate the stochastic environmental efficiency frontier as specified in equation (6.6). We began with the entire set of explanatory variables listed in Table 6.2. The contribution of each variable was evaluated by computing likelihood ratio test statistics. When a variable did not contribute significantly (at the 90% level) it was deleted. The dummy variables for soil and education were aggregated into a smaller number of categories whenever the number of observations in a category was small and the categories had a comparable impact. We ended up using one dummy variable for education (1 = agricultural education or higher education; 0 = otherwise) and two dummy variables for soil type (SOIL1 = 1 if soil type is sea sediment clay; 0 = otherwise; SOIL4 = 1 if soil type is sand; 0 = otherwise). A few region and soil type categories and an education category were not significant, and were deleted. This also applied for number of years experience as farm manager, off-farm income, 'growth and sales per cow' and the 1992 dummy variable. The remaining explanatory variables in the model and their parameter estimates are presented in column 'The standard model' of Table 6.3. column 'Restricted model' contains estimates of a restricted model in which two explanatory variables, feed per cow and N fertiliser per ha, were deleted. Although each is statistically significant in column standard model), and a likelihood ratio test rejects the hypothesis that they can be deleted from the model, each is arguably not exogenous. Fortunately, estimates and significance levels of the remaining parameters are robust to the deletion of these two variables. The rank correlation coefficient for the two sets of results is 0.981. Nonetheless the following discussion is based on the results reported in column 'standard model'.

We tested the appropriateness of the frontier specification by computing the skewness of the OLS residuals of equation (6.6) [9]. The $\sqrt{b_1}$ statistic (Schmidt and Lin, 1984) is -0.76, indicating that the OLS residuals do indeed exhibit the expected negative skewness, and that a stochastic frontier model is appropriate. We tested the robustness of the model by supplying starting values that differed from the OLS estimates, and found the parameter estimates to be robust to alternative starting values. The half normal restriction on the truncated normal model was rejected, with a likelihood ratio statistic of 69.6 for the null hypothesis that $\mu^* = 0$. The estimated value of γ [$= \sigma_{U*}^2/(\sigma_{V*}^2+\sigma_{U*}^2)$] indicates that environmental inefficiency exists, with a likelihood ratio statistic of 1,872 for the null hypothesis that $\gamma = 0$. The relatively large estimated value of γ indicates [10] that almost the total error component in the second stage is due to unexplained (by the explanatory variables) environmental inefficiency. The role of statistical noise in explaining the original environmental efficiency scores is very small.

The parameter estimates presented in Table 6.4 convey two types of information: (i) the impacts of the explanatory variables on environmental efficiency; (ii) estimates of adjusted environmental efficiency, obtained from equations (6.4) and (6.5) as the ratio of observed to maximum feasible environmental efficiency.

The parameter estimates provide estimates of partial elasticities of EE with respect to each explanatory variable. For most variables plausible expectations can be formed on the signs of the partial elasticities, but we have no expectations on their magnitudes. Agricultural education (in contrast to no education or general education) is positively related to technical efficiency. The effect of agricultural education on EE is positive but insignificant. Experience, as measured by the age of the farm manager, has a negative but insignificant effect on EE. This is in line with Weersink et al. (1990: 453), who argue that inexperienced farmers tend to be more knowledgeable about recent (environment-friendly) technological advances than are their older counterparts. Participation in the FADN has a positive and significant effect on EE, probably due to the knowledge they gain from extensive balance sheets and nutrient accounts provided by LEI. Farms must leave the FADN after having participated for seven years, because they are assumed to gain knowledge from participating FADN. The ratio of the quantity of labour by the manager(s) to total family labour has a positive and significant effect on EE. The herd size has a negative and significant effect on EE. Since

---

[9] The OLS regression restricts U^* to be zero, and provides starting values for all technology parameters in the MLE regression, which produces estimates of all parameters in the stochastic environmental frontier model.

[10] In fact γ is not equal to the ratio of the variance of the technical inefficiency effects to the residual variance; see Coelli (1995a). The relative contribution of the inefficiency effect to the total variance term (γ^*) is equal to $\gamma^*=\gamma/[\gamma+(1-\gamma)\pi/(\pi-2)] =0.955$.

Table 6.3 Parameter estimates of the second stage frontier

Variables b)	Standard model		Restricted model	
	Parameter Estimates	Standard deviation	Parameter Estimates	Standard deviation
Constant	0.294 a)	0.062	0.375 a)	0.057
Labour quality				
agricultural education (0.89) b)	0.097	0.052	0.093	0.051
age of the manager	-0.099	0.057	-0.128 a)	0.058
years FADN	0.059 a)	0.021	0.061 a)	0.021
share manager in family labour	0.109 a)	0.045	0.129 a)	0.046
Nitrogen in inputs				
feed per cow	-0.209 a)	0.035		
N fertiliser per ha	-0.162 a)	0.035		
Nitrogen in outputs				
percentage dairy	0.560 a)	0.188	1.024 a)	0.183
Capital specification				
number of cows	-0.206 a)	0.034	-0.211 a)	0.031
milk yield	0.706 a)	0.115	0.325 a)	0.104
Physical environment				
soil sea sediment clay (0.13) b)	0.200 a)	0.054	0.235 a)	0.055
soil sandy (0.49) b)	-0.151 a)	0.047	-0.169 a)	0.047
region 3 (0.37) b)	0.171 a)	0.049	0.157 a)	0.048
Institutional environment				
dummy 1993 (0.26) b)	0.079 a)	0.021	0.047 a)	0.020
dummy 1994 (0.25) b)	0.101 a)	0.024	0.081 a)	0.024
μ^*	-4.203 a)	0.439	-4.358 a)	0.594
γ	0.983 a)	0.228	0.983 a)	0.279
σ^2	4.494 a)	0.457	4.828 a)	0.532
Log likelihood function	-955.13		-983.42	
Mean AEE	0.5719		0.5641	

a) The parameter estimate differs significantly from zero at the 95% level; b) The parenthetical value behind the dummy variables indicates the percentage of the total observations that is described by each dummy variable.

more cows produce more manure, this estimate seems logical. Remarkably, the herd size is positively (significantly) correlated to the technical efficiency measure. Although we selected highly specialised dairy farms from the FADN, these farms can still have other activities like fattening hogs or veal calves. Farms without much side-activities are significantly more environmentally efficient, because they are not involved in activities that produce a large nitrogen surplus. Milk yield is strongly positively related to technical efficiency and to a smaller extent to environmental efficiency. Farms that buy a lot of feed per cow (these farms are also likely to have hogs or poultry) are significantly less environmentally efficient. This variable is not included in the restricted model, in which its effect is partly incorporated in the parameter estimate of the variable 'percentage dairy'. This latter estimate is therefore larger in the restricted model than in the standard model. Not surprisingly, a large N fertiliser application per ha is significantly negatively related to environmental efficiency. This variable is excluded from the restricted model as well. Feed per cow and N fertiliser per ha are positively correlated with the milk yield, therefore the parameter estimate of 'milk yield' is smaller in the restricted model.

The effect on environmental efficiency of having 'type 1' soil (rich in clay from sea sediments) is significantly positive, since this is a fertile soil type. Conversely, 'type 4' soil (which is sandy) has a significantly negative effect, since sand is the least fertile soil type in the Netherlands. Location in region 3 (a combination of eastern, middle and southern regions specialised in livestock production) has a significantly positive impact on environmental efficiency. A possible explanation is that due to the concentration of livestock farms in these regions the feed price is low. Finally, environmental efficiency exhibited significant improvement in 1993 relative to 1991 and 1992, and again in 1994 relative to 1993 (in accordance with the results of Reinhard et al., 1999).

The parameter estimates are elasticities indicating the impacts of explanatory variables on environmental efficiency. The mean contribution of the explanatory variables to the predicted environmental efficiency scores indicates the importance of the distinguished explanatory variables and provide the government information for their policy considerations. Explanatory variables with a large impact, which can be influenced relatively easily by the government, are the main target for developing policy. The number of cows and the milk yield show a relatively large contribution (Table 6.4). A more productive breed of cows can be expected to increase environmental efficiency. This leads also to a reduction of the herd conditional on the milk production, which will rise environmental efficiency too. The government can improve the milk yield by encouraging genetics research. However, a potential problem is that the milk yield is positively correlated to the 'feed per cow' and 'nitrogen fertiliser per ha' that will decrease environmental efficiency. Reduction of feed per cow and N fertiliser per ha will increase environmental efficiency as well. Our methodology does not provide a management advice to implement this reduced application of variable inputs. But technical extension is likely to offer suitable methods to reduce the amount of feed per cow and N fertiliser per ha. The mineral accounts that have been mandatory since 1998 for farms with more than 2.5 milch cows per ha (or equivalent livestock), will stimulate farms to reduce their nitrogen consumption as well. Young, well-educated farmers are the more environmentally efficient farmers, and so education of older farmers to acquaint them with new environment-friendly technologies is likely to increase environmental efficiency. Farmers that participate for a longer period in the FADN learn from the information they receive in the FADN balance sheets and nutrients accounts. When they are provided with extensive balance sheets and nutrient accounts of their farms, farm managers can be expected to learn how to improve their environmental performance.

Table 6.4 Mean contribution of the explanatory variables to the predicted environmental efficiency scores

	1991	1992	1993	1994	Total
Labour quality					
agricultural education	0.06	0.06	0.06	0.06	0.058
age of the manager	0.01	0.01	0.01	0.01	0.014
years FADN	0.02	0.02	0.02	0.02	0.021
share manager in family labour	0.01	0.01	0.01	0.01	0.013
Nitrogen in Inputs					
feed per cow	0.06	0.06	0.05	0.05	0.054
N fertiliser per ha	0.03	0.03	0.03	0.03	0.032
Nitrogen in outputs					
percentage Dairy	0.02	0.02	0.02	0.02	0.023
Capital specification					
number of cows	0.07	0.07	0.07	0.07	0.066
milk yield	0.06	0.06	0.06	0.06	0.064
Physical environment					
soil sea sediment (0.13)	0.02	0.02	0.02	0.02	0.018
soil sandy (0.49)	0.05	0.05	0.05	0.05	0.050
region 3 (0.37)	0.04	0.04	0.04	0.04	0.043
Institutional Environment					
dummy 1993	0.00	0.00	0.05	0.00	0.014
dummy 1994	0.00	0.00	0.00	0.07	0.017
AEE	0.54	0.54	0.50	0.48	0.516
Total	1.00	1.00	1.00	1.00	1.000

The explanatory variables contribute to about half of the total variation in environmental efficiency. Another rough indication of the overall contribution of the explanatory variables to variation in EE are the R^2 values for the OLS stage of second stage regression. The R^2 of the 'standard model' is 0.295 and of the 'restricted model' 0.253.

The unexplained shortfall of environmental efficiency beneath best practice observed in the sample is reflected in U*. These adjusted environmental efficiency scores, adjusted for the explanatory variables characterising each farm, are computed using equation (6.5). They provide estimates of environmental efficiency, conditional on the explanatory variables. The adjusted environmental efficiency scores can be viewed as the environmental efficiency scores when the explanatory variables are equal for all farms. Whereas in the first stage a farm may be penalised for its unfavourable circumstances, these factors are accounted for in the second stage.

The sample mean of the adjusted environmental efficiency scores (AEE) is 0.574 with a minimum value of 0.00^{+} and a maximum value of 0.95 (Table 6.5). In 92% of the observations the AEE score is larger than the EE score. The rank correlation of the first stage EE scores and the second stage AEE scores is 0.917. The dispersion of the EE scores and the AEE scores is of about the same magnitude, with sample standard deviations of 0.249 and 0.266 respectively. In Figure 6.4 the distribution of the adjusted environmental efficiency scores is presented. The distribution differs in large part from the distribution of the first stage environmental efficiency scores because no distribution is imposed on the EE scores while the AEE scores are assumed to follow a truncated normal distribution.

Table 6.5 Comparison of Environmental Efficiency (EE) scores and Adjusted Environmental Efficiency scores (AEE)

	Mean	Minimum	25^{th} perc	Median	75^{th} perc	Maximum
EE	0.441	0.00^{+}	0.225	0.441	0.640	0.94
AEE standard	0.574	0.00^{+}	0.354	0.641	0.810	0.95
AEE restricted	0.565	0.00^{+}	0.343	0.622	0.806	0.95

The correction of EE by the explaining variables leads to a higher AEE. The unexplained part of EE reflected by AEE are caused by: (i) We had to use proxies to model the factors that were omitted in the first stage or that were not accurately measured. (ii) We could not incorporate all relevant information in the second stage (e.g. farming styles). (iii) We only modelled the most important factors; for instance solar radiation, temperature and water are not modelled explicitly. (iv) The first stage environmental efficiency scores may not accurately reflect environmental efficiency; chapter 2, footnote 12.

The magnitude of the AEE gives an indication of the problem environmental policy is confronted with. We do not have explanatory variables available to clarify this portion of the environmental efficiency. Therefore we cannot readily provide instruments for policy-makers to reduce AEE. Complementary methods may provide more insight in the factors that determine AEE. For instance the farmer could be interviewed to obtain more information about his objectives, motivation and other elements of dairy farming that cannot be captured in a balance sheet.

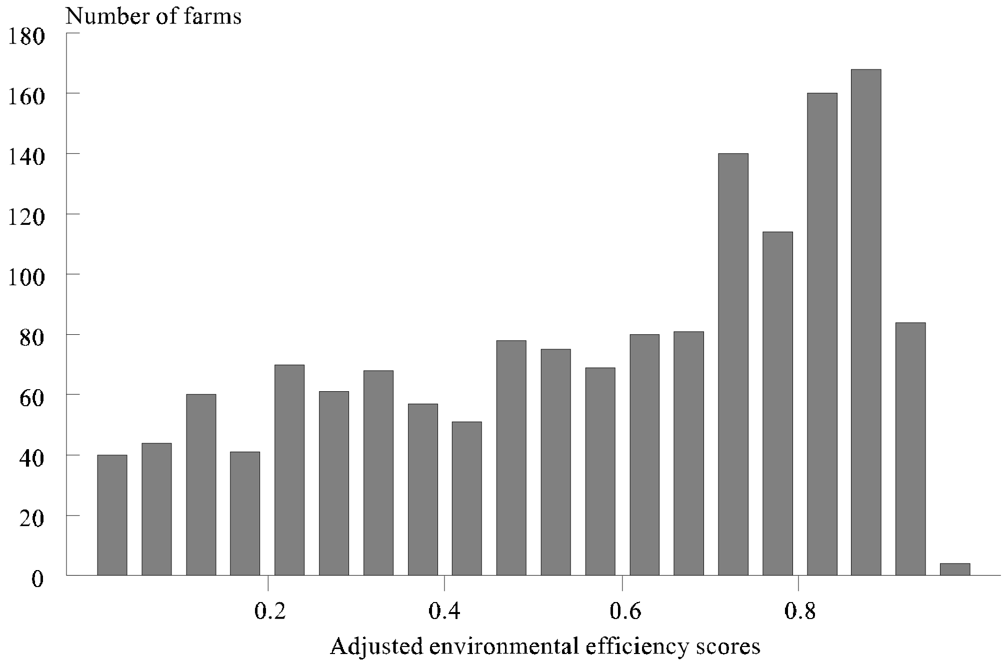

Figure 6.4 Histogram of Adjusted Environmental Efficiency Scores

6.6 Summary and conclusions

We have developed an analytical framework within which to estimate the impact of various explanatory variables on environmental efficiency scores as a second stage stochastic frontier. The environmental efficiency scores were computed in a first stage analysis. Our second stage differs from other approaches found in the literature, because we apply a stochastic frontier in the second stage. The second stage parameter estimates reflect impacts of explanatory variables that can guide policy to increase environmental efficiency. This methodology also supplies an adjusted environmental efficiency measure that identifies farms with relatively high and relatively low environmental efficiency, conditional on their explanatory variables. We showed that the second stage can be estimated appropriately with a stochastic frontier, by estimating adjusted environmental efficiency scores for each firm in a panel of 613 Dutch dairy farms during the 1991-1994 period.

The mean adjusted environmental efficiency is higher than the first stage environmental efficiency because we explain a portion of the environmental efficiency with the explanatory variables (among others, indicators of labour quality and the physical environment). We found that agricultural education, insight in the nutrient balance and the milk yield affect the environmental efficiency score positively.

7. Conclusions and discussion

7.1 Introduction

The objective of this thesis is to define, to estimate and to evaluate environmental efficiency of a panel of Dutch dairy farms.

Various methods have been developed in the preceding chapters to estimate environmental efficiency econometrically. They are based on existing econometric models to estimate technical (and allocative) efficiency. These models are adapted to enable computation of the farm's environmental efficiency. All three distinguished models (stochastic production frontier, distance function and cost system) allowed the calculation of environmental efficiency scores. We estimated environmental efficiency scores of an (incomplete) panel of Dutch dairy farms; nitrogen surplus was the environmentally detrimental variable. This study shows that if the environmental performance of dairy farms is improved, nitrogen emission could be reduced (the potential reduction depends on the model used). Finally the variation in environmental efficiency scores is explained. We scrutinised a model of dairy farming, to identify factors that affect environmental efficiency and we estimated the impact of these factors.

The objective of this chapter is threefold: (i) to answer the research questions and to derive conclusions that exceed the relevance of the separate chapters (ii) to determine the value of the developed environmental efficiency measures (iii) to summarise the contribution of this thesis to future LEI [1] research.

In section 7.2 the conclusions of the previous chapters are summarised and information contained in these chapters is used to answer the research questions, formulated in chapter 1. The environmental efficiency scores developed and applied in chapters 2 to 6 are evaluated in section 7.3. In that section the best method to compute environmental efficiency is selected as well. The value of the developed efficiency measures is determined by relating these measures to a set of criteria relevant for environmental indicators in section 7.4. The efficiency measures are compared to alternative environmental indicators currently used. The practical use of the methodology developed in this thesis for several lines of LEI research is presented in section 7.5.

[1] The Agricultural Economics Research Institute is abbreviated as LEI.

7.2 The research questions

In section 1.3 the six research questions were formulated. These questions were elaborated into objectives of the various chapters. The first two research questions: *How to define environmental efficiency? and How to compute environmental efficiency econometrically*? have been dealt with in chapters 2-5. The definition of environmental efficiency and the method to compute environmental efficiency differ with the assumptions made. The developed definitions have the characteristic in common that they compare the observed production process to the environmentally optimal production process. The exact definitions and methods are presented in the following paragraphs, summarising the conclusions of chapters 2-5.

The objective of chapter 2 is to find the best way to incorporate environmental effects in SFA and to compute environmental efficiency.
The Stochastic Frontier Approach (SFA) allows the computation of output-oriented technical efficiency. Technical efficiency scores reflect the possible increase in outputs conditional on a set of inputs. The stochastic production frontier allows only one (aggregated) output to be modelled. Because of the similarities between pollution and conventional inputs in the production function context, nitrogen surplus is modelled as an environmentally detrimental input in the stochastic production frontier. Environmental efficiency is defined as the ratio of minimum feasible use to observed use of an environmentally detrimental input, conditional on observed levels of the desirable output and the conventional inputs. The econometric method developed to compute environmental efficiency with SFA consists of the estimation and transformation of a translog stochastic production frontier that is estimated with standard software. *We showed that the standard output-oriented stochastic production frontier framework can be transformed into input-oriented efficiency measures. If the environmentally detrimental variable is modelled as an input, a single input efficiency score can reflect environmental efficiency.*

The objective of chapter 3 is first to analyse whether the method we put forward in the previous chapter can be extended to multiple environmentally detrimental inputs and second to investigate the strengths and weaknesses of SFA and DEA for estimating environmental efficiency.

The SFA method presented in chapter 2 is extended to the multiple environmentally detrimental input case. Environmental efficiency scores are based on nitrogen surplus, phosphorus surplus and total (direct and indirect) energy. This environmental efficiency measure is derived from the maximum radial contraction of all environmentally detrimental inputs. Environmental efficiency is defined as the ratio of minimum feasible use to observed use of multiple environmentally detrimental inputs, conditional on observed levels of the desirable output and conventional inputs. This comprehensive environmental efficiency measure is estimated with SFA and Data Envelopment Analysis (DEA). In contrast to DEA, an advantage of SFA is that the necessary assumptions with respect to the environmentally detrimental variables can be tested. However, in the three bad inputs case the monotonicity assumptions are violated, which means that the environmental efficiency scores cannot be computed for all observations. Therefore, the SFA environmental efficiency scores are based on nitrogen surplus and total energy. DEA can compute environmental efficiency measures based on the three bad inputs because regularity assumptions are imposed. *Although the SFA methodology allows multiple bad inputs, estimation of the frontier and computation of the environmental efficiency scores can be cumbersome. DEA can be used to compute environmental efficiency with respect to multiple environmentally detrimental variables.*

The objective of chapter 4 is to research whether the econometric approach to distance functions can be applied to model nitrogen pollution as an output, and to analyse the consequences of the materials balance definition of nitrogen surplus.

In chapter 4 nitrogen surplus is modelled as a bad output in an output distance function [2]. Nitrogen emission is a non-point source pollution and is measured by the materials balance definition as nitrogen surplus. The quantity of nitrogen in inputs has to be divided between desirable output and nitrogen surplus. This materials balance definition suggests that desirable output and nitrogen pollution are substitutes, contrary to the assumption made in the literature with respect to point-source pollution. In the output distance function the standard output-maximising technical efficiency measure does not provide an appropriate measure for environmental efficiency, because at the efficient point the production of bad output is larger than the observed bad output. Therefore, a different approach is used. The outputs are ex-post weighed according to their social value; a non-positive price for nitrogen surplus is used. Environmental efficiency is defined as the ratio of the revenue at the technically efficient output mix and the revenue at the optimal output mix (maximum feasible revenue) conditional on the inputs and a non-positive price of the bad output. Resource use efficiency reflects the efficient use of conventional resources (conventional inputs) and natural resources (nitrogen surplus). Resource use efficiency combines technical and environmental efficiency and is defined as the ratio of observed revenue and maximum feasible revenue. We find positive shadow prices for nitrogen surplus, contrary to the literature on point-source pollution. The distance function methodology can be extended to multiple bad outputs, but it is more difficult to determine the global optimum (the maximum ratio of good and bad output cannot be used). The distance function has identical data requirements to those of SFA. *We extended the distance function framework to fit non-point source pollution*

[2] Distance functions also allow for an input-oriented approach. This approach does not add much to the SFA methodology to compute environmental efficiency if the environmentally detrimental variables are modelled as inputs.

as well. We showed that environmental efficiency can be defined and estimated with an output distance function. We transformed the definitions of allocative and total efficiency into environmental efficiency and resource use efficiency measures respectively.

The objective of chapter 5 is to determine the possibilities a cost system offers to incorporate the materials balance definition and to estimate environmental efficiency.

To incorporate behavioural assumptions in the estimation of environmental efficiency, nitrogen surplus was incorporated in a cost function. Minimisation of nitrogen in inputs conditional on the outputs results in minimising nitrogen surplus (conditional on output), due to the materials balance definition. If we specify the nitrogen-containing inputs we do not have to model nitrogen surplus explicitly in a cost function framework. In this framework we identify cost-efficient production and the nitrogen-efficient production. Nitrogen efficiency is defined as the ratio of minimum application to observed application of nitrogen conditional on desirable output, the quasi-fixed inputs and nitrogen content of variable inputs [3]. Nitrogen efficiency has a technical and an allocative component similar to cost efficiency. The nitrogen content of the variable inputs determines the optimal ratio of these inputs from an environmental point of view. A shadow cost system is used, which allows a farmer to deviate from cost-minimising behaviour; he minimises shadow costs instead of market costs. Shadow prices are modelled as price distortion factors of market prices. Nitrogen distortion factors are added to the estimation results to calculate minimum nitrogen input. The relation between economic efficiency and environmental efficiency determines the (economic) sacrifice that is necessary to decrease the nitrogen surplus. The cost function approach is more demanding for the data; time series data are necessary to obtain variations in price. A disadvantage of the cost system methodology is that it cannot be easily extended to multiple environmentally detrimental variables. *We used the shadow cost system framework to allow for two optimal situations. One from an economic point of view (minimising costs) and one from an environmental point of view (minimising nitrogen input). Efficiency measures can be computed with respect to both optimums. The materials balance definition of the environmentally detrimental variable is exploited; minimising nitrogen input conditional on desirable output is equal to minimising nitrogen surplus.*

The objective of chapter 6 is to explain the variation found in environmental efficiency scores.

The variation in environmental efficiency is explained in a second stage analysis. We assume that environmental efficiency scores originate from omitted variables in the (first

[3] Pollution cannot enter the cost function as an (variable) input because market prices of the environmental variables do not exist. A cost function is also not suitable to treat the environmentally detrimental variables as bad outputs, because a cost function should be non-decreasing in (conventional and environmentally detrimental) outputs (Chambers, 1988:52).

stage) stochastic frontier analysis. A model of dairy farming is constructed based on different models of dairy farming (different aggregation level, different scientific background). This model is compared to the first stage translog production frontier. Omitted factors, measurement errors and aggregation of variables define the potential explanatory variables. Environmental efficiency scores from the first stage are regressed against the potential explanatory variables in a second stage stochastic frontier analysis. The second stage parameter estimates reflect impacts of the explanatory variables on environmental efficiency. This second stage stochastic frontier methodology also supplies an adjusted environmental efficiency measure that identifies farms with the largest environmental efficiency conditional on the explanatory variables. Variables that describe: the labour quality (e.g. number of years they participate in FADN), the nitrogen content of inputs and outputs, capital specification (e.g. herd size), physical environment and institutional environment, significantly affect the environmental efficiency scores. Environmental efficiency can be improved, for instance by encouraging a higher milk yield (stimulating genetics research) or by providing the farmer with more insight into the nutrient balance of his farm. *Our second stage analysis to estimate the impact of explanatory variables differs from other approaches found in the literature, because we apply a stochastic frontier in the second stage. The second stage parameter estimates reflect impacts of explanatory variables that can guide policy to increase environmental efficiency.*

How to model pollution in the neoclassical framework?

In this Ph.D.-thesis nitrogen surplus is modelled as an input and as an output in the neoclassical framework. An advantage of treating pollution as an input is that it can be treated similar to conventional inputs (see Pittman, 1981; Cropper and Oates, 1992) and existing methods to compute efficiency require relatively minor adaptations. A reduction of inputs (conventional or environmentally detrimental), conditional on output, enhances performance (chapters 2 and 3). For pollution as a bad output, the output-augmenting approach in the efficiency framework requires extensive modification to enable the estimation of environmental efficiency (chapter 4). In the cost system framework nitrogen surplus is modelled implicitly. The output quantity is given and its nitrogen content cannot be changed, therefore decreasing the nitrogen-containing input improves environmental performance.

Are the theoretical restrictions fulfilled?

To appropriately estimate the developed environmental efficiency scores, environmentally detrimental variables have been modelled into the neoclassical production framework. In line with the literature (e.g. Pitman, 1981; Coggens and Swinton, 1996) we use a translog functional form for the production frontier, the distance function and the cost system. A method to impose the necessary regularity assumptions globally in a translog specification is not available. Therefore we have to test whether the data support these assumptions for every observation.

In chapter 2 we found that the estimated production frontier satisfies monotonicity for all observations. The elasticities with respect to the conventional inputs estimated in chapter 2 were in accordance with previous results on Dutch dairy farming (Elhorst, 1986; Thijssen, 1992). In chapter 3 the monotonicity assumptions are violated in the case of multiple environmentally detrimental inputs. The test uncovered failure for 21% of the observations for nitrogen surplus input. Phosphate surplus was deleted from the estimation because the monotonicity assumption for phosphate surplus was violated in more than half of the observations. The mean output elasticity of energy is very large, larger even than the mean output elasticity with respect to variable inputs, possibly due to multicollinearity with the variable inputs. The manipulations used for computing environmental efficiency scores in SFA are based on the necessary assumptions for a production frontier. If these assumptions (in particular monotonicity) are violated, then the environmental efficiency score cannot be computed properly for all observations. In DEA monotonicity is implicitly imposed, allowing the computation of environmental efficiency for all distinguished environmentally detrimental variables.

In chapter 4 we found that the distance function is convex in good and bad output for 80% of the observations and satisfies monotonicity with respect to most of the conventional inputs and the desirable output. In 9% of cases monotonicity with respect to labour was violated. Violation of the monotonicity with respect to labour did not preclude the estimation of the environmental efficiency and resource use efficiency measure for all observations. The cost system (chapter 5) satisfies monotonicity with respect to price for all observations. However, we encountered problems due to violation of the concavity in prices restrictions. The cost function has to fulfil the theoretical restrictions also outside the bounds of sample data to allow the computation of environmental efficiency, because the optimal ratio of nitrogen-containing inputs (determined by nitrogen content) differs greatly from the ratio of market prices.

Thijssen (1992) also found that a production function estimated with a panel of Dutch dairy farms does not satisfy the neoclassical assumptions for all observations. In the agricultural economics literature these assumptions of production theory are often violated, if at all tested (Fox and Kivanda, 1994). In this thesis, violations of the assumptions of the neoclassical theory are presumably aggravated due to the incorporation of environmentally detrimental variables in the SFA and distance function model (chapters 3 and 4). A complicating factor for modelling nitrogen surplus in the neoclassical framework is that nitrogen surplus was not restricted during the research period. Farmers did not have to pay a levy based on excess nitrogen. The behaviour of farmers with respect to nitrogen surplus is therefore more difficult to predict than behaviour with respect to conventional inputs and outputs.

In the cost system framework (chapter 5) the environmentally detrimental variable is not explicitly modelled and cannot be the source of violation of the assumptions.

How to deal with the materials balance condition?
The quantity of nitrogen surplus produced depends on conventional inputs as well as on desirable output. If output is specified as a stochastic variable, nitrogen surplus is stochastic as well. This complicates an appropriate incorporation of nitrogen surplus as a variable in econometric models. If we assume a given quantity of nitrogen in inputs, the desired output and nitrogen surplus are substitutes, because nitrogen in inputs will be incorporated in either desirable output or nitrogen surplus. Therefore, a strict application of the materials balance concept affects the standard output distance function model (chapter 4). An advantage of the materials balance definition is that we do not have to model the environmentally detrimental variables explicitly. In chapter 5 we circumvented the aforementioned problems by modelling nitrogen surplus implicitly. We minimised nitrogen-containing inputs conditional on output. If the disadvantages of the materials balance definition (of nitrogen surplus) cannot be dealt adequately with, the method developed in chapter 5 is preferred in which the surplus is modelled implicitly. This approach can also be applied in SFA and in the distance functions framework.

7.3 Comparing the environmental efficiency scores of the different models

In this section the efficiency scores of the various models are compared. The mean technical efficiency scores obtained from econometric methods are of approximately the same magnitude (Table 7.1). The DEA-scores are lower presumably because in contrast to econometric methods, the efficiency scores incorporate random noise. The distinguished technical efficiency scores are strongly positively correlated, except for the technical efficiency scores from the cost system. These scores are based on explanatory variables in contrast to the other econometrically estimated technical efficiency scores, which are modelled in the error component. Also in the literature great variation is found in technical efficiency scores computed with different methods (e.g. Gong and Sickles, 1992; Hjalmarsson et al., 1996).

The mean environmental efficiency scores are very different in the various chapters. The high environmental efficiency scores in the multiple bad input SFA-model (chapter 3) are due to the fact that energy efficiency determines to a large extent the value of the environmental efficiency scores (efficiency scores based on a larger number of inputs lead to higher efficiency scores). The environmental efficiency scores in chapter 4 are high. They are computed as allocative efficiencies, in contrast to the environmental efficiency scores in chapters 2 and 3. The latter scores are derived from the technical efficiency scores computed with SFA and DEA. The mean resource use efficiency score (which is based on both technical and environmental efficiency) is lower (0.723) see Table 4.5 (in chapter 4). The environmental efficiency scores in chapter 5 are also a combination of technical and allocative efficiencies, and like the resource use efficiency scores they too are low. Technical efficiency is a prerequisite for environmental efficiency; except for the distance function framework in which environmental efficiency is defined as allocative efficiency (the optimal ratio of good and bad output).

A global optimum is defined in the distance function and cost system framework, because they combine both technical and allocative efficiency. When a global optimum is identified, the environmental pressure of farms with identical environmental efficiency scores is identical, conditional on either conventional inputs or output. In chapters 2 and 3 farms on the frontier (i.e. environmentally efficient) might have a different nitrogen surplus. Methods that allow the computation of technical and allocative efficiency (chapters 4 and 5) show a smaller correlation between the technical and environmental efficiency measures than the other methods (Table 7.1).

Table 7.1 Comparison of mean technical efficiency (TE) and environmental efficiency (EE) scores and rank correlations of the different chapters a)

	Ch2 SFA	Ch 3 SFA b)	Ch 3 DEA b)	Ch 4 Dist	Ch 5 Cost	Ch 6 2^{nd} st.
Mean TE	0.893	0.889	0.784	0.804	0.838	-
Mean EE	0.441	0.795	0.520	0.897	0.561	0.602
Rank correlation coefficients						
TE-EE	0.873	0.991	0.718	0.206	0.181	-
Rank correlation coefficients; upper triangle is TE, lower triangle is EE						
Ch 2 SFA	-	0.884	0.701	0.672	0.181	-
Ch 3 SFA b)	0.804	-	0.759	0.660	0.208	-
Ch 3 DEA b)	0.474	0.483	-	0.468	0.179	-
Ch 4 Dist	0.408	0.446	0.412	-	0.402	-
Ch 5 Cost.	0.234	0.407	0.223	0.322	-	-
Ch 6 2^{nd} st.	0.917	0.733	0.424	0.348	0.263	-

a) Environmental efficiency in equal to nitrogen efficiency in chapter 5; b) Comprehensive environmental efficiency (based on N surplus and total energy in SFA and on N surplus, P-surplus and total energy in DEA).

The environmental efficiency scores are positively correlated, but the rank correlation coefficients are generally smaller. The way environmental efficiency is modelled differs more across the chapters than the way technical efficiency is incorporated. Thus we expect a smaller rank correlation between the EE scores across the chapters. In chapter 3 the environmental efficiency scores are based on multiple bad inputs; in the other chapters nitrogen surplus is the only environmentally detrimental variable. The environmental efficiency scores derived from the cost system framework are correlated less to the environmental efficiency scores of the other methods due to the small rank correlations of technical efficiency. The different environmental efficiency measures provide diverse results.

The quality of the econometrically computed EE scores depends on the quality of the underlying models. SFA (with one bad input) fulfils the neoclassical assumptions better than distance function and cost system in this Ph.D.-thesis. A disadvantage of SFA is that environmental efficiency scores might not be computable if monotonicity is violated. A disadvantage of the cost system approach is that prices of variable inputs are the driving force behind this model, while the policy objective is a desired quantity of pollution and not a price. The econometrically estimated output distance functions have not yet been published extensively in literature, but this approach is promising (e.g. they allow multiple outputs and behavioural assumptions to be incorporated; Atkinson and Primont, 1998). Econometric estimation of environmental efficiency is preferred over DEA, because in agriculture missing variables (see chapter 6) and stochastic influences are likely to play a significant role. Another advantage of the econometric approach over DEA is that the first provides information about the development of the frontier and the response of farmers. The developed econometric models are adaptations of the extensive body of literature in which production, profit and cost functions to model dairy farming are used (e.g. Thijssen, 1992; Helming et al., 1993; Boots et al., 1997). If we should reject the presented econometric models; DEA is not an adequate solution as well, because it implicitly incorporates identical assumptions. If only a small sample is available DEA will be more useful than econometric methods. For analysis of one environmentally detrimental variable SFA is preferred. It can be computed with standard software. The distance function and shadow costs system are relatively new methods that are still discussed in the literature. When multiple (desirable) outputs have to be specified and stochastic influence is important, the distance function can be used. DEA is a useful option especially when multiple bad variables have to be specified. DEA requires that the environmentally detrimental variables are specified as bad inputs if they affect output negatively. The selection of the appropriate method should be made on a case-by-case basis.

7.4 Environmental indicators

To gain insight into the pros and cons of the developed environmental efficiency measures and to relate them to alternative environmental indicators, we compare each one against a set of criteria. The following environmental indicators are compared: (A) Nitrogen surplus per ha, that is the environmental indicator used by the government to define the standard loss quantities and to determine the excess nitrogen levy (MVROM and MLNV, 1995). (B) Cows per ha, used as a proxy for nitrogen surplus per ha [4] (MVROM and MLNV, 1995). (C) Net value added per kg nitrogen surplus (e.g. Brouwer et al., 1997:74). (D) Fertiliser efficiency, currently defined by LEI as the ratio of the annual change in fertiliser quantity and output quantity (Brouwer et al., 1997:58). (E) Environmental efficiency computed with SFA, see chapter 2. (F) Environmental efficiency computed with the output distance function, see chapter 4 (G) Environmental efficiency scores computed with a cost system as described in chapter 5 and (H) DEA environmental efficiency calculated according to the DEA-model presented in chapter 3.

Short lists of criteria for the selection of environmental indicators can be found in OECD (1997), Bakkes et al. (1994:6); Crabtree and Brouwer (1999:282); Oskam and Vijftigschild (1999) and Romstad (1999). The following criteria are selected based on their relevance to environmental performance measures of Dutch agriculture (Table 7.2).

- Indicators should have a *target* against with which to compare, so that users are able to comprehend the significance of the values associated with it (Bakkes et al., 1994). Environmental efficiency scores compare observations with best practice and readily show the potential improvement. Nitrogen surplus per ha can be compared with the maximum loss-standard (see section 1.1).
- Indicators should be consistent. They must capture changes in key state variables in a way that is comparable over time. It is not desirable for the indicators to fluctuate over time due to *stochastic* processes; e.g. weather (Romstad, 1999). Therefore, environmental indicators in agriculture should account for noise. Bakkes et al. (1994) call this criterion 'ability to show trends'. The econometric environmental efficiency methods incorporate the effects of noise; their efficiency scores do not fluctuate over time due to stochastic exogenous influences.
- Romstad (1999) defines reliability as the availability of long-term (*reliable*) time series *data*. The FADN data are readily available, and have been recorded since 1969. Data on the number of cows have been available for an even longer time period. Detailed information about nitrogen surplus is available from 1991 onward, and nitrogen surplus can be approximated for a longer time period.
- Indicators that are *directly measurable* are preferred, because they can be observed accurately. The number of cows per ha is directly measurable for all farms in the Netherlands. The other indicators cannot be measured directly. The nitrogen surplus of intensive livestock farms will be available in the 'Minas'-nutrient accounts (see chapter 1). The other indicators require computations at farm level.
- An indicator that can be computed for small and large data sets is preferred. Efficiency measures that use the sample to determine the best practice frontier can only be meaningfully applied if enough observations are available. DEA can generate efficiency

[4] This proxy is used to determine which farms are eligible for an extensive nutrient account.

scores on the basis of small samples, but the percentage of efficient farms will be very high. The econometric models cannot be used for *small samples*; the degrees of freedom will be too small. The simple partial indices (A-D) can even be computed if the data set contains just one observation.

- The environmental indicator should be *easy to communicate* with the target users (Crabtree and Brouwer, 1999:280). Simple partial indices (e.g. columns A and B) can easily be explained to policy-makers and technical scientists. The idea of a production frontier needs further explanation, but is quite easy to understand. Distance functions and cost functions are less accessible for non-economists.
- Indicators that are *linked with the economic theory* are preferred, because they allow for technical, economic and environmental performance to be computed and evaluated within the same framework. The efficiency measures (E-H) fit in an economic framework and consistent assumptions can be made regarding the development of these indicators under various policy options (e.g. chapter 6). Environmental efficiency measures are preferred because they combine comprehensive information of the production process based on the neoclassical framework with the environmental pressure caused by farm.
- Indicators that do not require *regularity* restrictions on the data are preferred. The simple partial indices can be computed for all data. They do not require the data and the model to fit certain regularity constraints. DEA implicitly imposes regularity. The econometric models can only estimate environmental efficiency scores if the estimated frontier satisfies the neoclassical assumptions (see section 7.2). These econometric models cannot guarantee environmental efficiency scores for all observations in the data set.
- As indicated above, partial indices do not require any assumptions with regard to the data, nor do they require any tests. The efficiency measures rely on regularity assumptions, which stem from neoclassical theory. To check whether the appropriate model is selected, it is important to test whether these assumptions are fulfilled. DEA imposes the required regularity conditions, and they cannot be tested. Econometric estimation of efficiency measures allows the *testing of the underlying assumptions.*
- Specification of the inputs and outputs is predetermined in the partial indices. The definition of the index determines the specific input or output taken into account. The distinguished environmental efficiency measures are flexible in the number of inputs (or outputs) taken into account. However, the econometric methods to compute environmental efficiency are susceptible to multicollinearity; especially when more than one environmentally detrimental variable is specified (chapter 3). The cost system will be less sensitive for *multicollinearity*, because it uses quantities and prices.

Table 7.2 Schematic overview of the characteristics of the distinguished environmental indicators; and their score on the criteria analysed (the more x *the better)*

Criteria	A	B	C	D	E	F	G	H
Target	x				x	x	x	x
Stochastic		x			x	x	x	
Reliable data	xx	xxx	xx	xx	x	x	x	x
Directly measurable	x	xx	x	x				
Small samples	xx	xx	xx	xx				x
Communication	xx	xx	x	x	x			x
Linked with economic theory					x	x	xx	x
Regularity	x	x	x	x				x
Test assumptions					x	x	x	
No multicollinearity	x	x	x	x			x	x
All conventional inputs			x		xx	xx	xx	xx
All desirable outputs			x		xx	xx	xx	xx
Cost	xx	xxx	xx	xx	x	x	x	xx

Legend
A = Nitrogen surplus per ha; B = Cows per ha; C = Net value added per unit of emission (N surplus per ha); D = Fertiliser efficiency (Brouwer et al., 1997:58); E = Stochastic Frontier Approach as described in chapter 2 and 3; F = Distance function as described in chapter 4; G = Shadow cost system as described in chapter 5; H = Data Envelopment Analysis in chapter 3.

- Obviously indicators that incorporate *all (relevant) conventional inputs* and *all desirable outputs* are preferred over partial indicators (see also chapter 1).
- Indicators that can be obtained at low *cost* are preferred over costly indicators (Crabtree and Brouwer, 1999:280). Econometric efficiency measures are costly to obtain, because they require an extensive body of good data. The estimation also requires several tests to be carried out. DEA uses identical data, but is straightforward to compute with standard software. The simple partial indices (A - D) are easiest to compute. The data required for the calculation of nitrogen surplus and net value added are almost as costly to gather as the data for efficiency analysis.

The distinguished criteria are not independent of one another. If an indicator is directly measurable, it can be monitored at low cost, used for small samples, it is easy to communicate, does not require regularity constraints and does not suffer from multicollinearity. Indicators linked with economic theory have to meet regularity conditions, so the latter two criteria are complementary.

Indicators require a clear *context* and *purpose,* in terms of the information to be transferred and the types of target users (Crabtree and Brouwer, 1999:280). Different indicators of systems performance are usually required at different hierarchical levels (Gallopin, 1997). We need to select the most appropriate indicator for our objective. The objective of this thesis is twofold: (i) estimation of the economic and environmental efficiency of dairy farms in order to identify farms with good economic and environmental performance, and (ii) evaluation of environmental efficiency differences across these farms. To show that the best choice for another objective may be different, also the selection of an indicator for annual monitoring of environmental performance is elaborated. First the significance of the distinguished criteria is analysed for the aforementioned objectives (see Table 7.3). Then the information summarised in Table 7.2 is used to select the best environmental indicators for each of the two distinguished objectives.

The objective of this thesis suits a single solid analysis of environmental indicators. Reliable data are important, but the focus is more on the recent development (since implementation of the National Environmental Policy Plan (NEPP)) than on long time series. The linkage with the economic theory is important to obtain farms that are both technically and environmentally efficient. This analysis does not have to be repeated every year, therefore the cost factor is less important. It also puts less restrictions on the sample size.

Table 7.3 Schematic overview of the significance of the distinguished criteria for the two research objectives (+ important; - less important; ~ indifferent)

Criteria	Objective of thesis	Annual monitoring
Target	~	+
Stochastic	+	+
Reliable data	+	+
Directly measurable	-	+
Small samples	-	+
Communication	~	+
Linked with economic theory	+	~
Regularity	+	~
Test assumptions	+	~
No multicollinearity	+	+
All conventional inputs	+	~
All desirable outputs	+	~
Cost	-	+

Annual monitoring requires a consistent set of indicators that shows whether the target is approximated during the course of time. This exercise has to be done each year, making costs and reliable data into important factors. In an annual study directly measurable indicators are preferred because measurement errors can be kept to a minimum. The results of annual monitoring should be easily communicable to policymakers to show whether legislation needs adaption. The importance of the criteria for the distinguished objectives are presented in Table 7.3.

The environmental efficiency measures defined and estimated in this thesis relate a firm's technical and economic performance to its environmental pressure (columns E-H in Table 7.2). They are based on neoclassical theory and combine a firm's economic and environmental performance into one framework. Resource use efficiency combines technical and environmental performance into one indicator. From the other distinguished indicators (columns A-D in Table 7.2) net value added per kg N surplus is the only one that combines information about the economic performance with environmental performance. Therefore, we focus on a comparison of columns C and E-H.

A disadvantage of 'net value added per unit of nitrogen surplus' compared to the econometrically estimated environmental efficiency measures is that it is not stochastic, not linked with economic theory and does not contain information about all the conventional inputs (see Table 7.2). The scores on criteria of the SFA, distance function and cost system do not differ greatly (see Table 7.2). The SFA measures are easier to communicate than distance function and cost function measures. For a thorough analysis of the environmental performance of farms an econometric analysis provides the most useful results.

When the objective is annual monitoring of the environmental performance of farms, one of the alternative environmental indicators (A - D) will be more useful. A disadvantage of the environmental efficiency measures compared to partial measures (especially nitrogen surplus per ha and cows per ha) with respect to this objective is that they are more costly to obtain. The efficiency measures also require relatively large data sets. The computability of the econometrically estimated environmental efficiency scores cannot be guaranteed from the outset. Environmental efficiency scores are more difficult to communicate to policymakers. The SFA parameters can be estimated in one period and they can be used in the following years to compute environmental efficiency. These additional environmental efficiency scores can be computed easily with the input and output quantities of the following years. A disadvantage of DEA for annual monitoring is that the DEA scores are specific for the sample used. DEA scores only reflect the dispersion of efficiencies within each sample, they say nothing about the efficiency of one sample related to the other (Coelli et al., 1998). Therefore, the data of the next year cannot be easily incorporated in the analysis, without affecting the efficiency scores of the previous years. Disadvantages of the partial measures are that the outputs are not incorporated (A and B) and not all conventional inputs are taken into account (A-D). The use of partial measures (e.g. nitrogen per ha and cows per ha) is likely to result in excessive use of those variables not included in the indicator.

The SFA based efficiency measure is preferred over the indicators currently in use, because the stochastic frontier approach allows for the computation of the technical performance and the environmental performance. SFA also incorporates stochastic influences but is more costly than simple partial indicators. This selection of the appropriate indicator for the two objectives is presented as an example. The preferred indicator could be selected best when the distinguished indicators are computed for a group of farms in a specific period. The elaboration of that selection process is outside the scope of this thesis.

7.5 This thesis and LEI research

This section discusses how the Agricultural Economics Research Institute (LEI) could benefit from the results of this Ph.D.-thesis. Policy-relevant research (e.g. government, agribusiness) is very important in the LEI portfolio. Therefore we focus on how this thesis can contribute to future policy-relevant research [5]. Environmental efficiency measures, technical efficiency scores, frontiers, leaders and laggards and models of production are discussed briefly.

a Environmental efficiency measures

LEI could use the developed tools to compute the environmental performance of farms (and firms in agribusiness). The proposed environmental efficiency measures combine the technical and economic performance of dairy farms and their environmental pressure better than the current indicators such as nitrogen surplus per ha or dairy cows per ha (see section 7.4). The environmental efficiency measures help the government to identify the farms that best suit their policy objective. They also provide clues as to what extent environmental pressure can be reduced conditional on the current technology. Extension services, research and agribusiness could also benefit from this information. The methodology put forward in this thesis also allows evaluation of policy options to increase environmental efficiency (see chapter 6). For policy analysis the nitrogen surplus could be computed exactly according to the Minas-rules (the Dutch mineral accounting system) [6]. A comparison of the environmental efficiency measures presented in this Ph.D.-thesis and the efficiency measures based on the Minas-definitions provides information about the discrepancy between optimal production according to the actual process and optimal production according to current legislation. Current legislation focuses on the environmental pressure caused by farms, and is likely to lead to excessive use of inputs not incorporated in the indicator.

The government, business community and research institutes need a systematic and regular publication on environmental indicators in which the developments in agriculture

[5] This thesis also contributes to the LEI objective to gain expertise in exploiting FADN data.

[6] In this thesis nitrogen surplus is broadly defined, it also incorporats nitrogen from deposition and mineralisation. These two flows are not used in Minas to compute nitrogen surplus.

(and horticulture) are related to economic indicators. LEI has been monitoring the environmental performance of farms since a number of years (in the periodical 'Agriculture, Environment and Economics'; e.g., Poppe et al., 1996; Brouwer et al., 1997). In this periodical, fertiliser efficiency is reported as the ratio of the annual change in fertiliser quantity and output quantity (Brouwer et al., 1997:58). A rise in fertiliser efficiency means a reduction in fertiliser use per unit of output. This definition differs from the efficiency definitions in literature, because it does not describe the actual performance (it only describes the change in performance) and it does not compare observations with a benchmark.

Instead of fertiliser efficiency, environmental efficiency scores can be presented. To accomplish a standard method to compute these scores each year (also in future years) and for each observation, SFA is an appropiate choice (see section 7.4). Data on inputs and outputs are available at LEI, and the SFA scores can be computed with parameter estimates found in previous years. Therefore the costs are relatively small.

b Technical efficiency scores

LEI annually reports economic performance measures of farms (Van Dijk et al., 1996). The technical efficiency measure adds the element of benchmarking to the performance measures reported nowadays. The participants in FADN receive a performance report about their farm. If technical (or economic) efficiency is included in this report they are informed about the performance of their farm related to the best practice in FADN. SFA is the preferred method, because it accounts for noise. An advantage of DEA is that it readily provides peer farms, which serve as examples for improving the performance. Technical efficiency also provides the government with an indicator for possible improvements in the sector.

c Frontiers

The government expects that technological development will contribute to a sustainable development (VROM et al., 1997). The government can redirect the technological development by means of specific R&D policies. A productivity index is often used to compute technological development, because it can be computed as the ratio of (annual) change in outputs and (annual) change in inputs. However, productivity changes incorporate changes in (productive) efficiency, changes in scale of production, structural changes (entry and exit of firms) and technological change (Balk, 1998:113; Brümmer et al., 1998). The development of the frontier is a better indicator for technological change. The best practice frontier is a by-product of efficiency measurement. The development of this frontier indicates whether the direction of (pure) technological development is consistent with formulated policy.

d Leaders and laggards

In agricultural and environmental policy reports the leaders (trendsetters) are often considered as a good example for the sector as a whole (e.g. VROM et al., 1997:51). Environmentally efficient farms set an example for less environmentally efficient farms. Laggards are assumed to develop towards current leading farms. Problems specific to leading farms are likely to hit the other farms too. If the government identifies these problems at an early stage, they can be solved before the majority of farms has to deal with them. Another aspect is that the leaders are more likely to continue their farms in the long run than the laggards. Hence leaders hold up a mirror for future farms. The methods presented in this thesis enable the description of best practice (environmental) performance and objective identification of leaders (and laggards).

e Models of production that combine economics and environment

Important research trajectories for LEI are the computation of consequences of environmental regulation for farms, and the effects of agriculture on the environment. The interaction between economics and the environment can be improved with the methodology put forward in this Ph.D.-thesis in which pollution is incorporated in the neoclassical framework. The developed links between economics and environment could, for instance, be used in a future micro-simulation model.

As shown in this section, this thesis presents valuable new methods for LEI that suit the institute's rich data set.

References

Ahmad, M. and B.E. Bravo-Ureta (1995) An Econometric Decomposition of Dairy Output-Growth. *American Journal of Agricultural Economics* 77:4 (November), 914-921.

Ahmad, M. and B.E. Bravo-Ureta (1996) Technical Efficiency Measures for Dairy Farms Using Panel Data: a Comparison of Alternative Model Specifications. *The Journal of Productivity Analysis* 7:4 (October), 399-415.

Aigner, D.J., C.A.K. Lovell and P. Schmidt (1977) Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics* 6:1 (July), 21-37.

Anderson, C.L. (1987) The Production Process: Inputs and Wastes. *Journal of Environmental Economics and Management* 14:1 (March), 1-12.

Andreakos, I., V. Tzouvelekas, K. Mattas and E. Papanagiotou (1997) Estimation of Technical Efficiency in Greek Livestock Farms. *Cahiers d'Economie et Sociologie Rurales* 0 (42-43) 1st-2nd Trimester, 93-107.

Atkinson, S.E., and C. Cornwell (1994a) Parametric etimation of technical and allocative inefficiency with panel data. *International Economic Review* 35:1 (February), 231-243.

Atkinson, S.E. and C. Cornwell (1994b) Estimation of output and input technical efficiency using a flexible functional form and panel data. *International Economic Review* 35:1 (February), 245-255.

Atkinson, S.E., R. Färe and D. Primont (1998) Stochastic estimation of firm inefficiency using distance functions. Working Paper, University of Georgia.

Atkinson, S.E. and R. Halvorsen (1984) Parametric Efficiency Tests, Economies of Scale, and Input Demand in U.S. Electric Power Generation. *International Economic Review* 25:3, 647-662.

Atkinson, S.E. and D. Primont (1998) Stochastic estimation of firm technology, inefficiency, and productivity growth using shadow cost and distance functions. Paper presented at Georgia Productivity Workshop III, Athens GA, October 1998.

Bakkes, J. (1997) Research Needs; Introduction. In: Moldan, B., S. Billharz and R. Matravers (eds.), *Sustainability indicators: a Report on the Project on Indicators in Sustainable Development*. New York, John Wiley & Sons, p. 379-388.

Bakkes, J.A., G.J. van den Born, J.C. Helder, R.J. Sart, C.W.Hope and J.D.E. Parker (1994) An Overview of Environmental Indicators: State of the art and perspectives. UNEP/ RIVM, Environment Assessment Technical Reports 94-01.

Balk, B.M. (1998) *Industrial Price, Quantity and Productivity Indices; The Micro-Economic Theory and an Application*. Boston etc., Kluwer Academic Publishers.

Balk, B.M. and G. van Leeuwen (1998) *Parametric estimation of technical and allocative efficiencies and productivity changes: a case study*. Voorburg, Statistics Netherlands, Research paper no. 9820 (Revised version).

Ball, V.E., C.A.K. Lovell, R.F. Nehring and A. Somwaru (1994) Incorporating Undesirable Outputs into Models of Production: An Application to US Agriculture. *Cahiers d'Economique et Sociologie Rurales* 31, 59-73.

Baltussen, W.H.M., R. Hoste, C.H.G. Daatselaar and S.R.M. Janssens (1992) *Differences in Mineral Surpluses Between Farms in the Livestock Sector and in the Arable Sector* (in Dutch). The Hague, Agricultural Economics Research Institute (LEI-DLO), Onderzoekverslag 101.

Banker, R.D., A. Charnes and W.W. Cooper (1984) Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science* 30:9 (September), 1078-92.

Banker, R.D. and R. Morey (1986) Efficiency Analysis for Exogenously Fixed Inputs and Outputs. *Operations Research* 34:4, 513-21.

Barbera, A.J. and V.D. McConnell (1990) The Impact of Environmental Regulations on Industry Productivity: Direct and Indirect Effects. *Journal of Environmental Economics and Management* 18:1 (January), 50-65.

Battese, G.E. (1992) Frontier production functions and technical efficiency: a survey of empirical applications in agricultural economics. *Agricultural Economics* 7, 185-208.

Battese, G. E. and T.J. Coelli (1988) Prediction of Firm-Level Technical Efficiencies with a Generalized Frontier Production Function and Panel Data. *Journal of Econometrics* 38 (July), 387-399.

Battese, G.E. and T.J. Coelli (1992) Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India. *Journal of Productivity Analysis* 3:1/2 (June), 153-69.

Battese, G.E. and T.J. Coelli (1995) A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics* 20, 325-332.

Belsley, D.A., E. Kuh and R.E. Welsch (1980) *Regression Diagnostics: Identification of Influential Data and Sources of Collinearity*. New York, John Wiley & Sons.

Berentsen, P.B.M. (1999) *Economic-environmental modelling of Dutch dairy farms incorporating technical and institutional changes*. Ph.D. thesis, Wageningen Agricultural University.

Bergh, J.C.J.M. van den and P. Nijkamp (1994) Dynamic macro modelling and materials balance; Economic-environmental integration for sustainable development. *Economic Modelling* 11:3, 282-307.

Billharz, S. and B. Molden, (1997) Elements of a Research Agenda. In: Moldan, B., S. Billharz and R. Matravers (eds.), *Sustainability indicators: a Report on the Project on Indicators in Sustainable Development.* New York. John Wiley & Sons. p.389-395.

Boggs, R.L. (1997) *Hazardous Waste Treatment Facilities: Modeling Production with Pollution as Both an Input and an Output*. Unpublished Ph.D. dissertation, University of North Carolina, Chapel Hill.

Boots, M., A. Oude Lansink and J. Peerlings (1997) Efficiency loss due to distortions in Dutch milk quota trade. *European Review of Agricultural Economics* 24:1, 31-46.

Bouwman, W.A.H.B., J. Dijk, J.P.M. van Dijk, K. Lodder and L.C. van Staalduinen (1997) *The sample for the Dutch FADN, farm selection 1997 en selection plan* 1998 (in Dutch). The Hague, Agricultural Economics Research Institute (LEI-DLO), Periodieke Rapportage 4-97.

Bravo-Ureta, B.E. (1986) Technical Efficiency Measures for dairy farms based on a probablistic Frontier Function. *Canadian Journal of Agricultural Economics* 34, 399-415.

Bravo-Ureta, B.E. and L. Rieger (1991) Dairy Farm Efficiency Measurement Using Stochastic Frontiers and Neoclassical Duality. *American Journal of Agricultural Economics* 73: 2 (May), 421-428.

Brouwer, F.M., W.H.M. Baltussen and C.H.G. Daatselaar (eds.), (1997) *Agriculture, environment and economics* (in Dutch). The Hague, Agricultural Economics Research Institute (LEI-DLO), Periodieke Rapportage 68-95.

Brouwer, F. and S. van Berkum (1998) The Netherlands. In: F. Brouwer and P. Lowe (eds.), *CAP and the rural countryside in transition: A panorama of national perspectives.* Wageningen, Wageningen Pers. p. 167-184.

Brouwer, F. and B. Crabtree (1999) Introduction. In: Brouwer, F. and B. Crabtree (eds.), *Environmental indicators and agricultural policy*. Wallingford, CAB International. p.1-11.

Brümmer, B., T. Glauben and G. Thijssen (1998) *Unraveling the Productivity Growth of European Dairy Farms.* Paper presented at Georgia Productivity Workshop III, Athens GA, October 1998.

Burrell, A. (1989) The demand for fertiliser in the United Kingdom. *Journal of Agricultural Economics* 40:1 (January), 1-20.

Caves, D.W., L.R. Christensen and W.E. Diewert (1982) Multilateral comparisons of output, input and productivity using superlative index numbers. *The Economic Journal* 92 (March), 73-86.

Caves, D.W., L.R. Christensen and J.A. Swanson (1981) Productivity Growth, Scale Economies and Capacity Utilization in US Railroads, 1955-74. *American Economic Review* 71:5 (December), 994-1002.

CBS (1995) *Monthly Statistics of Agriculture, October 1995* (in Dutch). Voorburg, Statistics Netherlands.

CBS/LEI-DLO (1996) *Agricultural Data 1996* (in Dutch). Voorburg/The Hague: Statistics Netherlands/Agricultural Economics Research Institute (LEI-DLO).

Chambers, R.G. (1988) *Applied production analysis; A dual approach*. Cambridge, Cambridge University Press.

Chambers, R.G., R. Färe, E. Jaenicke and E. Lichtenberg (1998) Using Dominance in Forming Bounds on DEA models: The Case of Experimental Agricultural Data. *Journal of Econometrics* 85, 189-203.

Chambers, R.G. and E. Lichtenberg (1996) A Nonparametric Approach to the van Liebig-Paris Technology. *American Journal of Agricultural Economics* 78 (May), 373-386.

Charnes, A., C.T. Clark, W.W. Cooper and B. Golany (1985) A Developmental Study of Data Envelopment Analysis in Measuring the Efficiency of Maintenance Units in the U. S. Air Forces. *Annals of Operations Research* 2, 95-112.

Charnes, A.,W. Cooper, A.Y. Lewin and L.M. Seiford (1995) *Data Envelopment Analysis; Theory, Method and Application.* Boston etc., Kluwer.

Coelli, T.J. (1994) *A Guide to FRONTIER, Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation*. Department of Econometrics, University of New England, Armidale, NSW, Australia.

Coelli, T. (1995a) Estimators and Hypothesis Tests for A Stochastic Frontier Functions: A Monte Carlo Analysis. *Journal of Productivity Analysis* 6:3 (September) 247-268.

Coelli T.J. (1995b) Recent developments in frontier modelling and efficiency measurement. *Australian Journal of Agricultural Economics* 39:3 (December), 219-245.

Coelli, T. and S. Perelman (1996) *Efficiency measurement, multiple-output technologies and distance functions: with application to European railways*. Crepp Working Papers 96/05, Universite de Liege.

Coelli, T., D.S.P. Rao and G.E. Battese (1998) *An introduction to efficiency and productivity analysis*. Dordrecht, Kluwer.

Coggins, J.S. and J.R. Swinton (1996) The Price of Pollution: A dual Approach to Valuing SO_2 Allowances. *Journal of Environmental Economics and Management* 30:1 (January), 58-72.

Conrad, K. and C.J. Morrison (1989) The Impact of Pollution Abatement Investment on productivity Change: An Empirical Comparison of the U.S., Germany and Canada. *Southern Economic Journal* 55:3 (January) 684-698.

Cornwell, C., P. Schmidt and R. Sickles (1990) Production frontiers with cross-sectional and time-series variation in efficiency levels. *Journal of Econometrics* 46, 185-200.

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

Crabtree B. and F. Brouwer (1999) Discussion and Conclusions. In: Brouwer, F. and B. Crabtree (eds.), *Environmental indicators and agricultural policy*. Wallingford, CAB International. p.279-286.

Cropper, M.L. and W.E. Oates (1992) Environmental Economics: A Survey. *Journal of Economic Literature* XXX:2 (June), 675-740.

Dawson, P.J. (1987) Farm-specific techncial efficiency in the dairy sector. *European Review of Agricultural Economics* 14, 383-394.

Dietz, F.J. (1992) The Choice of Instruments in Dutch Manure Policy: Some Normative and Positive Remarks. In: Heijman, W.J.M. and J.J. Krabbe, (eds.), Wageningen Agricultural University, *Issues of Environmental Economic Policy*. Wageningen Economic Studies 24, p. 111-130.

Dijk, J. (1990) *Representativeness and Precision of Dutch Farming Sector Income Statistics.* Paper presented at the VI-th Congress of the European Association of Agricultural Economists, The Hague 3-7 September 1990.

Dijk, J., C. Baarda, R. van Broekhuizen, T. de Haan, W. Hennen, J.D. van der Ploeg and G. van de Ven (1998) *Ins and Outs; A multidisciplinary study after input-output relations and their relation with the decision making of farmers* (in Dutch). The Hague, Agricultural Economics Research Institute (LEI-DLO), Onderzoekverslag 160.

Dijk, J., H. Leneman and M. van der Veen (1996) The Nutrient Flow Model for Dutch Agriculture: A Tool for Environmental Policy Evaluation. *Journal of Environmental Management* 46, 43-55.

Dijk, J.P.M. van, B.E. Douma and A.L.J. van Vliet (1996*) Farm results in agriculture; book years 1991/92 till 1994/95* (in Dutch) The Hague, Agricultural Economics Research Institute (LEI-DLO), PR 68-92.

Elhorst, J.P. (1986) *An estimation of the production function and the profit function for Dutch agriculture* (in Dutch). The Hague, Agricultural Economics Research Institute (LEI), Onderzoekverslag 25.

Elhorst, J.P. (1990) *Income formation and income distribution in Dutch agriculture explained by the household production theory* (in Dutch). The Hague, Agricultural Economics Research Institute (LEI), Onderzoekverslag 72.

Färe, R., S. Grosskopf, B. Lindgren and P. Roos (1992) Productivity Changes in Swedish Pharmacies 1980-1989: A Non-Parametric Malmquist Approach. *Journal of Productivity Analysis* 3:1/2 (June), 85-102.

Färe, R., S. Grosskopf, C. A. K. Lovell and S. Yaisawarng (1993) Derivation of Shadow Prices for Undesirable Outputs: a Distance Function Approach. *The Review of Economics and Statistics* 75:2 (May), 374-380.

Färe, R., S. Grosskopf, C.A.K. Lovell and C. Pasurka (1989) Multilateral Productivity Comparisons When Some Outputs are Undesirable: a Nonparametric Approach. *The Review of Economics and Statistics* 71:1 (February), 90-98.

Färe, R., S. Grosskopf and D. Tyteca (1996) An activity analysis model of the environmental performance of firms - application to fossil-fuel-fired electric utilities. *Ecological Economics* 18, 161-175.

Färe, R. and C.A.K. Lovell (1978) Measuring the Technical Efficiency of Production. *Journal of Economic Theory* 19:1 (October), 150-62.

Färe R. and D. Primont (1995) *Multi-Output Production and Duality: Theory and Applications*. Boston etc., Kluwer Academic Publishers.

Färe, R. and G. Whittaker (1995) An Intermediate Input Model of Dairy Production Using Complex Survey Data. *Journal of Agricultural Economics* 46:2, 201-213.

Farrell, M.J. (1957) The measurement of productive efficiency. *Journal of Royal Statistical Society* 120: 253-281.

Ferrier, G.D. and C.A.K. Lovell (1990) Measuring cost efficiency in banking: econometric and linear programming evidence. *Journal of Econometrics* 46, 229-45.

Fontein, P.F., G.J. Thijssen, J.R. Magnus and J. Dijk (1994) On Levies to Reduce the Nitrogen Surplus: The Case of Dutch Pig Farms. *Environmental and Resource Economics* 4, 455-478.

Fox, G. and L. Kivanda (1994) Popper or Production? *Canadian Journal of Agricultural Economics* 42, 1-13.

Gallopin, G.C. (1997) Indicators and their use: information for decision making, introduction. In: Moldan, B., S. Billharz and R. Matravers (eds.) *Sustainability indicators: a Report on the Project on Indicators in Sustainable Development*. John Wiley & Sons, p.13-27.

Gong, B.H. and R.C. Sickles (1992) Finite Sample Evidence on the Performance of Stochastic Frontiers and Data Envelopment Analysis Using Panel Data. *Journal of Econometrics* 51:1/2 (January/February), 259-84.

Greene, W.E. (1993) The econometric approach of efficiency measurement. In: Fried, H.O., C.A.K. Lovell and S.S. Schmidt (eds.), *The Measurement of Productive Efficiency; Techniques and Applications*. New York, Oxford University Press, p.69-119.

Greene, W.E. (1997a) *Econometric Analysis, third edition*. London, Prentice Hall.

Greene, W.E. (1997b) Frontier Production Functions. In: Pesaran, H. and P. Schmidt (eds.), *Handbook of Applied Econometrics, Vol. II, Microeconomics*. New York. New York University. p.81-166.

Grosskopf, S., K.J. Hayes, L.L. Taylor and W.L. Weber (1997) Budget-constrained frontier measures of fiscal equality and efficiency in schooling. *The Review of Economics and Statistics* 75, 116-124.

Hallam, D. and F. Machado (1996) Efficiency Analysis With Panel Data: A Study of Portugese Dairy Farms. *European Review of Agricultural Economics* 23, 79-93.

Hammond, A., A. Adriaanse, E. Rodenburg, D. Bryant and R. Woodward (1995) *Environmental indicators: A systematic Approach to Measuring and Reporting on Environmental Policy performance in the Context of Sustainable Development*. Washington, World Resources Institute.

Haynes, K.E., S. Ratick, W.M. Bowen and J. Cummings-Saxton (1993) Environmental Decision Models: U.S. Experience and a New Approach to Pollution Management. *Environment International* 19, 261-75.

Haynes, K.E., S. Ratick and J. Cummings-Saxton (1994) Toward a Pollution Abatement Monitoring Policy: Measurements, Model Mechanics, and Data Requirements. *The Environmental Professional* 16, 292-303.

Helming J., A. Oskam and G. Thijssen (1993) A micro-economic analysis of dairy farming in the Netherlands. *European Review of Agricultural Economics* 20, 343-363.

Hennen, W.H.G.J. (1995) *Detector, Knowledge-based systems for dairy farm management support and policy analysis; Methods and applications*. The Hague, Agricultural Economics Research Institute (LEI-DLO), Onderzoekverslag 125.

Heshmati, A. and S.C. Kumbhakar (1994) Farm heterogeneity and Technical Efficiency: Some Results from Swedish Dairy Farms. *The Journal of Productivity Analysis* 5:1 (April), 45-61.

Hetemäki, L. (1996) *Essays on the Impact of Pollution Control on a Firm: A Distance Function Approach*. Helsinki, The Finnish Forest Research Institute, Research Papers 609.

Higgins J. (1986) Input demand and output supply on Irish farms - A micro-economic approach. *European Review of Agricultural Economics* 13, 477-493.

Hjalmarsson, L., S.C. Kumbhakar and A. Heshmati (1996) DEA, DFA and SFA: A Comparison. *Journal of Productivity Analysis* 7:2/3 (July), 303-327.

Huang, C.J. and J.T. Liu (1994) Estimation of a Non-Neutral Stochastic Production Function. *Journal of Productivity Analysis* 5, 171-180.

Ittersum, M.K. van and R. Rabbinge (1997) Concepts in Production Ecology for Analysis and Quantification of Agricultural Input-Output Combinations. *Field Crops Research* 52, 197-208.

Jamison, D.T. and L.J. Lau (1982) *Farmer Education and Farmer Efficiency*. Baltimore and London, Johns Hopkins University Press.

Judge, G., C. Hill, W. Griffths, T. Lee and H. Lutkepol (1982) *An Introduction to the Theory and Practice of Econometrics*. New York, John Wiley & Sons.

Kalirajan, K. (1990) On Measuring Economic Efficiency. *Journal of Applied Econometrics* 5, 75-85.

Koeijer, T.J. de, G.A.A. Wossink, M.K. van Ittersum, P.C. Struik and J.A. Renkema (1998) A Conceptual Model for Analysing Input-Output Coefficients in Arable Farming Systems: From Diagnosis Towards Design. Forthcoming in *Agricultural Systems.*

Kopp, R.J. (1981) The Measurement of Productive Efficiency: a Reconsideration. *Quarterly Journal of Economics* 96:3 (August), 477-503.

Kopp, R. and W. Diewert (1982) The Decomposition of Frontier Cost Function Deviations into Measures of Technical and Allocative Efficiency. *Journal of Econometrics*, 19:2/3 (August), 319-332.

Kumbhakar, S.C. (1993) Short Run Returns to Scale, Farm Size, and Economic Efficiency. *The Review of Economics and Statistics* 75:2, 336-341.

Kumbhakar, S.C. (1996) Efficiency Measurement with Multiple Outputs and Multiple Inputs. *Journal of Productivity Analysis* 7:2/3 (July), 225-256.

Kumbhakar, S.C. (1997) Modeling allocative inefficiency in a translog cost function and cost share equations: an exact relationship. *Journal of Econometrics* 76:1-2 (January-February), 351-356.

Kumbhakar, S.C. and A. Bhattacharyya (1992) Price, Distortions and Resource-Use Efficiency in Indian Agriculture: A Restricted Profit Function Approach. *The Review of Economics and Statistics* 74:2 (May), 231-239.

Kumbhakar, S.C., B. Biswas and D.V. Bailey (1989) A study of economic efficiency of Utah dairy farmers: a system approach. *The Review of Economics and Statistics* 71:4 (November), 595-604.

Kumbhakar, S.C., S. Ghosh and J.T. McGuckin (1991) A Generalized Production Frontier Approach for Estimating Determinants of Inefficiency in U.S. Dairy Farms. *Journal of Business and Economic Statistics* 9, 279-286.

Kumbhakar, S.C. and A. Heshmati (1995) Efficiency measurement in Swedish Dairy Farms: An Application of Rotating Panel Data, 1976-88. *American Journal of Agricultural Economics* 77:3 (August), 660-674.

Kumbhakar, S.C. and L. Hjalmarsson (1993) Technical Efficiency and Technical Progress in Swedish Dairy Farms. In Fried, H.O., C.A.K. Lovell and S.S. Schmidt (eds.), *The Measurement of Productive Efficiency; Techniques and Applications*. New York, Oxford University Press, p.256-270.

Kumbhakar, S.C. and C.A.K. Lovell (1999) *Stochastic Frontier Analysis*. New York, Cambridge University Press.

Land. K., C.A.K. Lovell and S. Thore (1993) Chance-Constrained Data Envelopment Analysis. *Managerial and Decision Economics* 14:6 (November/December), 541-554.

Lau, L.J. and P.A. Yotopoulos (1971) A test for relative efficiency and application to Indian agriculture. *American Economic Review* 61:1, 94-109.

Lovell, C.A.K. (1993) Production Frontiers and Productive Efficiency. In: Fried, H.O., C.A.K. Lovell and S.S. Schmidt (eds.), *The Measurement of Productive Efficiency; Techniques and Applications*. New York, Oxford University Press, p.3-67.

Lovell, C.A.K., S. Richards, P. Travers and L.L. Wood (1994) Resources and Functionings: A New View of Inequality in Australia. In: W. Eichhorn (ed.), *Models and Measurement of Welfare and Inequality*. Berlin, Springer-Verlag, p. 787-807.

Lovell, C.A.K. and R.C. Sickles (1983) Testing efficiency hypotheses in Joint Production. *Review of Economics and Statistics* 65:1 (February), 51-58.

Lund, M., B.H. Jacobson and L.C.E. Hansen (1993) Reducing Non-Allocative Costs on Danish Dairy Farms: Applications of Non-Parametric Methods. *European Review of Agricultural Economics* 20, 327-341.

Maddala, G.S. (1988) *Introduction to Econometrics*. New York, Macmillan.

Meeusen, W. and J. van den Broeck (1977) Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *International Economic Review* 18:2 (June), 435-444.

MLNV (1990) *Structuurnota Landbouw, Regeringsbeslissing.* Den Haag, Staatsuitgeverij and Ministry of Agriculture Nature conservation and Fisheries

Morrison, C.J. and W.E. Johnston (1996) *Efficiency in New Zealand Sheep and Cattle Farming: Pre- and Post- Reform.* Paper presented at Georgia Productivity Workshop II, Athens GA, November 1996.

Müller, J. (1974) On Sources of Measured technical Efficiency: The Impact of Information. *American Journal of Agricultural Economics* 56:4 (November), 730-738.

MVROM, MEZ, MLNV and MV&W (1997) *Nota Milieu en Economie; op weg naar een duurzame economie*. Ministry of Housing, Regional development and the Environment, Ministry of Economic affairs, Ministry of Agriculture, Nature conservation and Fisheries and the Ministry of transport and public works.

MVROM and MLNV (1995) *Integrale Notitie Mest- en Ammoniakbeleid*. Den Haag. Ministry of Housing, Regional development and the Environment and Ministry of Agriculture Nature conservation and Fisheries.

OECD (1994) *OECD Environmental performance reviews; Netherlands*. Paris, OECD.

OECD (1997) *OECD Environmental Indicators for Agriculture*. Paris, OECD.

Olesen, O.B. and N.C. Petersen (1995) Chance Constrained Efficiency Evaluation. *Management Science* 41:3 (March), 442-57.

Oskam, A. (1991) Productivity measurement, incorporating environmental effects of agricultural production. In: Burger K., M. de Groot, J. Post and V. Zachariasse (eds.), *Agricultural economics and policy: international challenges for the nineties; essays in honour of prof. Jan de Veer*. Amsterdam etc., Elsevier, Developments in Agricultural Economics 7. p.186-204.

Oskam, A. and R. Vijftigschild (1999) Towards Environmental Pressure Indicators for Pesticide Impacts. In: Brouwer, F. and B. Crabtree. *Environmental indicators and agricultural policy*. Wallingford, CAB international. p.157-176.

Oude Lansink, A. and J. Peerlings (1997) Effects of N surplus taxes: Combining technical and historical information. *European Review of Agricultural Economics* 24:2, 231-247.

Oum, T.H. and Y. Zhang (1995) Competition and Allocative Efficiency: The Case of the U.S. Telephone Industry. *Review of Economics and Statistics* 77:1 (February), 82-96.

Parris, K. (1999) Environmental indicators for agriculture: OECD progress report. In: Brouwer, F.M. and B. Crabtree (eds.), *Environmental indicators and agricultural policy*. Wallingford, CAB International, p.25-44.

Perman R., Y. Ma and J. McGilvray (1996) *Natural Resources & Environmental Economics*. London & New York, Longman.

Piot-Lepetit I. and D. Vermersch (1998) Pricing Organic Nitrogen Under The Weak Disposability Assumption: An Application to the French Pig Sector. *Journal of Agricultural Economics* 49:1, 85-99.

Pitt, M. and L.F. Lee (1981) The Measurement and Sources of Technical Inefficiency in the Indonesian Weaving Industry. *Journal of Development. Economics* 9 (August), 43-64.

Pittman, R.W. (1981) Issues in Pollution Control: Interplant Cost Differences and Economies of Scale. *Land Economics* 57:1 (February), 1-17.

Pittman, R.W. (1983) Multilateral Productivity Comparisons with Undesirable Outputs. *Economic Journal* 93 (December), 883-91.

Ploeg, J.D. van der, H. Renting and J. Roex (1994) *Multiple comparisons and a lot of unknowns: a exploring research after empirical input-output relations in Dutch dairy farming* (in Dutch). The Hague, NRLO, Rapport 94/1.

Poppe, K.J. (ed.), (1992) *The Dutch FADN from A till Z* (in Dutch). The Hague, Agricultural Economics Research Institute (LEI-DLO), Publikatie 3.151.

Poppe, K.J., F.M. Brouwer, J.P.P.J. Welten and J.H.M. Wijnands (eds.), (1995) *Agriculture, environment and economics* (in Dutch). The Hague, Agricultural Economics Research Institute (LEI-DLO), PR 68-92.

Reifschneider, D. and R. Stevenson (1991) Systematic Departures from the frontier: A Framework for the Analysis of Firm Inefficiency. *International Economic Review* 32:3 (August), 715-723.

Reinhard, S. and G. Thijssen (1998) Resource Use Efficiency of Dutch Dairy Farms; A Parametric Distance Function Approach. Selected Paper Presented at the Annual Meeting of the AAEA, Salt Lake City, August 1998. Abstract in *American Journal of Agricultural Economics* 80:5, 1205.

Reinhard, S. and M. van der Zouw (1995) Regional Efficiency Differences in Dutch Horticulture. In: Sotte F. (ed.), *The Regional Dimension in Agricultural Economics and Politics*. Proceedings of the 40th EAAE Seminar, 26-28th June. Ancona, Italy, p.617-631.

Reinhard, S., C.A.K. Lovell and G. Thijssen (1999) Econometric Estimation of Technical and Environmental Efficiency: An Application to Dutch Dairy Farms. *American Journal of Agricultural Economics* 81:1 (February), 44-60.

RIVM (1988) *Care for tomorrow; national environment study 1985-2010* (in Dutch). Alphen aan den Rijn, Samson.

Romstad, E. (1999) Theoretical Considerations in the Development of Environmental Indicators. In: Brouwer, F. and B. Crabtree (eds.), *Environmental indicators and agricultural policy*. Wallingford, CAB International p.13-24.

Rougoor, C.W., G. Trip, R.B.M. Huirne and J.A. Renkema (1998) How to Define and Study Farmers' Management Capacity: Theory and Use in Agricultural Economics. *Agricultural Economics* 18, 261-272.

Rutten, H. (1992) *Productivity Growth of Dutch Agriculture, 1949-1989*. The Hague, Agricultural Economics Research Institute (LEI-DLO), Mededeling 470.

Schmidt, P. and C.A.K. Lovell (1979) Estimating Technical and Allocative Inefficiency Relative to Stochastic Frontiers and Cost Frontiers. *Journal of Econometrics* 9, 343-366.

Schmidt, P. and T-F. Lin (1984) Simple Tests of Alternative Specifications in Stochastic Frontier Models. *Journal of Econometrics* 24, 349-361.

Shephard, R.W. (1953) *Cost and Production Functions*. Princeton, Princeton University Press.

Shephard, R.W. (1970) *Theory of Cost and Production Functions*. Princeton, Princeton University Press.

Simar, L., C.A.K. Lovell and P. Vanden Eeckaut (1994) *Stochastic frontiers incorporating exogenous influences on efficiency*. Discussion paper, Institut de statistique, Université Catholique de Louvain-la-Neuve.

Smith, J.B. and S. Weber (1989) Contemporaneous Externalities: Rational Expectations, and Equilibrium Production Functions in Natural Resource Models. *Journal of Environmental Economics and Management* 17:2 (September), 155-170.

Stefanou, S.E. and S. Saxena (1988) Education, Experience, and Allocative Efficiency: A Dual Approach. *American Journal of Agricultural Economics* 70:2 (May), 338-345.

Stevenson, R.E. (1980) Likelihood Functions for Generalized Stochastic Frontier Estimation. *Journal of Econometrics* 13:1 (May), 58-66.

Stigler, G.J. (1976) The Xistence of X-Efficiency. *American Economic Review* 66:1 (March), 213-216.

Tauer, L.W. (1998) Productivity of New York Dairy farms Measured by NonParametric Malmquist Indices. *Journal of Agricultural Economics* 49:2 (Spring), 234-249.

Thijssen, G. (1992) A Comparison of Production Technology Using Primal and Dual Approaches: The Case of Dutch Dairy Farms. *European Review of Agricultural Economics* 19:1, 49-65.

Tracy, M. (1989) *Government and Agriculture in Western Europe, 1880-1988*. London, Harvester-Wheatsheaf.

Turner, J.A. (1995) *Measuring the Cost of Pollution Abatement in the U.S. Electric Utility Industry: A Production Frontier Approach.* Ph.D. dissertation, University of North Carolina, Chapel Hill.

Tyteca, D. (1996) On the Measurement of Environmental Performance of Firms: A Literature Review and a Productive Efficiency Perspective. *Journal of Environmental Management* 46, 281-308.

Tyteca, D. (1997) Linear Programming Models for the Measurement of Environmental Performance of Firms--Concepts and Empirical Results. *Journal of Productivity Analysis* 8:2 (May), 183-198.

Uhlin, H-E. (1985) *Concepts and Measurement of Technical and Structural Change in Swedish Agriculture.* Uppsala, Sweden, Institutionen for Ekonomie och Statistik, Swedish University of Agricultural Sciences.

Vatn, A., L.R. Bakken, P. Botterweg, H. Lundeby, E. Romstad, P.K. Rorstad and A. Vold (1997) Regulating nonpoint-source pollution from agriculture: An integrated modelling analysis. *European Review of Agricultural Economics* 24:2, 207-230.

Vellinga, Th.V. and E.N. van Loo (1994) *Impact of Grass Breeding on Farm Income and Mineral Surpluses.* Lelystad, PR, Rapport nr. 151.

Wang, J., E.J. Wailes and G.L. Cramer (1996) A Shadow-Price Frontier Measurement of Profit Efficiency in Chinese Agriculture. *American Journal of Agricultural Economics* 78:1 (February), 146-156.

Weersink, A., C.G. Turvey and A. Godah (1990) Decomposition Measures of Technical Efficiency for Ontario Dairy Farms. *Canadian Journal of Agricultural Economics* 38, 439-456.

Williamson, O.E. (1998) Transaction Cost Economics: How It Works, Where it is Headed. *De Economist* 146, 23-58.

Wit, C.T. de (1992) Resource Use Efficiency in Agriculture. *Agricultural Systems* 40, 125-151.

Yadav, S.A., W. Peterson and K.W. Easter (1997) Do Farmers Overuse Nitrogen Fertilizer to the detriment of the Environment? *Environmental and Resource Economics* 9, 323-340.

Yaisawarng, S. and J.D. Klein (1994) The Effects of Sulfur Dioxide Controls on Productivity Change in the US Electric Power Industry. *Review of Economics and Statistics* 76:3 (August), 447-460.

Zoebl, D. (1996) Controversies around Resource Use Efficiency in Agriculture: Shadow or Substance? Theories of C.T. de Wit (1924-1993). *Agricultural Systems* 50, 415-24.

Zofio, J.L. and A.M. Prieto (1996) *DEA Environmental Standards Modelling.* Working Paper, Department of Applied Economics, Universidad Autónoma de Madrid, Spain.

Appendix A Overview of papers on efficiency measurement in dairy (livestock) farming

Reference	Country	Period	# of farms (obs)	Estimation a) [Specification]	Average in-efficieny	Explains efficiency
Ahmad & Bravo-Ureta, 1995	USA (Vermont)	71-84	96 (1,072)	SFA - FE [CD]	TE 0.77	Yes Corr.Coef.
Ahmad and Bravo-Ureta, 1996	USA (Vermont)	71-84	96 (1,072)	SFA - FE [CD - STL]	TE 0.764	Yes Corr.Coef.
Andreakos, et al., 1997	Greece	89-92	60 (240)	RE - FE [CD]	TE 0.76	Yes (OLS)
Bravo-Ureta, 1986	USA (New England)	1980	222	PFPF [CD]	TE 0.822	No
Bravo-Ureta and Rieger, 1991	USA (New England)	1984	511	SFA [CD]	TE 0.830 AE 0.846 OE 0.702	Yes (Anova)
Dawson, 1987	United Kingdom	76/7 80/1 84/5	490 406 406	SFA [TL]	TE 0.85	No
Färe and Whittaker, 1995	USA	1989	137	DEA	TE 0.709 b)	No
Hallam and Machado, 1996	Portugal	89-92	85 (340)	FE-RE- SFA [TL]	TE 0.69	Yes (OLS)
Heshmati and Kumbhakar, 1994	Sweden	76-78 79-91 82-84 86-88	740 (2,220)	FE+MLE [TL]	TE 0.813 TE 0.832 TE 0.822 TE 0.823	No
Kumbhakar et al., 1989	USA (Utah)	1985	89	MLE +shares [CD]	TE 0.885 b) AE 0.963 SE 0.888	Yes, 3 samples
Kumbhakar et al., 1991	USA	1985	519	MLE +shares [CD]	TE 0.695 b)	Yes, in prod. func
Kumbhakar, 1993	USA (Utah)	1985	89	MLE +shares [ZR]	No scores	Yes, in prod. func
Kumbhakar and Hjalmarson, 1993	Sweden	60-67 68-75	29 (232) 76 (608)	FE+MLE [TL]	TE 0.879 (1963) TE 0.900 (1970)	No

Reference	Country	Period	# of farms (obs)	Estimation a) [Specification]	Average in-efficieny	Explains efficiency
Kumbhakar and Heshmati, 1995	Sweden	76-88	1131 (4,890)	GLS+MLE [TL]	OE 0.847 PC 0.909 RC 0.932	No
Lund et al., 1993	Denmark	85-89 (mean)	248	Non parametric	CE 0.806 PCE 0.845 SE 0.953	Farm size
Müller, 1974	USA (Califor)	60-63 &64	152 39	OLS [modified CD]	No Scores	Yes, in prod. func
Reinhard et al., 1999	the Nether-lands	91-94	613 (1,545)	SFA [TL]	TE 0.89 EE 0.44	Intensity
Stefanou and Saxena, 1988	USA (Penn-syl)	131	1982	Profit function [Leontief]	No Scores	Education Managem.
Tauer, 1998	USA (N.York)	85-93	70 (630)	DEA distance functions	TE 0.918	No
Uhlin, 1985	Sweden	60-67 68-75	29 76	Non parametric	TE 0.75 TE 0.69 SE 0.80 SE 0.99	Yes (OLS)
Weersink et al., 1990	Canada (Ontario)	87	105	Non parametric	OE 0.92 TE 0.95 CE 0.998 SE 0.97	Yes Censored regr.

a) Default is a production frontier, the abbreviations are explaned in the legend; b) The results of the medium size farms are reported.

Legend

Estimation/Specification

SFA = Stochastic Frontier
FE = Fixed Effects
RE = Random Effects
MLE = Maximum Likelihood
DEA = Data Envelopment Analysis
CD = Cobb Douglas
TL = full Translog
STL = Simplified translog
ZR = Zellner-Revankar generalised production function
PFPF = Probablistic Frontier prod function

Efficiency Measures

OE = Overall efficiency (Technical and Allocative)
TE = (pure) Technical efficiency
AE = allocative efficiency
SE = Scale efficiency
CE = Congestion
EE = Environmental efficiency
PCE = Pure Cost Efficiency
PC = Persistent Component
RC = Residual Component

Appendix B Aggregation of Farm Accountancy Data Network (FADN) data

The data set used for this study is extracted from the Dutch Farm Accountancy Data Network (FADN) at LEI. The FADN is a stratified random sample. Every farm in the FADN has a weighing factor; the number of farms it represents. Annual data of participating farms are available. In this appendix the aggregation of accounting data into variables used for estimation is described. These aggregations are weighed with the weighing factor of the corresponding stratum.

In the FADN the costs (expenses) of inputs and the revenues from produce sold are recorded extensively. Implicit quantity indices for variable inputs, capital stock and outputs are obtained as the ratio of the value to the price index. These variables (quantity indices) are expressed in prices of a specific year; 1991 is the base year in this research. The price index varies over the years but not over the farms, implying that differences in the composition or quality of a netput are reflected in the quantity (Cox and Wohlgenant, 1986). The price index used in this study is the average of the multilateral Törnqvist price index over the farms (Higgins, 1986; Caves et al., 1982). The variable input quantity index contains hired labour, concentrates, roughage, fertiliser and other variable inputs. Capital stock includes equipment, buildings, breeding and utilisation livestock and land. The output quantity index consists of milk, meat, fattening livestock and roughage sold.

The quantity acquired is registered for many input components (e.g. nitrogen fertiliser) and outputs. The information about value and quantity of a component is used to compute the actual price paid (quotient of the value and the quantity). These prices are used to compute Törnqvist price indices. The method is elaborated for aggregation of variable inputs; identical formulas apply for capital stock and output.

$$\ln w_{jit} = \sum_{k=1}^{K} 0.5(s_{jkit} + \bar{s}_{jkb})(\ln w_{jkit} - \ln \overline{w}_{jkb}) \tag{B1}$$

where

s_{jkit}= share of component, k, in total expenses of input, j, on farm, i, in year, t.

s_{jkb}= average share of component, k, in total expenses of input, j, in base year.

$w_{jit=}$ price of input j (with k components), on farm, i, in year, t.

$w_{jkit=}$ price of component, k, on farm, i, in year, t.

$\ln \overline{w}_{jkb}$ = average of the logarithm of the prices of component, k, of input,j, in base year.

The price index used per farm is not the index of equation (B1), but the average of this price index over the farms in a specific year:

$$w_{jt} = \frac{1}{I} * \sum_{i=1}^{I} w_{jit} \tag{B2}$$

The quantity applied of input, j, on farm, i, in year,t is then:

$$x_{jit} = \frac{v_{jit}}{w_{jt}} \tag{B3}$$

where
x_{jit} is the quantity of input, j, on farm, i, in year,t.
v_{jit} is the value (costs) of input, j, on farm, i, in year,t.

When for a single observation the quantity of a component, k, is not available, the price cannot be computed as described above in equation (B1). In this situation we assume that the price paid by the farmer is identical to the average price in that year. If the quantity of a component, k, is not available at all in the FADN, prices are used from CBS/LEI. These CBS/LEI prices do not vary across farms.

The price index of capital stock (except land) is calculated as the multilateral Törnqvist index of the revaluations of the capital stock in the sample. The value of equipment, breeding and utilisation livestock and buildings is known at the start-balance and end-balance of each year. The difference between the start-balance of year, t, and the end-balance of year, t-1, is due to revaluation of capital stock (Elhorst, 1986:82). The price of capital is computed as:

$$w_{kit} = w_{ki(t-1)} * (1 + (vsb_{kit} - veb_{ki(t-1)}) / veb_{ki(t-1)}) \tag{B4}$$

where:
w_{kit} = price of capital category, k, on farm, i, in year, t;
vsb_{kit}= value at start-balance of capital category, k, on farm, i, in year, t;
$veb_{\mathrm{ki(t-1)}}$= value at end-balance of capital category, k, on farm, i, in year, t-1;

We distinguish two types of livestock: breeding and utilisation stock (e.g. milch cows, sheep, breeding sows, laying hens) and fattening stock (hogs, pigs, table chickens and veal calves). The quantity of breeding stocks is considered to be a capital component. The purchase and sale of breeding stocks are treated as investments. Growth of the breeding stock herd and differences in the book value of fattening stock are revenues.

In the FADN only buildings owned are accounted for. It is not possible to divide the rent paid into a portion related to land and one related to buildings. We used OLS to relate the value of buildings to the total standard size units of the farm (other variables like the quantity of livestock standard size units did not contribute significantly). We estimated this relation for farms that (i) own more than two third of their land or (ii) own more than one third and the value of their buildings is more than NLG 20,000. The parameter estimates are used to estimate the value of buildings for the other farms.

For each soil type [1] a free market price for arable land and for grassland is given in LEI/CBS. To prevent large fluctuations of the land price, the three year moving average price is used. The value of the land is computed as the product of the price per ha for the relevant soil type and the farm's acreage. When a farm has land on two soil types, two third of the acreage is assumed to be of the major type and one third of the minor type [2]. A multilateral Törnqvist price index (similar to equation B1) is used to aggregate the price indices of the components of capital stock (buildings, equipment, livestock and land).

[1] The land prices are given by 14 regions (soil types) in LEI/CBS, in the FADN 7 soil types are used. This information is combined into 5 soil types; sea sediment clay, river sediment clay and loss, peat and clay on peat, sand, reclaimed peatland.
[2] The major and minor soil types are available in the FADN.

Summary

For a long time, the objective of policies regarding the Dutch agricultural sector was to increase agricultural productivity. The productivity has increased rapidly in the Netherlands since World War II; technological development enabled the substitution of variable inputs (fertiliser, feed and pesticides) for labour. The increased use of variable inputs led to environmental side effects. The nitrogen emission of livestock farming was the largest source of the high concentration of nitrates in the ground water and discharge of ammonia. The emission of ammonia contributed to acid rain. The objective of the government with respect to agriculture has changed; now it aims for a competitive and sustainable agriculture and save food. This objective is translated into legislation with respect to the production and application of manure. Since 1998, dairy farms with more than 2.5 cows per hectare have to keep a nutrient balance sheet and the nutrient surplus is taxed. The government needs to know which farms are efficient with respect to the conventional inputs (e.g. capital and feed) and with are efficient with respect to the environment as well; these farms are competitive and sustainable. In line with the traditional policy on agriculture, the technical and economic efficiency of dairy farms has been researched intensively. With the increasing consciousness about the environmental problems caused by agriculture, the environmental performance of farms has become increasingly important. Although indicators are available for both the economic and environmental objectives of the government, a comprehensive performance measure that combines economic and environmental performance has not yet been developed. At present, the supply of quantitative information about agri-environmental linkages is inadequate. The standard method to capture the environmental pressure into one indicator is to use a relative performance measure, such as the nitrogen surplus per hectare. These relative performance measures have a serious flaw, in that they only consider a portion of the relevant production process. The use of partial measures in the formulation of policy advice is likely to result in excessive use of those inputs, which are not included in the performance measure.

The standard efficiency methodology is an attractive framework to analyse the environmental performance of farms. Technical efficiency reflects the ability of a farm to obtain maximum output from a given set of inputs. Allocative efficiency reflects the ability of a firm to use the inputs in the optimal proportions. These two components are then combined to provide a measure of total economic efficiency (the possibility to educe the costs). Efficiency scores are expressed on a 0 to 1 scale, where an efficient farm has a score of unity. The efficient farm is indicative for the other firms. Advantages of this efficiency framework

are that the technical efficiency measures do not need price information, the efficiency scores readily show the potential improvements. Another advantage of the efficiency methodology is that it fits in with the expression ‘eco-efficiency’ or ‘environmental efficiency’ that is often used in policy reports. The two important methods to compute technical efficiency are mathematical programming methods and econometric methods. This thesis focuses on the econometric methods. These latter methods are preferred in agriculture, where stochastic influences (e.g. weather and diseases) play an important role. The three important methods to estimate efficiency econometrically are (i) stochastic frontier approach; (ii) distance function and (iii) cost function.

Recently the efficiency methodology was applied for environmental problems. Environmental efficiency scores are only computed with mathematical programming methods. To estimate environmental efficiency econometrically the environmentally detrimental variables have to be adequately incorporated in the neo-classical production model. The most important environmental problem of the dairy sector is the emission of nitrogen. Nitrogen emission is an example of non-point source pollution, the discharge of nitrogen from a dairy farm can hardly be measured. The quantity of nitrogen emitted, is commonly estimated by using the materials balance. Therefore this thesis focuses on the nitrogen surplus. This surplus is defined as the difference between nitrogen in inputs (mainly fertiliser and feed bought) and nitrogen in outputs (milk and beef). In this thesis data are used that describe the production process of highly specialised dairy farms that are included in the Dutch Farm Accountancy Data Network (FADN). Since 1991, detailed information is available about the nutrient accounts of these farms.

The objective of this thesis is to define, estimate and evaluate the environmental efficiency of Dutch dairy farms.

In chapter 2 the stochastic frontier approach (SFA) is used to estimate environmental efficiency. Nitrogen surplus is modelled as in input in the production process. Environmentally detrimental variables and inputs have identical impact on the production frontier. SFA estimates the potential increase of production (till the frontier is reached), conditional on inputs applied. To compute environmental efficiency the output-oriented SFA efficiency scores are transformed into an input-reducing orientation. Environmental efficiency is defined as the ratio of minimum feasible use to observed use of environmentally detrimental input. The mean environmental efficiency score of the dairy farms in the panel is 0.44. According to this model the discharge of nitrogen can be reduced with 56% without a loss in production.

The SFA method presented in chapter 2 is extended to the multiple environmentally detrimental input case. Environmental efficiency scores are based on nitrogen surplus, phosphate surplus and total (direct and indirect) energy. This environmental efficiency measure is based upon the maximum radial contraction of all environmentally detrimental inputs. Environmental efficiency is defined as the ratio of minimum feasible use to observed use of multiple environmentally detrimental inputs, conditional on observed levels of the desirable output and conventional inputs. We show that this comprehensive environmental efficiency measure can be estimated with SFA and Data Envelopment Analysis (DEA). In contrast to DEA, an advantage of SFA is that the necessary assumptions with respect to the environmentally detrimental variables can be tested. However, in the three bad input case the monotonicity assumptions required by neo-classical production theory are violated. Therefore, the SFA environmental efficiency scores are based on nitrogen surplus and total energy (mean environmental efficiency is 0.80). DEA can compute environmental efficiency measures based on the three bad inputs because regularity assumptions are imposed (mean environmental efficiency is 0.52).

In the previous chapters environmentally detrimental variables were modelled as inputs. The distance function allows more than one output to be modelled. In chapter 4 nitrogen surplus is modelled as a bad output in an output distance function. Nitrogen emission is a non-point source pollution and is measured by to the materials balance definition as nitrogen surplus. The quantity of nitrogen in inputs has to be divided between desirable output and nitrogen surplus. This materials balance definition suggests that desirable output and nitrogen pollution are substitutes, contrary to the assumption made in the literature with respect to point-source pollution. In the output distance function the standard output-maximising technical efficiency measure does not provide an appropriate measure for environmental efficiency, because at the efficient point the production of bad output is larger than the observed bad output. Therefore, a different approach is used. The outputs are ex-post weighed according to their social value; a non-positive price of nitrogen surplus is used. Environmental efficiency is defined as the ratio of the revenue at the technically efficient output mix and the revenue at the optimal output mix (maximum feasible revenue) conditional on the inputs and a non-positive price of the bad output. Resource use efficiency reflects the efficient use of conventional resources (conventional inputs) and natural resources (nitrogen surplus). Resource use efficiency combines technical and environmental efficiency and is defined as the ratio of observed revenue and maximum feasible revenue. The mean resource use efficiency is 0.725. The resource use efficiency is positively correlated with the number of cows per hectare. We find positive shadow prices for nitrogen surplus, contrary to the literature on point-source pollution.

To incorporate behavioural assumptions in the estimation of environmental efficiency, nitrogen surplus was incorporated in a cost function. Minimisation of nitrogen in inputs conditional on the outputs results in minimising nitrogen surplus (conditional on output), due to the materials balance definition. If we specify the nitrogen-containing inputs in a cost function framework we do not have to model nitrogen surplus explicitly. In this framework we identify the cost-efficient production and the nitrogen-efficient production. Nitrogen efficiency is defined as the ratio of minimum application to observed application of nitrogen conditional on desirable output, the quasi-fixed inputs and nitrogen content of variable inputs. Nitrogen efficiency has a technical and an allocative component similar to cost efficiency. The nitrogen content of the variable inputs determines the optimal ratio of these inputs from an environmental point of view. A shadow cost system is used which allows a farmer to deviate from cost-minimising behaviour; he minimises shadow costs instead of market costs. Shadow prices are modelled as price distortion factors of market prices. Nitrogen distortion factors are added to the estimation results to calculate minimum nitrogen input. The relation between economic efficiency and environmental efficiency determines the (economic) sacrifice that is necessary to decrease the nitrogen surplus. The nitrogen surplus at nitrogen efficient production is half the current nitrogen surplus, the costs only increase by three percent.

The variation in environmental efficiency is explained in a second stage analysis. We assume that environmental efficiency scores originate from omitted variables in the (first stage) stochastic frontier analysis. A model of dairy farming is constructed based on different models of dairy farming (different aggregation level, different scientific background). This model is compared to the first stage translog production frontier. Omitted factors, measurement errors and aggregation of variables define the potential explanatory variables. Environmental efficiency scores from the first stage are regressed against the potential explanatory variables in a second stage stochastic frontier analysis. The second stage parameter estimates reflect impacts of the explanatory variables on environmental efficiency. This second stage stochastic frontier methodology also supplies an adjusted environmental efficiency measure that identifies farms with the largest environmental efficiency conditional on the explanatory variables. Variables that describe: the labour quality (e.g. number of years they participate in FADN), the nitrogen content of inputs and outputs, capital specification (herd size and milk yield), physical environment and institutional environment, significantly affect the environmental efficiency scores. Environmental efficiency can be improved, for instance by encouraging a higher milk yield (stimulating genetics research) or by providing the farmer with more insight in the nutrient balance of his farm.

The value of the developed environmental efficiency measures is determined by comparing them to environmental indicators currently used. Indicators are parameters that summarise or otherwise simplify and communicate relevant information. Currently partial measures such as nitrogen surplus per hectare are used to provide information on the environmental pressure caused by farms. The virtue of the developed econometrically estimated environmental efficiency measures is that they combine the economic and technical performance of the farm to its environmental pressure. These measures also take stochastic disturbances (e.g. weather conditions and diseases) into account. These environmental efficiency scores are very suitable for a solid analysis of the environment problems. The byproducts of this analysis provide for instance information about the technological development of firms. A disadvantage of these measures is that they are relatively expansive to obtain; for a quick insight in the partial measures are more suitable. Moreover the different environmental efficiency measures provide diverse results. Another disadvantage of the econometric efficiency measures is that they cannot be estimated if only a few observations are available. In that case DEA is an attractive alternative.

Samenvatting

Lange tijd was het vergroten van de productiviteit het belangrijkste doel van het landbouwbeleid. De productiviteit in de landbouw is na de tweede wereldoorlog snel gestegen; door de technologische ontwikkeling kon arbeid worden vervangen door kapitaalgoederen, bestrijdingsmiddelen, kunstmest en voer. Deze laatste productiemiddelen hebben in Nederland tot milieuproblemen geleid. De stikstofuitstoot van de veehouderij was de belangrijkste oorzaak van te hoge gehaltes van nitraat in het grondwater en emissie van ammoniak. De uitstoot van ammoniak draagt bij aan 'zure regen'. De beleidsdoelen van de overheid ten aanzien van de landbouw zijn gewijzigd; nu wordt gestreefd naar een concurrerende en duurzame landbouw en veilig voedsel. Deze doelstelling komt tot uitdrukking in wet- en regelgeving ten aanzien van de productie en gebruik van dierlijke mest. Zo moeten sinds 1998 melkveehouderijbedrijven met meer dan 2,5 koeien per ha, een mineralenboekhouding bijhouden en een heffing betalen voor een mineralenoverschot. Voor de overheid is het van groot belang om na te gaan welke landbouwbedrijven zowel goed omgaan met de traditionele productiemiddelen (bijvoorbeeld kapitaalgoederen en voer) als ook zuinig omgaan met het milieu; deze zijn zowel concurrerend als duurzaam. Overeenkomstig het traditionele landbouwbeleid is er veel onderzoek uitgevoerd om de productiefactoren en producten te analyseren. Met de toenemende aandacht voor het milieu zijn ook de prestaties van het bedrijf op milieugebied belangrijker geworden. Hoewel er indicatoren zijn die òf de economische prestaties òf de milieuprestaties van een landbouwbedrijf in beeld brengen, is er geen maatstaf voorhanden die beide op een consistente wijze combineert in een kengetal. De standaard methode om de milieubelasting en het productieproces in een getal te vangen is een partiële maatstaf, zoals stikstofoverschot per ha. Het nadeel van deze eenvoudige kengetallen is dat ze slechts een klein deel van het relevante productieproces beschrijven. Beleidsaanbevelingen op basis van deze partiële maatstaven leiden dan vaak tot buitensporig gebruik van productiefactoren die niet zijn opgenomen in de partiele maatstaf.

De methodologie om technische en economische efficiency van bedrijven te berekenen, is een aantrekkelijk raamwerk om ook de milieuprestaties van bedrijven mee te bepalen. Technische efficiency maakt duidelijk of de ingezette middelen optimaal worden benut. Allocatieve efficiency geeft aan in hoeverre de productiemiddelen in de beste verhouding worden ingezet. De combinatie van technische en allocatieve efficiency geeft de economische efficiency weer (de mate waarin de kosten kunnen worden verlaagd). Efficiency scores worden uitgedrukt op een schaal van 0 tot 1, waarbij een efficiënt bedrijf een score 1 heeft. Het efficiënte bedrijf is dus maatgevend voor de andere bedrijven. Voordelen van dit efficiency raamwerk zijn bijvoorbeeld dat voor de berekening van technische efficiency maatstaven geen prijsinformatie nodig is, verder geven deze maatstaven de grootte van de mogelijke verbeteringen weer. Ook spoort de efficiency methodologie met het veelvuldig gebruik van eco-efficiency en milieu-efficiency in beleidsrapporten. In de efficiency literatuur worden twee belangrijke methoden onderscheiden; mathematische programmering methoden en econometrische methoden. In dit proefschrift gaat de aandacht uit naar de econometrische methoden. Deze laatste hebben de voorkeur in de landbouw, waar het productieproces met veel onvoorziene factoren te maken heeft. De drie belangrijkste manieren om efficiency econometrisch te bepalen zijn (i) de stochastische frontier methode; met een frontier wordt de grens van wat technisch en economisch haalbaar is op een bepaald moment weergegeven (ii) de afstandfunctie (iii) de kostenfunctie.

Recent is in de literatuur de efficiency methodologie ingezet voor milieuproblemen. Milieu-efficiency scores zijn echter alleen nog via mathematische programmering berekend. Om milieu-efficiency econometrisch te kunnen bepalen moeten de milieubelastende stoffen op een correcte wijze worden opgenomen in het standaard neoklassieke economische raamwerk. Het belangrijkste milieuprobleem van de melkveehouderij is de uitstoot van stikstof. Daarom concentreert dit onderzoek zich op het stikstofoverschot. Aangezien stikstof op een groot aantal plaatsen via het productieproces in het milieu terechtkomt, is de stikstofuitstoot van een melkveebedrijf nauwelijks te meten. De hoeveelheid stikstofvervuiling wordt doorgaans bepaald door middel van de materiaalbalans als het verschil tussen stikstof in productiemiddelen (voornamelijk kunstmest en aangekocht veevoer) en stikstof uit de gewenste producten (voornamelijk melk en vlees). Voor dit onderzoek wordt gebruikgemaakt van het Bedrijven-Informatienet van het LEI. Uit dit bestand zijn de sterk gespecialiseerde melkveehouderijbedrijven geselecteerd, van deze bedrijven is vanaf 1991 gedetailleerde informatie beschikbaar van hun mineralenboekhouding.

De doelstelling van dit onderzoek is het definiëren, schatten en evalueren van de milieu-efficiency van Nederlandse melkveehouderijbedrijven.

In hoofdstuk 2 is de stochastische productiefrontiermethode (SFA) gebruikt om milieu-efficiency te berekenen. Stikstofoverschot is gemodelleerd als een productiemiddel in het productieproces. Milieuvervuilende stoffen en productiemiddelen werken op dezelfde manier in, op de productiefrontier. Standaard schat SFA hoeveel de productie kan toenemen totdat de frontier is bereikt; gegeven de gebruikte productiemiddelen. Om milieu-efficiency te kunnen berekenen is deze output oriëntatie van SFA getransformeerd in een input besparende oriëntatie. Milieu-efficiency is gedefinieerd als de verhouding van het minimaal mogelijke stikstofoverschot tot het geobserveerde stikstofoverschot. De gemiddelde milieu-efficiency score van de onderzochte melkveehouderijbedrijven is 0,44. Volgens dit model kan de uitstoot van stikstofoverschot met 56% worden gereduceerd bij een gelijkblijvende productie.

In hoofdstuk 3 is de hierboven beschreven methode aangepast om de milieu-efficiency te kunnen berekenen van verscheidene milieuvervuilende stoffen. De milieu-efficiency scores zijn gebaseerd op stikstofoverschot, fosfaatoverschot en het totale energieverbruik (directe energie en indirecte energie). De berekening van milieu-efficiency is gebaseerd op de maximale evenredige vermindering van de milieubelastende productiemiddelen. We tonen aan dat deze maatstaf kan worden geschat in SFA en DEA ('dataomhullingsmethode'). De door de neoklassieke theorie opgelegde veronderstellingen van afnemende meeropbrengsten worden geschonden in de SFA-aanpak als we deze drie milieubelastende productiemiddelen meenemen in de schatting. De SFA-scores zijn daarom gebaseerd op stikstofoverschot en energie (gemiddelde milieu-efficiency is 0,80). DEA legt deze veronderstellingen op, dus kunnen de milieu-efficiency scores op basis van de drie vervuilende stoffen met DEA worden berekend (gemiddeld 0,52).

In de voorgaande hoofdstukken werden de milieubelastende stoffen gemodelleerd als productiemiddelen. De afstandfunctie staat toe dat meer dan één eindproduct wordt gemodelleerd. In hoofdstuk 4 wordt het stikstofoverschot beschouwd als een ongewenst eindproduct van de melkveehouderij. Door de materiaalbalans definitie van stikstofoverschot hangt dit overschot af van de hoeveelheid stikstof in productiemiddelen en in eindproducten. Als de productiemiddelen gegeven zijn, is ook de hoeveelheid stikstof in productiemiddelen gegeven en hangen productie en stikstofoverschot negatief met elkaar samen. Met de afstandsfunctie wordt technische efficiency bepaald als de maximale evenredige toename van alle eindproducten. Dit verschaft ons geen bruikbare maatstaf voor milieu-efficiency omdat ook de hoeveelheid milieubelastende stof toeneemt in de efficiënte situatie. We bepalen ex-post de opbrengsten om milieu-efficiency scores te berekenen, bij de berekening van de opbrengst wordt de milieuvervuilende productie negatief of niet gewaardeerd. Milieu-efficiency geeft aan in hoeverre de waargenomen mix van eindproducten afwijkt van de voor het milieu optimale mix. Grondstoffenefficiency combineert technische efficiency met milieu-efficiency en is gedefinieerd als de verhouding van de geobserveerde opbrengsten en de maximale opbrengsten, gegeven de productiemiddelen en een niet-positieve prijs van de milieubelastende stof. De gemiddelde grondstoffenefficiency is 0,725. De milieu-efficiency en grondstoffen efficiency nemen toe met het aantal koeien per ha.

Om gedragsveronderstellingen (zoals kosten minimalisatie door de landbouwer) in te kunnen bouwen, is het stikstofoverschot ook gemodelleerd in de kostenfunctie. Als we uitgaan van een gegeven hoeveelheid eindproduct en de hoeveelheid stikstof in de productiemiddelen wordt geminimaliseerd dan wordt ook het stikstofoverschot geminimaliseerd. Als de stikstofhoudende productiemiddelen worden gespecificeerd in een kostenfunctie dan behoeven we niet meer expliciet het stikstofoverschot te modelleren. Stikstofefficiency is gedefinieerd als de verhouding van de minimale tot de waargenomen hoeveelheid stikstof in de productiemiddelen, gegeven de productie, de vaste productiemiddelen en het stikstofgehalte van de variabele productiemiddelen. Normaliter wordt er vanuit gegaan dat melkveehouders de werkelijke kosten minimaliseren. Persoonlijke voorkeuren van een landbouwer kunnen er toe leiden dat hij hiervan afwijkt, hij minimaliseert dan schaduwkosten in plaats van de marktkosten. We hebben een schaduwkostenfunctie geschat, waarin we deze schaduwkosten modelleren. De schattingsresultaten van deze schaduwkostenfunctie en de stikstofgehaltes van de variabele productiemiddelen worden gebruikt om de stikstofefficiency scores te berekenen. De relatie tussen stikstofefficiency en economische efficiency geeft de kosten weer die verbonden zijn met het verminderen van het stikstofoverschot. Het stikstofoverschot bij stikstofefficiënte productie is minder dan de helft van het huidige overschot, terwijl de kosten slechts met drie procent toenemen.

De gevonden verschillen in milieu-efficiency scores tussen bedrijven worden verklaard in een twee stappen analyse. We veronderstellen dat we milieu-efficiency scores vinden omdat niet alle relevante variabelen zijn meegenomen in de berekening van deze scores. Een denkmodel van de melkveehouderijproductie is samengesteld uit verschillende modellen die afkomstig zijn van verschillende wetenschappelijke disciplines en die verschillende aggregatie niveaus van de melkveehouderij processen beschrijven (bijvoorbeeld: gras is het laagste niveau). De specificatie van de frontier in de eerste stap van de analyse (hoofdstuk 2) wordt vergeleken met dit model. Factoren die niet zijn meegenomen in de specificatie van de productiefrontier, meetfouten en aggregatie van variabelen bepalen de verklarende variabelen van de tweede stap (onder andere de melkgift per koe, het aantal jaren dat bedrijven participeren in het Bedrijven-Informatienet van het LEI). In de tweede stap gebruiken we nog een keer SFA om de milieuefficiency scores te relateren aan verklarende variabelen, de schattingen van de parameters geven de inwerking van deze variabelen op de milieuefficiency weer. Deze tweede stap levert ook bijgestelde milieu-efficiency scores op, deze zijn gecorrigeerd voor de verschillen in de verklarende variabelen tussen bedrijven. Dit resulteert in de conclusie dat de milieu-efficiency kan worden vergroot door te bevorderen dat de melkgift per koe toeneemt of door melkveehouders meer inzicht te geven in hun mineralenbalans.

Het nut van de ontwikkelde milieu-efficiency maatstaven wordt bepaald door ze te vergelijken met de milieu-indicatoren die nu worden gebruikt in het beleid. Indicatoren zijn parameters die complexe en belangrijke processen vereenvoudigd weergeven en de communicatie vergemakkelijken. Op dit moment worden partiële kengetallen gebruikt, zoals stikstofoverschot per ha, om de milieubelasting door nutriënten in beeld te brengen. Het voordeel van de ontwikkelde econometrische milieu-efficiency maatstaven is dat ze de economische en technische prestatie van het bedrijf koppelen aan de geproduceerde milieubelasting. Ze houden ook rekening met stochastische verstorende invloeden (bijvoorbeeld weersomstandigheden, ziekten). Voor een grondige analyse van de milieuproblematiek zijn deze milieu-efficiency scores erg geschikt. De bijproducten van de analyse leveren informatie op over onder andere de technologische ontwikkeling van bedrijven. Een nadeel van deze maatstaven is dat het relatief kostbaar is om ze te bepalen; voor een snel inzicht zijn de partiële indicatoren een beter hulpmiddel. Bovendien geven de verschillende milieu-efficiency maatstaven nog zeer uiteenlopende resultaten. Een ander nadeel van de econometrische efficiency indices is dat ze onmogelijk kunnen worden geschat met weinig waarnemingen. In dat geval is DEA een aantrekkelijk alternatief.

Curriculum Vitae

Augustinus Joseph Reinhard werd op 13 november 1961 geboren in de stad Utrecht. Hij bezocht het Coornhert gymnasium in Gouda en behaalde in 1980 het diploma. Daarna studeerde hij aan de (thans) Wageningen Universiteit. Hij liep in 1985 stage bij de Klamath Indian tribe in Oregon (VS). In 1988 studeerde hij af met hoofdvakken cultuurtechniek en algemene agrarische economie en bijvakken informatica en staathuishoudkunde. Voor zijn scriptie cultuurtechniek en informatica (een simulatiemodel voor de Klamath tribe) ontving hij de Wageningen scriptieprijs. Vanaf 1986 tot zijn afstuderen werkte hij als werkstudent bij de vakgroep Algemene Agrarische Economie van de Wageningen Universiteit. Van 1 mei tot 1 oktober 1988 was hij medewerker van voorgenoemde vakgroep. Vanaf 1 oktober 1988 is hij in dienst bij het Landbouw-Economisch Instituut in Den Haag, eerst bij de afdeling Structuuronderzoek en later bij de afdeling Landbouw. Op deze laatste afdeling werkte hij van augustus 1995 tot mei 1999 aan dit promotieonderzoek. In december 1997 kreeg hij het diploma van het Netwerk Algemene en Kwantitatieve Economie (NAKE) uitgereikt.